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**Mikko Nurmi**

# Temporal constraints and creativity in bass lines of eminent jazz musicians

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UNIVERSITY OF JYVÄSKYLÄ  
FACULTY OF HUMANITIES AND  
SOCIAL SCIENCES

JYU DISSERTATIONS 679

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**Mikko Nurmi**

# **Temporal constraints and creativity in bass lines of eminent jazz musicians**

Esitetään Jyväskylän yliopiston humanistis-yhteiskuntatieteellisen tiedekunnan suostumuksella  
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## ABSTRACT

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The first main aim of this exploratory research is to investigate how temporal constraints (as operationalized by tempo and harmonic rhythm) are related to creativity in pattern use (as operationalized by the variability of melodic patterns) in bass lines of eminent jazz bassists. As the second main aim, the research investigates whether learning a large storage of melodic patterns is a necessary requirement for creativity in the generation of bass lines. The research material consists of 42 transcribed bass lines by Paul Chambers and Ron Carter, which corresponds to 9,335 bars of notation. In this study, the original bass lines were reduced to sequences of quarter notes.

Kendall's tau partial correlation analysis was performed to determine the relationship between tempo/harmonic rhythm and the variability of melodic patterns, when controlling for the length of analyzed bass line reductions. The research was not able to find statistically significant correlations between tempo/harmonic rhythm and the variability of melodic patterns. In Paul Chambers's bass line reductions ( $n = 30$ ), the results indicated a statistically non-significant and weak negative correlation between tempo and the variability of melodic patterns (mean absolute  $\tau\text{-}b = .18$ ) and a statistically non-significant and negligible correlation between harmonic rhythm and the variability of melodic patterns (mean absolute  $\tau\text{-}b = .08$ ). In Ron Carter's bass line reductions ( $n = 12$ ), the results indicated a statistically non-significant and weak correlation between tempo and the variability of melodic patterns (mean absolute  $\tau\text{-}b = .15$ ) and a statistically non-significant and weak correlation between harmonic rhythm and the variability of melodic patterns (mean absolute  $\tau\text{-}b = .14$ ). Although the results are inconclusive, they provide preliminary evidence that tempo and harmonic rhythm may have a small or negligible effect on the variability of melodic patterns in bass lines of eminent jazz bassists. Except for the relationship between tempo and the variability of melodic patterns in Paul Chambers's bass line reductions, the results did not allow to make conclusions on effect directions.

In Paul Chambers's bass line reductions, 15.8% to 16.9% of all recurring melodic pattern classes occurred at least twice in two or more bass line reductions and covered 41.2% to 83.2% of all melodic patterns depending on pattern length. In Ron Carter's bass line reductions, 11.2% to 19.4% of all recurring melodic pattern classes occurred at least twice in two or more bass line reductions and covered 13.4% to 63.1% of all melodic patterns depending on pattern length. The results indicate that even if recurring melodic pattern classes covered a large proportion of all melodic patterns at least when the length of analyzed melodic patterns was only two notes, a large proportion of recurring melodic pattern classes did not occur at least twice in two or more bass line reductions. This finding suggests that pre-learned melodic patterns may have a surprisingly small role in the generation of jazz bass lines at least for Paul Chambers and Ron Carter.

Keywords: temporal constraints, creativity, jazz, improvisation, expertise

## TIIVISTELMÄ (ABSTRACT IN FINNISH)

Nurmi, Mikko

Ajalliset rajoitteet ja luovuus huipputason jazzmuusikoiden bassolinjoissa

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Tämän eksploratiivisen tutkimuksen ensimmäisenä päätavoitteena on selvittää, miten päätöksentekoon ja toiminnan suunnitteluun käytettävissä oleva aika (esitettävän musiikin tempon ja harmonisen rytmin mukaan mitattuna) on yhteydessä luovuuteen huipputason jazzbasistien bassolinjoissa, kun luovuutta mitataan sävelkuvioiden vaihtelevuutena. Tutkimuksen toisena päätavoitteena on selvittää, onko laajan tietovaraston oppiminen välttämätön edellytys luovuudelle bassolinjojen rakentamisen yhteydessä. Aineisto koostuu 42:sta Paul Chambersin ja Ron Carterin bassolinjan nuotinnoksesta, joissa kaikki neljäsosanuoteista poikkeavat sävelkestot on joko poistettu tai muutettu neljäsosanuoteiksi. Aineiston koko vastaa 9 335 tahtia nuotinnoksia.

Tutkimuksessa käytettiin Kendallin osittaisjärjestyskorrelaatiota selvittämään, miten esitettävän musiikin tempo ja harmoninen rytmi ovat yhteydessä sävelkuvioiden vaihtelevuuteen, kun bassolinjareduktioiden pituuden vaikutus tuloksiin on poistettu. Tutkimuksessa ei löydetty tilastollisesti merkitseviä yhteyksiä tempon/harmonisen rytmin ja sävelkuvioiden vaihtelevuuden välillä. Paul Chambersin bassolinjareduktioissa ( $n = 30$ ) havaittiin tilastollisesti ei-merkitsevä ja heikko negatiivinen korrelaatio tempon ja sävelkuvioiden vaihtelevuuden välillä (keskimääräinen absoluuttinen  $\tau\text{-}b = .18$ ) ja tilastollisesti ei-merkitsevä ja käytännössä olematon korrelaatio harmonisen rytmin ja sävelkuvioiden vaihtelevuuden välillä (keskimääräinen absoluuttinen  $\tau\text{-}b = .08$ ). Ron Carterin bassolinjareduktioissa ( $n = 12$ ) havaittiin tilastollisesti ei-merkitsevä ja heikko korrelaatio tempon ja sävelkuvioiden vaihtelevuuden välillä (keskimääräinen absoluuttinen  $\tau\text{-}b = .15$ ) sekä harmonisen rytmin ja sävelkuvioiden vaihtelevuuden välillä (keskimääräinen absoluuttinen  $\tau\text{-}b = .14$ ). Tulokset antavat alustavaa näyttöä siitä, että tempolla ja harmonisella rytmillä saattaa olla vähäinen tai käytännössä olematon vaikutus sävelkuvioiden vaihtelevuuteen huipputason jazzmuusikoiden bassolinjoissa. Tulokset eivät mahdollistaneet efektin suuntaa koskevia päätelmiä lukuun ottamatta Paul Chambersin bassolinjareduktioita tempon ja sävelkuvioiden vaihtelevuuden välisen yhteyden osalta.

Vähintään kahdessa eri bassolinjareduktiossa ja vähintään kahdesti toistuvien sävelkuvioluokkien osuus kaikista toistuvista sävelkuvioluokista oli 15,8–16,9 prosenttia Paul Chambersin bassolinjareduktioissa (kattaen 41,2–83,2 prosenttia kaikista sävelkuvioista) ja 11,2–19,4 prosenttia Ron Carterin bassolinjareduktioissa (kattaen 13,4–63,1 prosenttia kaikista sävelkuvioista) sävelkuvioiden pituudesta riippuen. Tulokset viittaavat siihen, että vaikka toistuvat sävelkuvioluokat kattoivat suuren osan kaikista sävelkuvioista ainakin kun tarkasteltujen sävelkuvioiden pituus oli vain kaksi nuottia, suuri osa toistuvista sävelkuvioluokista ei esiintynyt toistuvasti vähintään kahdessa eri bassolinjareduktiossa. Sävelkuvioita koskevan tietovaraston koolla saattaa näin ollen olla yllättävän vähäinen merkitys ainakin Paul Chambersin ja Ron Carterin luovuudelle.

Avainsanat: ajalliset rajoitteet, luovuus, jazz, improvisointi, eksperttiys

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Mikko Nurmi

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ABSTRACT

TIIVISTELMÄ (ABSTRACT IN FINNISH)

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# 1 INTRODUCTION

Over the last 20 years or so, researchers' interest in creativity research has grown significantly especially in the fields of psychology, social sciences, arts and humanities, business and management, and education. As an example, a total of 3,250 papers related to creativity research were published in the year 2020 alone (Mejia et al., 2021). The amount of research is not surprising given the many benefits of creativity research. In addition to increasing our understanding of outstanding achievements, everyday innovations, and benefits of creativity in education and work, the research field has much to offer to help us understand our thinking, behavior, and our existence as human beings.

Creativity is ubiquitous in human life and underlies virtually all aspects of human existence (Boden, 2004). It is a universal ability to create original works of art, find novel solutions to problems, find new ways of doing everyday activities, make inventions, and create any other kinds of novel (or original, unique, unpredictable, etc.) products or ideas. In the present study, creativity is defined as novel (i.e., unpredictable, different) and appropriate products or ideas and the ability to create such products or ideas (where the novelty of a product or an idea only requires that it is new to the creator instead of the society). In this study, the function of the second component of the definition (appropriateness), however, is merely to remind that all actions are constrained and completely random actions are not the most creative ones.

The present research investigates creativity in bass lines of eminent jazz bassists. The research has two main goals. The first main goal is to investigate how temporal constraints in decision-making and action planning are related to creativity among expert jazz musicians. When tempo and/or harmonic rhythm are slow, improvising musicians have more time to make decisions and to plan their actions in a present musical context compared to a fast tempo and a fast harmonic rhythm. The question is how temporal constraints affect expert jazz musicians' playing and how expert jazz musicians can circumvent challenges related to time pressures. The second main goal is to determine the significance of learning a large storage of melodic patterns in expert jazz improvisation. Several studies have noted that jazz musicians often reuse the same melodic patterns in

their improvisations to some extent (e.g., Owens, 1974; Berliner, 1994; Weisberg et al., 2004; Norgaard, 2014; Norgaard & Römer, 2022). Even if jazz improvisers probably always make use of pre-learned melodic patterns at least to some extent, it is the claim that learning a large storage of melodic patterns is a necessary requirement for fluent jazz improvisation (e.g., Owens, 1995) which is questioned here. Implications on chunking theory, action planning, and other areas of interest are discussed. Finally, some basic mechanisms underlying musical creativity in jazz improvisation are reviewed and their relation to the present results are discussed with the aim of providing implications for further theory building and modeling on expert jazz improvisation.

The thesis is divided into eight main chapters. In Chapter 2, the main topics of the research (improvisation, creativity, expertise, and transfer of learning) are discussed in general. In addition, previous research on the role of executive functions in musical creativity, dual-processing theories, perceptual and motor chunking, anticipation of actions, and action planning is reviewed. In Chapter 3, memory for melodies and the significance of formulaic and schematic knowledge in jazz improvisation are discussed. In this chapter, I will also review important theories of jazz improvisation as well as implications from expert systems research, neuroscience of musical improvisation, and the 4E cognition and dynamic systems research. Finally, problems related to experts' insights into their creative process are discussed. In Chapter 4, various sources of idea generation are presented including a discussion on the role of sensory feedback in idea generation. In addition, the role of constraints on memory and the role of temporal constraints in imagery and generation of music are discussed. The chapter also includes a discussion on the role of context familiarity in jazz improvisation and the duration of integrated units in perception and action. In Chapter 5, the research questions and methods are presented. Chapter 6 presents the results of the study. In Chapter 7, conclusions from the study are discussed. Finally, limitations of the study and recommendations for further research are presented in Chapters 8 and 9.



## 2 IMPROVISATION, CREATIVITY, AND EXPERTISE

### 2.1 What is improvisation?

In the *Oxford Dictionary of Music*, improvisation is defined as follows: “a performance according to the inventive whim of the moment, i.e. without a written or printed score, and not from memory” (Kennedy et al., 2013, para. 1). In the *Grove Music Online*, improvisation is defined as:

The creation of a musical work, or the final form of a musical work, as it is being performed. It may involve the work’s immediate composition by its performers, or the elaboration or adjustment of an existing framework, or anything in between. To some extent every performance involves elements of improvisation, although its degree varies according to period and place, and to some extent every improvisation rests on a series of conventions or implicit rules. (Nettl et al., 2014, para. 1.)<sup>1</sup>

These two definitions address three claims which have been repeated in various publications: (1) improvisation is spontaneous invention generated in real time without a possibility for revision, (2) improvisation can only exist in absence of written scores, and (3) improvisation is not absolutely different from composition. I will next discuss the pros and cons of these claims.

The first claim, even if intuitively convincing, is not exactly true. Expert-level musicians frequently “post-edit” their own or other musicians’ ideas by playing whatever fits the context. By doing so, even the most surprising events are not seen as mistakes but merely events that need a response. (Torrance & Schumann, 2019, p. 254.) Also, it is not exactly true that all decisions in improvised music are done in “real time.” Improvising musicians always rely on musical knowledge that they have gathered throughout their lives. Without such musical knowledge, they could not know how to improvise within the limits of a particular musical style,

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1 Rules refer to “organizing principles which are independent of the specific material used in a given instance” (Perruchet & Pacton, 2006, p. 233).

for example. It is thus an exaggeration to claim that improvising musicians invent all their musical ideas from scratch during the performance.

The second claim, according to which improvisation can only exist in absence of notation, is problematic because it implies that composition and improvisation are two completely different things and fails to recognize improvisatory aspects in performance of composed music (see Gould & Keaton, 2000; Nettl, 1974). Compositions do not usually specify all aspects of how they should be performed and therefore two performances of the same composition can differ substantially (Whittall, 2011). There is also a spectrum of jazz styles regarding how improvisatory they are. On the other extreme, improvisation can merely refer to ornamentation of the melody, whereas any constraints can be abandoned at the other extreme (Torrance & Schumann, 2019)<sup>2</sup>. However, there are usually at least some constraints in jazz performance (e.g., fixed form, fixed chord progression, or fixed order of soloists).

According to the third claim, the distinction between composition and improvisation is not clear-cut. According to Nettl (1974), there is no essential difference between composition and improvisation. Instead, they can be merely seen as two ends of a continuum, where composers who work quickly and more or less spontaneously can be located on one end and composers who continually rework their music to achieve a result with which they were satisfied on the other (Nettl, 1974). However, Nettl's criticism of the distinction between composing and improvising is not entirely convincing. Johnson-Laird (1988, p. 210) argued that composition and improvisation must be based on at least partly different processes, since all skilled composers are not also skilled improvisers and vice versa. Although it may be difficult to identify whether a piece of music is composed or improvised based on listening experience (Lehmann & Kopiez, 2010; Engel & Keller, 2011),<sup>3</sup> any skilled composer may also be a great improviser only if he or she has acquired domain-specific skills for both activities.

Several researchers have underlined that improvisation refers to a multitude of practices. According to Nettl (2013), improvisation means too many different things to use a single concept. In his view, it is not clear whether everything from Schubert's improvisational style of composing, children's songs, virtuosic cadenzas, folk singers' variations of traditional songs to musicians playing Persian *radif* have enough common properties to justify the use of a single concept. Similarly, Alperson (2016, p. 428) argued that there is a large number of improvisatory practices even within jazz and that this multitude of practices makes it unlikely to find a single all-embracing model for improvisation.

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2 Also note that even if improvised solos have great importance in jazz, free flowing solos of indeterminate length are not always prioritized in jazz performances. For instance, many of the great big band performances led by jazz musicians such as Duke Ellington or Count Basie allowed only short solos to be performed by selected musicians (Torrance & Schumann, 2019).

3 In one study, music students were not able to distinguish between composed and improvised versions of music from the classical and romantic era (Lehmann & Kopiez, 2010). In another study, the accuracy of judging whether heard melodies were either improvised or imitated was 55% on average among a group of jazz musicians (Engel & Keller, 2011).

Several researchers have also noted that improvisation is a part of all or at least most of our actions. For example, Alperson (2016) claimed that “there is of course an element of improvisation in every intentional action or set of actions in the sense that every action is, in at least a minimal sense, a unique event that requires a degree of human agency” (p. 424). In addition, Iyer (2016) argued that “most behaviors include improvised and non-improvised components. [...] In light of these observations, it becomes more and more problematic to identify moments of ‘pure’ improvisation, or to disambiguate them from the execution of pre-ordained programs” (Iyer, 2016, p. 75).<sup>4</sup>

To avoid the above-mentioned problems, improvisation is defined here as a mode of performing any task which gives rise to a product that is, at least to some extent, unpredictable and not predetermined.

## 2.2 General perspectives on creativity

Creativity is a universal ability to create inventions and original artistic works, find novel solutions to problems, find new ways of doing everyday activities, and create any other kinds of novel (or original, unique, unpredictable, etc.) products or ideas. Creativity is “one of the defining features of humanity” (Wiggins et al., 2018, p. 287) and underlies virtually all aspects of human existence (Boden, 2004, p. 1). In addition to being a part of everyone’s daily life, creativity in science, medicine, technology, and several other areas have changed the world as we know it<sup>5</sup>. The volume of creativity research has grown significantly over the last 20 years or so, most notably in the fields of psychology, social sciences, arts and humanities, business and management, and education according to a search in the Scopus and the Web of Sciences databases. The research field is livelier than ever before with about 3,000 papers published annually at the moment (Mejia et al., 2021).

Despite this positive trend, the field has long suffered from widespread myths and negative assumptions (Plucker et al., 2004), some of which may still influence public understanding of creativity and the reputation of creativity research. For example, it is still widely believed that creativity somehow vanishes after childhood (Benedek et al., 2021) or that creativity usually follows from sudden or divine inspiration (Benedek et al., 2021; Kim, 2019). One of the most stubborn myths related to creativity is that creativity is a rare trait (Plucker et al., 2004). This misunderstanding is probably caused by the historical association of mystical qualities and creativity,<sup>6</sup> and the traditional emphasis on the creativity of

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4 The ubiquity of improvisation in life has led some authors (e.g., Torrance & Schumann, 2019) to suggest that improvisation should be given a more important role in cognitive science. Musical improvisation, especially jazz improvisation, is often thought to be an ideal paradigm for the scientific study of spontaneous creativity (Weisberg et al., 2004; McPherson & Limb, 2013; Faber & McIntosh, 2019).

5 Note that creativity is not always a positive thing. One can also be creative for immoral, malevolent, and criminal purposes (Cropley, 2011).

6 An association between mysticism and creativity dates back to possibly the earliest views of creativity, where creative products were seen as a result of an unexplained

highly eminent experts (Plucker et al., 2004, p. 84). Particularly harmful, Plucker and his colleagues observed that:

Creativity is too often associated with negative assumptions and characteristics held by researchers, practitioners, and laypeople. As a result, people who study problem solving, abductive reasoning, cognitive flexibility, or functional fixedness would never dare utter the 'C word,' yet they are essentially investigating aspects of creativity. (Plucker et al., 2004, p. 85.)

Several researchers (e.g., Parkhurst, 1999; Plucker et al., 2004) have also criticized the existence of various definitions of creativity and that researchers have not always provided any explicit definition of the concept at all in their publications (Plucker et al., 2004)<sup>7</sup>. For instance, in a sample of 90 scientific articles published between 1996 and 2002 with the word 'creativity' in their title, 38% of these articles included an explicit definition of creativity while 21% included no definition at all (Plucker et al., 2004). Puryear and Lamb (2020) recently attempted to replicate the results of Plucker et al. (2004) by using a large sample of publications (600 articles) ranging from 2004 to 2016. According to their results, the proportion of articles with an explicit definition of creativity was higher (53%) compared to Plucker et al.'s sample (38%). The proportion of articles from 2013 to 2016 in which the concept of 'creativity' was not defined at all was 9% (compared to 21% in the sample of Plucker and his colleagues).

Although the exact definition of creativity is still an open question (Sternberg & Kaufman, 2018), the basic components of the standard definition of creativity are mentioned in most definitions of creativity (Said-Metwaly et al., 2017, p. 243)<sup>8</sup>. For example, most authors who participated in the *Handbook of Creativity* (published in 1999) endorsed "the idea that creativity involves the creation of an *original* and *useful* product" (Mayer, 1999, p. 449). Similarly, Mumford (2003) wrote: "over the course of the last decade [...] we seem to have reached a general agreement that creativity involves the production of novel, useful products" (p. 110). More recently, Brandt (2021, p. 1) argued: "in a field with many hotly debated questions, creativity as some version of novel-and-appropriate has become widely accepted [...] and underlies almost every experiment." According to Puryear and Lamb (2020), novelty was explicitly mentioned in 90% of the articles published between 2004 and 2016. After novelty, the most usual component in explicit definitions of creativity was usefulness or appropriateness (mentioned in 73% of the articles). Even Parkhurst (1999, p. 3), after claiming that there is no

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divine intervention where a person was suddenly filled with otherworldly inspiration (Sternberg & Lubart, 1999).

7 Of course, this problem is not solely related to creativity research. As an example, the concept of musicality is often used in even academic contexts as such a broad construct that its meaning is obscured – making it necessary to narrow the scope and meaning of the concept (Nurmi, 2019).

8 According to the standard definition of creativity, creative products are both original (or novel, unique, etc.) and effective (or useful, valuable, appropriate, etc.) (Runco & Jaeger, 2012, p. 92). There are also other versions of this definition. For example, Plucker and Beghetto (2004) argued that the "two key elements in the definition of creativity are novelty (i.e., original, unique, new, fresh, different) and usefulness (i.e., specified, valuable, meaningful, relevant, appropriate, worthwhile)" (p. 157).

general agreement on what creativity means, noted: “the one area of agreement among writers on this topic is that creativity is demonstrated by some sort of novel outcome.” In addition, Parkhurst noted that novelty has been considered a primary component of creativity ever since the beginning of modern creativity research (Parkhurst, 1999, pp. 15-16)<sup>9</sup>.

The notion of creativity has also been criticized for its “imprecision and subjectivity” (Wiggins et al., 2018, p. 287). However, it should be noted that both alleged drawbacks can mean different things, and therefore it is unclear what is actually criticized. Regarding the subjectivity of creativity judgments, no product is inherently creative or non-creative (if one accepts the view that all creativity judgments are necessarily social or communal). For example, Gardner (1994, p. 145) argued that “no person, act, or product is creative or noncreative in itself. Judgments of creativity are inherently communal, relying heavily on individuals expert within a domain.” Second, this claim can refer to a view that both external evaluation of creativity and creativity tests are subjective measures of creativity, since external judgments are based on subjective criteria and most tests use expert judges to validate their method of measurement (Katz & Giacommelli, 1982). The claim that creativity is an imprecise or vague concept can also mean different things. First, it can mean that definitions of creativity cannot distinguish between creativity and non-creativity or between creativity and closely related concepts such as intelligence. Second, this claim can refer to the lack of details in definitions of creativity. For example, Kamylyis and Valtanen (2010) argued that it is often not clear whether an external evaluation of creativity is required, whether it is enough that a product is novel and appropriate to an individual (in contrast to the society), and to what extent a product should be novel and appropriate to be considered as a creative product (Kamylyis & Valtanen, 2010, p. 203).<sup>10</sup> Even if more clarity in criticism regarding the definition of creativity is certainly needed, it is important to take seriously “the view that creativity is a highly complex and multidimensional phenomena” (Dietrich, 2019a, p. 38). Given this view, it is no wonder that an all-encompassing definition of creativity is hard to come by.

Although the standard definition of creativity is widely accepted, there are several reasons why disputes on the definition of creativity continue to occur. For example, Diedrich et al. (2015) found that novelty and usefulness are not equally important criteria for creativity: usefulness plays a role in creativity assessment only if ideas or products are highly novel.<sup>11</sup> Also, it is still an open question

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9 The beginning of modern creativity research is often associated with Guilford’s (1950) presidential address to the American Psychological Association (e.g., Piirto, 1992, p. 12; Copley, 2011; Rhodes, 1961). Even though this was an important event in the history of creativity research, the development of creativity research had started earlier and because of Guilford’s presidential address “[it] simply moved into a phase in which applications and evaluation are receiving more attention” (Barron, 1988, p. 76).

10 To avoid ambiguity in creativity research, Plucker et al. (2004, p. 92) suggested that researchers should explicitly define the concept of creativity in their publications, “avoid using scores of creativity measures as the sole definition of creativity,” explain how their definition of creativity is similar or different from other definitions, and “address the question of creativity for whom and in what context.”

11 Runco et al. (2005) only found a weak correlation between the originality and appropriateness scores in divergent thinking tests. In another study, Runco and Charles

whether creativity requires other components in addition to novelty, and if so, what those components might be (Sternberg & Kaufman, 2018). Some have also questioned whether creativity can be defined at all. According to Silvia (2018, p. 292), “a consistent definition of creativity” can only be achieved if we allow its constituent criteria (novelty, usefulness, appropriateness, etc.) to mean many different things. As another problem related to the standard definition of creativity, conceptions of creativity are culture-dependent (Shao et al., 2019). The Western conception of creativity is product-oriented and emphasizes originality, but these qualities are less important in Eastern cultures (Lubart, 1999). For example, creative individuals are expected to defy the crowd in the United States. In contrast, appropriateness is valued over novelty in China. Chinese people also tend to place more emphasis on practice and learning, whereas people in the United States are more likely to concentrate on providing inspiration at early age. (Niu & Kaufman, 2013.)<sup>12</sup>

The standard definition may also underestimate the prevalence of creativity. There are various degrees of creativity where the smallest variability of actions presents the lowest level of creativity and the most groundbreaking works of science, innovation, arts, music, and other forms of culture presents the highest level of creativity. Whereas the latter kind of creativity is rare, all actions are creative (at the lowest level) since it is impossible to reproduce any action with perfect accuracy. Such an accuracy can only be achieved with the use of machines. In other words, actions are never absolutely non-creative if even the smallest amount of variability is a sufficient condition to consider something as a creative action. For example, it is impossible to replicate movements without any variation, even though variability in motor actions is known to decrease with practice (Dhawale et al., 2017). Human actions are also inherently subject to variability in the sense that random fluctuations are indicated at all levels of the nervous system, from neural activity to motor control and motor execution (for reviews, see Faisal et al., 2008; Renart & Machens, 2014).

Researchers have been reluctant to consider actions that are only slightly different from others as instances of creativity. For example, Kaufmann (2003) argued that creativity is not “applicable to any small difference relative to the existing state of affairs” (p. 242)<sup>13</sup>. However, setting a threshold level for what

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(1993) found an inverse relationship between originality and appropriateness, which indicates that creative responses are not necessarily both original and appropriate.

12 One can distinguish between a weak and a strong form of the culture-bound creativity thesis, the latter of which states that there are no standard components of creativity that are shared between all cultures. According to a weak form of the thesis, people from diverse cultures have different conceptions of creativity and they appreciate different aspects of creativity (Shao et al., 2019). In this sense, there could be both culture-independent core components of creativity (e.g., novelty), culture-bound components of creativity that are used to evaluate creative products (e.g., value, usefulness, relation to tradition, etc.), and cognitive processes that are used more often in some cultures compared to others.

13 Kaufmann (2003) also suggested that creativity should only refer to novel and unconventional actions. However, most expert-level jazz improvisers, for example, would fail to be recognized as creative persons if unconventionality was a necessary criterion for creativity. Only those jazz improvisers who produced unconventional products in

actions are sufficiently novel may lead to considerable problems. In addition, there are at least three other reasons why it is helpful to identify several degrees of creativity from the basic variability of actions to the most respected achievements of all times. First, increasing knowledge on processes involved in variability of actions may also increase our knowledge on processes that underlie higher-level creativity (e.g., creativity of eminent jazz improvisers). Second, variability is often a valued aspect of actions. For instance, variability in loudness and tempo have been linked to spontaneity (Chaffin et al., 2007; Keller et al., 2011), which is a highly valued aspect of music in several musical traditions. Finally, identification of various degrees of creativity could help us to increase our understanding of the function of creativity in general.

It is also important to note that the standard definition of creativity is focused on products and does not specify any underlying processes that lead to the emergence of novel and useful products (see Glăveanu, 2018; Glăveanu & Beghetto, 2020). There are several types of creativity (which may not share the same underlying processes) and different sociocultural conceptions of creativity (with different assumptions on advantages and disadvantages of creative behavior). For example, Dietrich (2019b) underlined that creativity cannot be reduced to any single process or mechanism and proposed a classification of three subtypes of creativity: deliberate mode, spontaneous mode, and flow mode. Glăveanu (2018) also distinguished between three types of creativity: spontaneous creation of original artworks, invention in science and technology, and creativity in craftsmanship and everyday living – each of which has its own history and relation to society. In accordance with Dietrich (2019b), Glăveanu (2018) argued that “creativity is not a unitary construct or phenomenon [...] it is a scientific label applied to a variety of human actions or activities that leads to outcomes appreciated as more or less to novel, original, valuable or meaningful” (p. 25).

In his highly influential article, Rhodes (1961) identified four perspectives in definitions of creativity: creativity as a product, creativity as a process, characteristics of creative individuals (e.g., their personality, values, intelligence, and so on), and the environment or context in which creativity takes place (which may encourage or inhibit creative idea generation or influence creative process in some way)<sup>14</sup>. The two first mentioned perspectives are essential to the current study<sup>15</sup>. From the products perspective, creativity refers to any kind of tangible or intangible outcome or idea which is novel and appropriate either to its creator

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relation to their time, such as Ornette Coleman in the 1950s and 1960s, would be recognized as creative persons.

- 14 The diversity of work labelled as creativity research and the need to address new questions that have been previously ignored have recently led to the rise of new frameworks for creativity research. For example, Glăveanu (2013) proposed a five A's framework with the aim of drawing more attention to relationships between different components of creativity and to place creative actors in a larger sociocultural context. In addition, Lubart (2017) proposed a classification of creativity research based on seven main themes: Creators, Creating, Collaborations, Contexts, Creations, Consumption, and Curricula.
- 15 Characteristics of creative individuals and environmental perspectives are beyond the scope of the present study and will not be discussed further.

or to the society. From the process perspective, creativity is any kind of an activity or mechanism which produces a tangible or intangible outcome or idea that is novel and appropriate either to its creator or the society. However, it is not always possible to distinguish between creativity as a process and creativity as a product since a new way of doing something does not always lead to a creative outcome besides the act itself. For example, washing the dishes in a new way is a creative action but the outcome of this action is inseparable from the process. In other words, the process of washing the dishes in a new way is a creative action because it produces a novel and appropriate solution to washing the dishes.

### **2.2.1 Creative products perspective**

As noted in the previous chapter, the standard definition of creativity states that creative products are both original (or novel, unique, etc.) and effective (or useful, valuable, appropriate, etc.) (Runco & Jaeger, 2012, p. 92). A number of details are not specified with this definition (e.g., the question of whether creativity requires that no one else has ever come up with similar products or not). To clarify this problem, I will discuss some useful distinctions that have been proposed in previous studies.

According to Boden (2004), psychological creativity refers to the emergence of novel and valuable ideas from that person's point of view who created them. In this type of creativity, it makes no difference if someone else has produced similar ideas before. In contrast, historical creativity refers to novel and valuable ideas that no one else has produced before. (Boden, 2004, p. 2.) Researchers have disagreed whether creativity refers to products which are novel to its creator (cf. psychological creativity) or products which are novel to society (cf. historical creativity) (see Parkhurst, 1999; Cropley, 2011). It is important to note that the answer to this problem has important implications on the prevalence of creativity. If creative products must be novel to society, much of everyday creativity would be disregarded since many ideas which first seem to be novel may later turn out to be invented a long time ago.

One can also distinguish between personal creativity and external creativity. Csikszentmihalyi (2013, p. 25) defined personal creativity as a form of creativity, where a person develops novel ideas without anyone else knowing about that. Here, creativity is evaluated based on a subjective evaluation of one's own work. In contrast, the evaluation of creativity may also occur externally by relevant others. As a special case of external evaluation, consensual creativity requires that the creativity of products is judged by relevant others (e.g., stakeholders, critics, or experts), and that these judges agree on the creativity of that product. In the words of Amabile, who created the consensual definition and assessment of creativity, "a product or response is creative to the extent that appropriate observers independently agree it is creative. Appropriate observers are those familiar with the domain in which the product was created or the response articulated." (Amabile, 1982, p. 1001.) In other words, something is creative only if experts of the field say so.



Before moving on, it is important to discuss the distinction between the big C and the little c creativity. According to Gardner (1993), the big C creativity refers to “the kind of breakthrough which occurs only very occasionally,” whereas the little c creativity refers to “the sort [of creativity] which all of us evince in our daily lives” (p. 29). However, it may sometimes be difficult to distinguish between these two forms of creativity, because this distinction gives too few options to categorize various degrees of creativity (Kaufman & Beghetto, 2009). For example, “the accomplished jazz musician who makes a living playing jazz (but clearly is no John Coltrane) might be put into same category as the high school jazz student who plays (passable) jazz in school concerts and the occasional birthday party, wedding, or family gathering” (Kaufman & Beghetto, 2009, p. 2).

It is noteworthy that the standard definition of creativity emphasizes the role of value in creativity judgments. According to Merker (2006, p. 25), value is a necessary criterion of creativity because increasing creativity should lead to better cultural products. According to another line of justification, Runco and Jaeger (2012) argued that originality (i.e., without being effective) does not suffice to be a sole criterion of creativity since “originality can be found in the word salad of a psychotic and can be produced by monkeys on word processors” (p. 92). These authors also argued that completely random processes may generate original products, but they are unlikely to be useful or valuable (Runco & Jaeger, 2012, p. 92). In another study, Runco et al. (2005) argued that original responses in divergent thinking tests can be sometimes highly inappropriate and therefore not creative. As an example, “the individual who says ‘brick’ when asked to ‘name all the round things you can think of’ has found an original idea, but just as clearly, it is an inappropriate one” (Runco et al., 2005, p. 138).

However, the use of value as a criterion of creativity may cause severe problems in arts and music (Weisberg, 2015; Brandt, 2021; Schubert, 2021)<sup>16</sup>. Brandt (2021) presented several reasons of why creativity as a process that yields novel products should be distinguished from judgments of value. In his view, expert judgments “can be biased or prejudiced, excluding creative efforts on the basis of gender, race, religion, social class, sexual preference, and more” (Brandt, 2021, p. 4). Evaluations on the creativity of art works can also vary according to “the viewers’ beliefs about the identity of the painter or the amount of time they believed was expended on completing the work” (Cropley, 2011, p. 360). In addition, judgments on the value of artistic works may change from time to time (Weisberg, 2015; Brandt, 2021), which can lead to absurd statements like ‘Vincent van Gogh only became creative after he died’ (Weisberg, 2015)<sup>17</sup>. Moreover, the originality

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16 According to Schubert (2021), it is also problematic to apply the criterion of usefulness in the context of artistic creativity. In his view, “answering the question ‘how is a song or a symphony useful’ could raise a wide range of rather subjective responses, making empirical investigation problematic, and suggests that such a criterion misses the point” (Schubert, 2021, p. 7).

17 Statements like this are common in studies which emphasize the social nature of creativity. As an example, Csikszentmihalyi (2013) claimed that “Mendel was not creative during his years of relative obscurity because of his experimental findings were not that important until a group of British geneticists, at the end of the nineteenth century, recognized their implications for evolution” (p. 30).

(or novelty) of an artistic work and judgments of its value may be contradictory. Highly original products are not always valuable, and products can be valued because they represent existing tradition rather than depart from it (Williamon et al., 2006, p. 171). Finally, judgments of value are subjective and unreliable (Weisberg, 2015; Brandt, 2021) and evaluators may find it difficult to explain their judgments (Jordanous, 2011)<sup>18</sup>. Consistent with this view, Juslin et al. (2023) recently found that there was little agreement in aesthetic judgments between different listeners. According to this study, most listeners also had little insight on their judgment strategies.

There are several ways of how even expert judges may fail to provide fair judgments of value. For example, Flôres and Ginsburgh (1996) found that rankings in an international music competition depended on which day the candidate performed. Those candidates who performed early in the competition were less likely to achieve a high ranking compared to those who performed on the fifth day of the competition. In another study, Duerksen (1972) asked students to listen to pairs of identical music performances that were said to be performed either by a professional musician or a student. Performances that were reported to be performed by professionals were considered superior compared to student performances even if the performances were identical. The difficulty of providing fair judgments of value is also evident in that important works in the fields of literature and arts have often initially received negative reviews (Sternberg, 2006, p. 7). Most dramatic examples come from those whose work has been acknowledged only posthumously (Simonton, 2018b, p. 333).

Even if relevant cultural norms cannot be overlooked when creativity is assessed or measured,<sup>19</sup> there are also problems with applying appropriateness as a criterion of creativity in music and arts. Creative works of art are occasionally in opposition to prevailing cultural values and definitions of art (for example, Cage's *4'33''* or Duchamp's *Fountain* were in opposition to prevailing cultural values) (see Brandt, 2021, p. 6). Because of such opposition to prevailing values, these works of art would be considered inappropriate which leads to the same problems as discussed earlier with value judgments. Also, note that appropriateness can be considered from different points of view (the same also applies to usefulness). For example, even if some may consider particular innovations appropriate or useful based on their economic success or usefulness to users, others may regard the same innovations in negative terms due to poor working conditions for those who made them (Silvia, 2018, p. 293).

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18 Weisberg (2015, p. 119) proposed that creativity should be defined as intentional or nonaccidental production of novel outcomes (where value is disregarded). However, given the role of chance in some of the most important findings in the history of science (e.g., the discovery of penicillin) and its function as a source of creative ideas (e.g., Simonton, 2003; Cropley, 2011), this definition only leads to new problems. In fact, it would be less complicated to argue that creative products are not always valuable or useful, or that value judgments are not always important features of creative products, rather than to define creativity as an intentional generation of novel products.

19 For example, there are boundaries to what kind of a performance is considered acceptable in Western classical music tradition (Williamon et al., 2006, p. 172).

In addition, it is often unclear how appropriateness can be applied in studies of musical creativity. For example, it is difficult to judge whether note choices are appropriate or not besides obvious mistakes and accurate execution of notes (e.g., played in tune). In addition, regarding expert-level jazz musicians, the appropriateness of their note choices cannot be judged with the same rules as with less capable musicians. For example, Miles Davis's second classic quintet (with Miles Davis, Wayne Shorter, Herbie Hancock, Ron Carter and Tony Williams) was known for their extraordinary ability to adapt to surprising note choices produced by any of the musicians. Based on basic music theory, such note choices might be considered inappropriate regarding the predefined chord progression, yet such "inappropriate" note choices work fine when the band can adapt to surprises. Based on these problems and those discussed earlier regarding value and usefulness, the standard definition of creativity is problematic in the context of musical and artistic creativity where it is often difficult to assess the appropriateness, value, and usefulness of products. Nevertheless, at least appropriateness is an important component in definitions of musical and artistic creativity (or creativity in general). If appropriateness was not considered as a relevant criterion of creativity, completely random actions and ideas would be considered examples of the highest creativity.

In addition to the standard definition of creativity, alternative definitions have also been proposed. As noted above, Brandt (2021) proposed that usefulness and value should be removed from definitions of creativity, and creative products should be separated from their reception. Boden (2004) and Simonton (2018a) both proposed a three-criterion definition according to which creative products are original, useful, and surprising (or novel, valuable, and surprising). Simonton's proposal is particularly interesting. He argued that creativity can be measured by using the following formula:  $c = (1 - p)u(1 - v)$ , where ' $p$ ' is the probability of an idea, ' $u$ ' is its usefulness, ' $v$ ' is the prior knowledge of its usefulness, and ' $c$ ' is creativity. This proposal allows to distinguish between maximal creativity and seven types of maximal uncreativity. (Simonton, 2018a.)

In the present study, creativity is defined as novel (i.e., unpredictable, different) and appropriate products or ideas and the ability to create such products or ideas (where the novelty of a product or an idea only requires that it is new to the creator instead of the society). Moreover, the relevant criteria of creativity are considered to differ between types of creativity. With musical and artistic creativity, it is helpful to consider novelty and appropriateness as sufficient criteria for creativity to circumvent problems that arise from subjectivity of aesthetic judgments.

## 2.2.2 Creative processes perspective

From the process perspective, creativity refers to any cognitive mechanism that leads to the emergence of novel (or original) and appropriate (or valuable or

useful) products<sup>20</sup>. Creativity relies on several cognitive processes. These include long-term memory, working memory, selective attention, stream segregation, generation of ideas, evaluation of ideas, expectation, prediction, and cognitive flexibility (Loui & Guetta, 2019, p. 275). Obviously, many of these processes are not exclusive to creativity. Previous studies have also proposed that cognitive processes such as remote association (Mednick, 1962), cognitive flexibility and cognitive persistence (Nijstad et al., 2010), variable attention (Vartanian, 2009), and mind wandering (Palhares et al., 2022) may explain creativity to some extent. In addition, Orth et al. (2017) argued that creative motor actions emerge from exploration of movements in a space defined by individual, task, and environmental constraints. According to these authors, adaptation to changing constraints requires continuous exploration which leads to enhanced variability of movements. These movements may or may not turn out to be functional in terms of the task at hand.

In his classic paper, Campbell (1960) claimed that all “real gains [in knowledge] must have been the products of explorations going beyond the limits of foresight or prescience, and in this sense blind” (p. 381). In other words, Campbell argued that not knowing of which ideas are useful (until they are tested) underlies all advances in knowledge.<sup>21</sup> More recently, Simonton (2003) proposed that scientific creativity is a result of constrained stochastic processes where scientists try to find original and useful solutions to their research problems by making quasi-random combinations of existing knowledge<sup>22</sup>. In such a process, the probability of success is small, and a considerable amount of time is required to find a successful solution (Simonton, 2003, p. 478). In a similar way, cognitive load theorists like Sweller (2010) have argued that random search processes and subsequent tests on whether the solution is effective are required whenever one is faced with novel problems.<sup>23</sup> In addition, Hommel et al. (2016, p. 96) proposed that whenever an action has never been executed before, it is impossible to know its effects and so the generation of novel actions always has a random origin.

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20 Some researchers have distinguished between processes and mechanisms. According to Mumford (2003, p. 112), “any given process may be executed using a variety of mechanisms or mental operations. Thus conceptual combination may occur through analogical feature mapping, use of metaphors, or construction of a visual image, whereas information search may involve the elimination of irrelevancies, identification of anomalies, or search for structuring principals.”

21 Interestingly, Huovinen (2021) found that students in musicology and music education (nearly 40% of the students also had a conservatory degree) saw blind variation and selective retention as one of the least appealing theories of creativity. In addition, he found that general theories of creativity were considered most problematic when their application to musical improvisation was discussed.

22 Note that variability in action may also not always be as random as it seems. For example, variability may be sometimes illusory and caused by incomplete knowledge of underlying variables (Renart & Machens, 2014). Moreover, even though humans can make arbitrary choices naturally, their ability to make truly randomized choices is poor (which implies that one choice influences the others to some extent) (Johnson-Laird, 1988, p. 207).

23 According to Sweller (2010), “random generation followed by tests of effectiveness provide the initial source for the generation of all information held in long-term memory” (pp. 31-32).

Randomized idea generation is also a common feature in expert system algorithms (see Chapter 3.3.1: Implications from expert systems research).

Cropley (2011, pp. 360-361) distinguished between four situations in which chance can lead to the emergence of novel outcomes. In the first case, the creator has no role in the emergence of a creative outcome except for being at the right place at the right time. Second, creativity may emerge because of serendipity. Serendipity refers to situations where the creator is unintentionally faced with something novel and important (e.g., the discovery of penicillin is a famous example of serendipity). Third, an advantageous chance may also occur because of diligence. After a series of trial and error, diligent people may eventually find something worthwhile. Fourth, characteristics like attention to details, acquired knowledge, and expertise may increase the possibility of self-induced luck.

Another influential idea in creativity research is that novel ideas are always built on pre-existing knowledge. As an example, Thagard (2012) argued that all major discoveries in science and technology can be traced to combinations of different mental representations. Similarly, Canonne and Aucouturier (2016) argued that “improvised music is invented as it is being performed, but it is never really *creatio ex nihilo*. Every form of improvisation is built on pre-existing musical atoms” (p. 544). Likewise, Daikoku and his colleagues recently claimed that “there is no doubt that creativity is intricately linked to acquired knowledge; however, the underlying mechanisms remain unclear” (Daikoku et al., 2021, p. 2).<sup>24</sup> As an extreme form of argument, Weisberg (1999, pp. 248-249) even claimed that the relationship between creativity and knowledge is so strong that creative accomplishments can be explained as a consequence of acquired knowledge. In his view, “the reason that one person produced some innovation, while another person did not, may be due to nothing more than the fact that the former knew something the latter did not” (Weisberg, 1999, pp. 248-249).

According to Mednick’s (1962) associative theory of creativity, creative process is characterized by “the forming of associative elements into new combinations which either meet specified requirements or are in some way useful” (p. 221), where creativity is assessed by the distance of elements in a hierarchy of associations (the creativity of a solution is greater with associations of remote instead of closely related elements). The organization of associations also affects what solutions are most likely to occur and the “speed of attainment of a creative solution” (p. 222). Mednick also argued that the number of associations related to a specific problem influences the probability of achieving a creative solution. In other words, the greater the number of associations, the greater the probability of finding a creative solution. However, in case of ill-defined problems (where there are no pre-defined solutions to problems), the selection of creative combinations is typically achieved by “producing random combinations of elements”

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24 This idea is also evident in Johnson-Laird’s NONCE definition of creativity, according to which: (1) Creativity is associated with products that are novel at least to their creator; (2) Optionally, creative products may also be novel to the society; (3) Creativity is nondeterministic; (4) Creativity is based on pre-existing constraints; (5) Creativity can never occur *ex nihilo* (out of nothing) as even the most creative products are created from pre-existing materials. (Johnson-Laird, 2002, pp. 419-420.)

(p. 225). In addition, any combination of elements requires that all elements must already exist. To use Mednick's example, "an architect who does not know of the existence of a new material can hardly be expected to use it creatively" (p. 222).

Based on associative theories, Schubert (2011) proposed that musical creativity emerges from the spontaneous formation of new links between pre-existing nodes, which also produces pleasure or other positive emotions and simultaneous inhibition of pain or other negative emotions. According to this theory, information is stored in units (called nodes), which may differ in their size from single objects (e.g., a single note) to much larger units (e.g., an entire musical work). Importantly, it is not the activation of existing links between nodes that produces creative products but the formation of new links and associated positive feelings and inhibition of negative feelings. As such, this theory is compatible with the notion that creativity is based on combinations of pre-existing knowledge with an additional focus on emotion. Another important aspect of Schubert's theory is that musical creativity is considered as a subset of problem solving. Problems in composition and improvisation are typically ill-defined, which means that there are no pre-defined solutions to such problems and, as a result, no obvious target nodes from which the solution can be retrieved. In line with this view, Paavilainen (2020, p. 274) argued that the role of the default mode network may be emphasized in jazz improvisation, where there are no pre-defined goals that should be satisfied<sup>25</sup>.

The fundamental role of pre-existing knowledge in creativity is partly supported by recent studies. For instance, Weisberg et al. (2004) found that the average proportion of notes captured by recurring 4-interval melodic patterns was 90% in six solos by Charlie Parker. As a result, these authors concluded that pre-learned melodic patterns "played a major role" in Charlie Parker's improvisations (Weisberg et al., 2004, Capture of notes by formulas section, para. 1). In their review, Schacter et al. (2007) argued that the imagination of what events might occur in the future shares common brain structures with memory recall. More recently, Benedek et al. (2014b, 2018) found that the recall of original ideas from memory and the generation of novel ideas showed similar brain activation patterns except for the left supramarginal gyrus (which showed increased activation during the generation of novel ideas). Other research has suggested that pre-existing knowledge may have a different role in science and the arts. Building on pre-existing knowledge is obviously a crucial component in scientific and technological breakthroughs. In contrast, pre-existing knowledge may have a smaller role in artistic creativity in comparison to scientific and technological creativity (Cropley, 2011, p. 361).

Boden (2004, pp. 3-6) proposed that there are three fundamental forms of creativity based on their underlying processes: making unfamiliar combinations of existing ideas, exploring existing conceptual spaces, and inventing new conceptual spaces. Meyer (1989) distinguished between stylistic rules and strategies,

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25 Default mode network refers to interconnected brain regions associated with spontaneous internally oriented processes such as mind wandering and task-independent thought (Andrews-Hanna, 2012).

which resembles Boden's distinction between exploring pre-existing conceptual spaces and inventing new conceptual spaces. According to Meyer, there are three levels of constraints involved in the musical style of any performer or composer: laws (i.e., physical, physiological, and psychological constraints that apply in all cultures and all times), rules (i.e., stylistic constraints that apply in a particular culture), and strategies (i.e., constraints that influence how rules are realized) (Meyer, 1989, pp. 13-23). As an example of inventing new rules, Meyer cited Schoenberg's work with the twelve-tone method (Meyer, 1989, p. 31) and argued that changes in rules have rarely occurred in the history of Western music and such changes have only occurred in-between long-term epochs such as the Middle Ages, the Renaissance, the Age of Tonality, and the Age of Modernity (Meyer, 1989, p. 20).

### 2.2.3 The role of executive functions in musical creativity

Executive functions consist of basic cognitive abilities that are needed in mental imagery, focusing on a task, resisting temptations, and so on. There are three core executive functions: inhibition (control of attention, thoughts, or emotions to evade predisposed patterns of behavior), working memory (maintenance and manipulation of information), and cognitive flexibility (e.g., approaching a problem from a different point of view). (Diamond, 2013.)

In one study, Beaty et al. (2013) investigated the relationship between basic cognitive abilities (divergent thinking, working memory, and fluid intelligence) and expert ratings of ten undergraduate jazz students' improvisations. Their results showed negative correlations between improvisers' cognitive abilities and expert ratings of their improvisations except for divergent thinking (which is related to cognitive flexibility). As noted by these authors, negative correlations between scores from working memory/fluid intelligence tests and expert ratings were probably influenced by characteristics of the data (e.g., restricted variance). Other studies have found that even if expert musicians without improvisation training show higher scores on divergent thinking tests compared to non-musicians and musicians without formal training in music (Palmiero et al., 2020), jazz musicians show higher divergent thinking task scores compared to musicians specialized in other musical styles (Benedek et al., 2014a), and musicians with training in improvisation perform better on divergent thinking tasks compared to musicians without such training (Kleinmintz et al., 2014).<sup>26</sup>

Working memory (the ability to temporarily maintain and manipulate information) plays a fundamental role in a number of tasks. For example, playing

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26 Although divergent thinking tests are widely used in creativity research, Dietrich (2019a, 2019b) argued that there are several problems in their use. First, there is a lack of evidence that the alternative uses test (which is widely used in divergent thinking studies) is a valid measure of creativity (Dietrich, 2019a, p. 36). Divergent thinking is also "incapable of identifying the processes that turn normal thinking into creative thinking" since both divergent thinking and its opposite (convergent thinking) can produce creative results (Dietrich, 2019b, p. 2). In addition, divergent thinking involves several different mental processes but there is no knowledge of what those underlying processes could be (Dietrich, 2019a, p. 37; Dietrich, 2019b, p. 2).

a string, wind, or brass instrument requires constant monitoring of auditory feedback to adjust intonation and attack if necessary (Nichols et al., 2018). This constant comparison between action goals and auditory feedback requires short-term maintenance of relevant information in working memory. In addition, pianists with higher working memory capacity perform better on sight reading tasks compared to other pianists (Meinz & Hambrick, 2010). According to another study, improvisations produced by semiprofessional cellists with high working memory capacity were more creative compared to cellists with low working memory capacity (De Dreu et al., 2012). High working memory capacity can also support learning to identify absolute pitch categories (Van Hedger et al., 2015). Working memory is also related to inhibition of irrelevant or negative thoughts and being able to concentrate despite of external distractors (Redick et al., 2007), inhibition of stereotyped actions (Bengtsson et al., 2007), and coordination of “tasks and subtasks in complex actions” (Hommel et al., 2016, p. 171). In addition, working memory facilitates creativity, because it allows to maintain attention to the current task and enables persistent cognitive effort on a specific problem (De Dreu et al., 2012). On the other hand, there is also some evidence that high working memory capacity may be a disadvantage sometimes (Van Stockum & DeCaro, 2013).

A correct balance between excitatory neuronal activities and inhibition (i.e., suppression of neuronal activity) plays an important role in successful motor control of complex movements. For instance, correct timing in music performance requires knowing exactly when to play a particular musical sequence and when to wait. (Gerloff & Hummel, 2012, p. 239.) Inhibition of stereotypical actions (Norgaard et al., 2019) as well as risk-taking, an ability to surprise, and avoidance of redundancy (Wopereis et al., 2013) are also associated with musical creativity and jazz improvisation. In accordance with these studies, Beaty et al. (2014) found stronger connectivity between the inferior frontal gyrus (IFG) (associated with inhibition and cognitive control) and the default mode network (associated with spontaneous cognitive processes like mind wandering) among participants with higher scores in divergent thinking tasks. In another study, Ivancovsky et al. (2018) investigated cross-cultural differences in creativity between participants from a more traditional culture (South Korean) and a less traditional culture (Israeli). The generation of original ideas was associated with the posterior cingulate cortex (a portion of the default mode network) in both groups. However, the Israeli participants showed lower activation in the left IFG compared to the South Korean participants. Increased activation in the left IFG was associated with lower scores in divergent thinking test, which suggests that increased inhibitory control may have a negative effect on divergent thinking<sup>27</sup>.

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27 The relationship between reduced inhibition and creativity is also supported by other studies (Carson et al., 2003; Kleinmuntz et al., 2014; Nijstad et al., 2010).



## 2.2.4 Dual-processing theories in creativity research

According to dual-processing theories, information is processed by two types of processing: Type 1 (or System 1) (rapid, automatic, and unconscious processing) and Type 2 (or System 2) (slow, deliberate, and conscious processing) (Evans, 2008, p. 256). According to Evans (2008, p. 270), “type 2 processes are those that require access to a single, capacity-limited central working memory resource, while type 1 processes do not require such access.” As a result, Type 2 processing occupies working memory and can be disrupted by cognitive load. Type 1 processing does not occupy working memory and is not affected by the limits of working memory. (Evans, 2008, p. 270.)

Both types of processing are essential in expert-level creativity in tasks like jazz improvisation (Rosen et al., 2020). However, experts in jazz improvisation tend to rely more on Type 1 processing compared to Type 2 processing (Limb & Braun, 2008; Liu et al., 2012; Adhikari et al., 2016; Lopata et al., 2017; Rosen et al., 2016, 2017, 2020), which allows them “to inhibit or relax executive-control processes and improvise creatively based on unconscious, associative processes” (Rosen et al., 2020, p. 2). In contrast, relying on Type 2 processing is beneficial for novice improvisers (Rosen et al., 2016, 2017, 2020). In addition to expertise, task complexity and time pressure may also influence which one of these two types of processing is more relied on in performance. Experts tend to rely on Type 1 processing if the task is less complex and the time pressure is high, but they rely on both types of processing when the task is more complex and there is “enough time to think” (Gobet, 2016, p. 101). Torrance and Schumann (2019, p. 258) proposed that human actions (including jazz improvisation) are characterized by “a tension between” the two types of processing: improvisation requires fast, unconscious, and intuitive processing, but also monitoring and controlling processes based on slower, conscious, and deliberate thinking. In their view, “much of the skill of the improviser consists of knowing how to mediate between these two speeds of output” (Torrance & Schumann, 2019, p. 258).

As an application of dual-processing theories to creativity research, the dual pathway to creativity model states that there are two different pathways to create creative products: cognitive flexibility and cognitive persistence (Nijstad et al., 2010). Creativity can occur both as a combination of these two pathways, or in absence of the other pathway (Nijstad et al., 2010, pp. 36, 63). Cognitive flexibility refers to the ability to switch between different approaches and perspectives, whereas cognitive persistence refers to “sustained and focused task-directed cognitive effort” (Nijstad et al., 2010, p. 42). The relationship between cognitive flexibility and creativity has been approved in several studies. For instance, Kleinmuntz et al. (2014) found that musicians who were trained in improvisation performed better on divergent thinking tasks compared to non-musicians and musicians without improvisation training, probably because of the less strict evaluation of ideas among musicians with improvisational training. In another study, Carson et al. (2003) found that creative achievements were more common among people who showed low inhibition scores.

Creativity may also occur as a product of systematic, focused, and persistent cognitive effort on a specific problem. This pathway, called the cognitive persistence pathway, often leads to unsurprising and obvious results at first, but may lead to creative results when unsurprising but unsuccessful ideas are examined and rejected thus giving more space for the examination of more unconventional ideas (De Dreu et al., 2012, p. 658). The cognitive persistence pathway is, however, likely to lead to successful results only if there is enough time to concentrate on a specific problem (Nijstad et al., 2010, p. 56).

In accordance with the dual pathway to creativity model, recent research has found evidence for partly different neural correlates associated with artistic versus scientific creativity (Shi et al., 2017) and musical creativity versus literary and artistic creativity (Chen et al., 2020). However, Hommel and Wiers (2017) argued that attempts to make a clear-cut division between the two types of processing have failed, because there is no evidence for completely automatic actions that are not intentional, or goal directed. Moreover, Hommel and Wiers argued that the common way of solving this problem by allowing some degree of continuity between the two types of processing is not satisfactory, because there are no generally agreed criteria to locate specific behaviors on this continuum. As a result, Hommel and Wiers argued that dual-processing theories should be abandoned and replaced with a unitary approach to action control. In their view, the dichotomy between automaticity and intentionality could still be useful for its descriptive value, but underlying processes of both types of processing can be best described with a single model. (Hommel & Wiers, 2017.)

According to Hommel and Wiers (2017), all actions are goal-directed and represented by their expected effects. Action goals are determined based on both endogenous (e.g., preferred responses) and exogenous criteria (e.g., instructions provided by other people). Depending on whether these criteria are specific (e.g., pay attention to the object close to your left hand) or not (e.g., do something), the number of actions that fulfill these criteria varies. Uncertainty in action selection (where several actions fulfill the selection criteria) can be reduced either by specifying further selection criteria or by a process of random selection. Action control is also influenced by a meta control mechanism which is responsible for specifying which features of action (e.g., speed or accuracy) are emphasized in action control. (Hommel & Wiers, 2017.)

## **2.3 Underlying mechanisms in expertise**

### **2.3.1 Expertise as advanced knowledge and skills**

According to Gobet (2016), an expert refers to “somebody who obtains results that are vastly superior to those obtained by the majority of the population” (p. 5). Despite the simplicity of this definition, it is important to recognize that expertise can be difficult to measure. Reliable criteria to measure expertise exist only in a few domains (the Elo rating for chess players is a rare exception) (Gobet,

2016, pp. 3-4). In terms of music, problems also arise from that in countries such as the United States there are no uniform criteria to measure musical expertise (e.g., in the form of national exams) (Halpern & Bartlett, 2010, p. 247). As such, it is not surprising that few studies have used competency tests. Instead, duration of musical experience, years of formal training, and performing experience have been frequently used to measure expertise. (Halpern & Bartlett, 2010, p. 247.) This convention is problematic, however, since the expertise of self-taught musicians may be underestimated when formal training is used as a measure of expertise. In a similar way, prodigies and young musicians in general are underrated if years of musical experience is used as a single measure of expertise.

Parallel to the distinction between little-c and big-C creativity, it is helpful to distinguish between different levels of expertise. As an example, Starkes et al. (2004) distinguished between routine expertise and transcendent expertise. According to these authors, there are individuals in any field of expertise whose performances transcend everything what has been done before. As a result, these experts should be distinguished from other experts in the field. (Starkes et al., 2004, p. 269.)

To say that the performance of these individuals is at the same level as other national or international athletes in their respective sports is to deny the genius that characterizes their performances. Unfortunately, most of the skill and expertise research to date has been performed on those individuals who certainly exhibit levels of routine expertise, but only in rare cases broach transcendent levels of expertise. The scarcity of such individuals and the difficulty of accessing them as experimental participants means that we will probably never truly understand what makes these experts so remarkable. (Starkes et al., 2004, p. 269.)

The notions of automatic and controlled processing (Schneider & Shiffrin, 1977) and the fundamental role of automation in expert performance (Fitts & Posner, 1967) have been highly influential theoretical foundations to expertise research. Automatic processing refers to uncontrolled activation of long-term memory as a response to input. Automatic processing does not require attention or stress the processing capacity. Controlled processing, on the other hand, refers to attention-demanding activation of long-term memory, which is controlled by a person and limited by constraints of the processing capacity. (Schneider & Shiffrin, 1977.)

The relative importance of controlled and automatic processing in terms of both creativity and expertise is still under debate. As an extreme view, Dreyfus and Dreyfus (1986) proposed that skill acquisition develops through five stages, from the use of context-free rules into intuitive coping with situational factors. At the first stages, performance is rigid and guided by rules which are followed in any context. When skills gradually get better and more experience is gathered from different situations, slow and deliberate decision-making is replaced by rapid and intuitive actions. Instead of rules, skilled performers use their experience to recognize similarities between current situations and those experienced in the past, and they use this knowledge to perform actions which they know to work. If all goes as usual, experts do what has worked before instead of making decisions or solving problems. (Dreyfus & Dreyfus, 1986.) Dreyfus and Dreyfus's claims are appealing in that they seem to explain the effortlessness of actions

among experts and how experts can function efficiently even in case of severe time limits.

However, several authors have argued that Dreyfus and Dreyfus pushed too far in their emphasis on intuitive, non-deliberate, and non-reflective aspects of expertise. For instance, in a study based on interviews with a world-renowned string quartet, Høffding (2014) claimed that the Dreyfusian notion of skilled coping is too general and includes several types of intentionality and awareness that span from highly reflective modes of intentionality (e.g., thinking about page-turning) to rare trance-like states with little self-awareness even of one's own actions (e.g., being highly absorbed to just playing music and being able to remember close to nothing about the actual experience afterwards). Recent neuroscientific research on improvisation has also proposed that both the default mode network and the executive control network play an essential role in musical creativity and musical expertise (see Chapter 2.2.3: The role of executive functions in musical creativity and Chapter 3.3.2: Neuroscience of musical improvisation). Similarly, Christensen et al. (2019) proposed that both automatic processing and cognitive control are involved in most skilled actions. In their view, while automation undoubtedly plays a significant role in skilled actions and improves their efficiency, most skilled actions are not fully automated, and they also require cognitive flexibility (the ability to adjust to changing situations) which depends on cognitive control.

### 2.3.2 Perceptual and motor chunking

In a seminal work on the psychology of expertise and cognitive psychology in general, Chase and Simon (1973) showed that expert chess players' superior recall of chess positions can be explained by a higher number and larger size of chunks among experts compared to less skilled players<sup>28</sup>. Chunking refers to a process of constructing perceptual and motor units "built from several smaller elements" (Gobet et al., 2016, p. 1) that "can be retrieved by a single act" (Gobet & Simon, 1998, p. 226). According to another definition, chunking refers to "a process through which one reorganizes or groups presented information to compress information" (Gilchrist, 2015, p. 1). For example, when one aims to memorize a non-random series of numbers (e.g., 1234234534564567), one does not need to memorize each number separately. Instead, it would be easier to memorize these numbers as separate units (chunks) (e.g., 1234, 2345, 3456, and 4567). Experiences that cannot be easily chunked into meaningful units of information may be difficult to memorize (Snyder, 2000, p. 54).

Chunking is widely used to explain expert-level performance on diverse areas such as chess, motor learning, music perception, and language acquisition. For example, playing chess at a master's level requires a large knowledge base of

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28 Previously, Miller (1956) had shown that the organization of information into chunks allows to circumvent the limits of short-term memory. Both Miller's and Chase and Simon's work have had a considerable influence on subsequent research. Based on a search in the Scopus database, Miller (1956) has been cited in about 12,000 papers by now, whereas Chase & Simon (1973) has more than 2,000 citations up to now.

familiar patterns which suggest what moves are the best ones in a particular situation (Simon & Chase, 1973, p. 403). According to Simon and Chase (1973), chess masters need to learn roughly 50,000 patterns of chess pieces in order to perform at this level. In addition, Simon and Gilmarin (1973) estimated that achieving the level of a chess master or grandmaster requires learning from about 10,000 to less than 100,000 patterns of chess pieces. More recent studies on skill development suggest large variation in the time needed to obtain expert-level skills in chess (e.g., Gobet & Campitelli, 2007), which undermines the credibility of the above-mentioned estimates. If a considerable amount of time is necessarily required to learn thousands of chess positions to recognize and select the best moves, how is it possible that some exceptionally talented players can reach the highest level of skills in a relatively short time?

More recent studies have also shown that chess masters may use much larger chunks compared to the original findings of Chase and Simon (1973), according to which the average size of the first chunk was 3.8 pieces in middle game positions among chess masters (with a physical chess board)<sup>29</sup>. Gobet and Simon (1998) found that “the mean of the median largest chunks” was 16.8 pieces among chess masters in a recall task (in this study, a computer display was used instead of a physical chess board). In another study, Gobet and Clarkson (2004) found that the median maximum size of chunks among chess masters was 14.8 pieces in a recall task when computer display was used.<sup>30</sup> Moreover, chess masters are able to perform better compared to less experienced players even at very short presentation times. According to Gobet and Simon (2000), chess masters were able to recall about the same amount of correct game positions in one second as what experts did in 10 seconds and Class A players in 30 seconds.

Chunking also plays an important role in sequence production. For example, Park and Shea (2005) found that sequences with ten elements were organized to a smaller number of subsequences and executed faster compared to 16-element sequences. According to the classic motor chunking framework, the acquisition of motor chunks (i.e., action sequences that can be recalled as a single unit) leads to a smaller number of time-consuming transitions between distinct actions, which contributes to faster execution of action sequences and allows to release cognitive resources to higher-level processes (Thompson et al., 2019). Similarly, using terminology from the motor program literature (see Chapter 3.1.4: Schema theory of motor skills), the acquisition of longer motor programs leads to a situation, where “the response-programming stage is involved less often and attentional space [...] is freed up to perform other higher-order activities, such as the monitoring of movement form or style in gymnastics or dance, the development of strategic plans in tennis, or paying attention to safety hazards in operating earth-moving equipment” (Schmidt & Wrisberg, 2004, p. 133). Figure 1 illustrates

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29 As noted by Gobet and Simon (1998, p. 226), only a single chess master participated in Chase and Simon’s original study (the overall number of subjects was three) and this chess master was not particularly active in chess at the time of the study.

30 Using a physical chess board, the maximum size of chunks is influenced by the number of chess pieces it is possible to grasp in a single hand (Gobet & Simon, 1998; Gobet & Clarkson, 2004).

how chunking leads to a smaller amount of distinct action units. Whereas all actions are distinct and preceded by a time-consuming planning stage at the early stages of skill development, the number of transitions between actions decreases and the size of chunks increases with skill level.

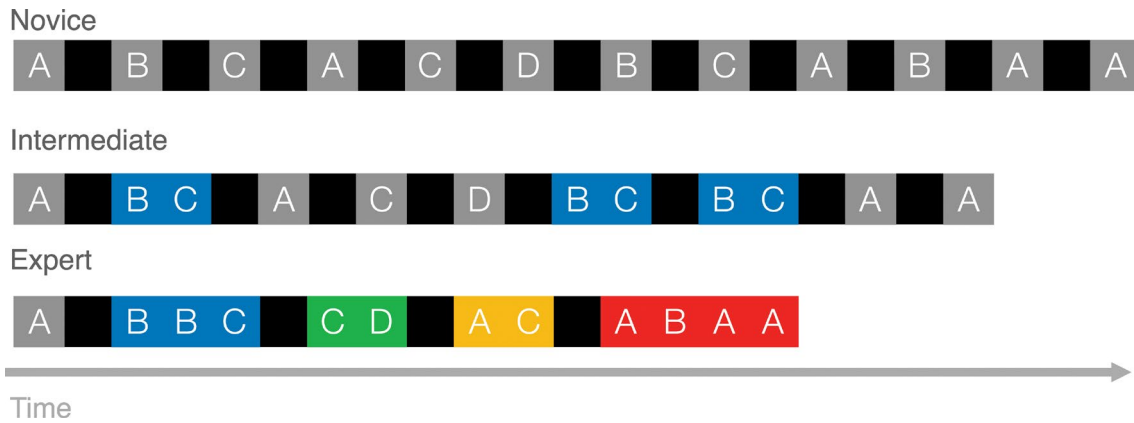


FIGURE 1 Accumulation of chunks in relation to skill level (reprinted from Thompson et al., 2019; licensed under a Creative Commons Attribution 4.0 International License, <https://creativecommons.org/licenses/by/4.0/>)

In addition to motor chunks, perceptual chunks also play an important role in different skills. For example, perception of familiar groupings in lead sheets contributes to faster learning of new musical works. Figure 2 shows two simple examples of chunks in music. With elementary knowledge of music theory, one can immediately recognize that the notes in the first example form a C major scale and that the notes in the second example form a C major ninth chord. In addition, these familiar patterns of notes can be recalled from memory as a single chunk. Such knowledge is important, for instance, when music is reproduced from notation where an extensive knowledge of common regularities in music is an important advantage for a sight-reader. Similarly, readers benefit from perceiving texts as groups of familiar words and sentences. Because of this knowledge, texts do not have to be read sign by sign.



FIGURE 2 Simple perceptual chunks in music

Interestingly, Thompson et al. (2019) recently found that the classic motor chunking framework fails to explain increased diversity of actions among experts and lack of time savings acquired through chunking. These authors analyzed a large number of game files in *StarCraft 2*, which is a game that allows to automatically collect all actions played during the game, to investigate whether the number of chunks and the proportion of chunked actions increase with expertise, and whether chunked sequences are executed faster than non-chunked sequences.

According to their results, chunks were detected in most game files and the number of chunks increased with skill level (as predicted by classic motor chunking framework). However, the proportion of chunked actions remained stable across skill levels. Action sequences were also more varied among expert players. The authors did not find evidence for faster execution of chunked sequences compared to non-chunks. Instead, better players played faster regardless of their use of chunking mechanism.

Note that the number of distinct action types was only seven in this study (see Thompson et al., 2019, pp. 6-7). As a result, it is possible that these results cannot be generalized to more complex tasks such as musical improvisation where there are many more options available in any situation. Nevertheless, as noted by Thompson and his colleagues, much of the previous motor chunking research has been done in laboratory conditions and most of the studies in naturalistic context have focused on typing (Thompson et al., 2019, p. 2). Thus, it is important to investigate to what extent chunking mechanisms can explain behavior in different areas of expertise (Thompson et al., 2019, p. 2).

In naturalistic settings, it is often difficult to identify the beginning and the end of a chunk (Thompson et al., 2017, p. 469). According to Chase and Simon (1973), chunk boundaries can be identified by a perception task (where chess players were asked to reconstruct chess positions from a chess board to an empty chess board which they could not see simultaneously with the other board) or a memory task (where chess players were asked to view a chess position for five seconds and then recall it by placing pieces on a board). In the perception task, chunk boundaries were detected by attentional shifts (pieces reconstructed on a chess board after one glance correspond to one chunk). In the memory task, pieces reconstructed on a board in less than two seconds “between successive pieces” correspond to one chunk (Chase & Simon, 1973, p. 64). Yet another way to identify chunk boundaries is simply to detect recurring sequences of actions. In this case, the beginning and the end of chunks are identified by the beginning and the end of recurring sequences. Problems in detecting chunk boundaries based on this method are discussed in Chapter 5.3.1: Methodological problems related to segmentation.

Chunking is related to statistical learning, the latter of which has received considerable attention since the seminal work of Saffran et al. (1996)<sup>31</sup>. According to this influential work, statistical learning (automatic extraction of regularities from the environment) plays an important role in language acquisition (Saffran et al., 1996; Saffran, 2003). Statistical learning also plays a role in musical creativity (e.g., Norgaard, 2014; Daikoku, 2018; Daikoku et al., 2021). The brain codes both macroscale probabilities (i.e., global probabilities) and microscale probabilities (i.e., local probabilities) of the occurrence of various kinds of stimuli (Hasson, 2017; Daikoku, 2018). Macroscale probability refers to “summary statistics,” in

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31 However, the relationship between these two processes is not clear. It has been proposed that statistical learning and chunking may be either two independent processes or they are “two successive steps in the learning process,” in which chunks are “inferred from prior statistical computations.” Another possibility is that statistical learning is merely a by-product of chunk formation. (Perruchet & Pacton, 2006, p. 235.)

which the level of uncertainty is computed “into a single value” (Hasson, 2017, p. 2). Microscale probability, on the other hand, refers to transitional probability between single units or entities (e.g., the probability of B given that A has occurred) (Hasson, 2017). The information content of familiar patterns (microscale statistics) is positively correlated with the overall conditional entropy (macro-scale statistics) in 1st to 5th order Markov models. This suggests that when improvisers are more creative at pattern level, the overall conditional entropy (summary statistics) increases also. Another interaction between these two levels of probabilities is that dependence on previous events and microscale statistics are negatively correlated in 3rd to 5th order Markov models. (Daikoku, 2018.) Thus, when improvisers “strongly depend on previous sequential information to improvise music, they tend to use familiar phrases because familiar phrases with higher [transitional probabilities] [...] tend to have strong dependence on previous sequential information” (Daikoku, 2018, p. 9).

### 2.3.3 Anticipation and planning in skilled performance

Experts differ from non-experts in their adaptation to task-specific constraints, advanced memory, and their superior anticipation of future events (Ericsson & Lehmann, 1996). The last-mentioned skill, anticipation of future events, is critical for expert performance in various domains. For example, expert squash players outperform novice players in their ability to predict the ball direction and force, which allows them to have more time to respond and to act without a hurry. In sports, experts’ superior anticipation can be explained by their advanced skills to extract essential kinematic information from an opponent’s movements and their superior knowledge of situational probabilities. (Abernethy et al., 2001.) Situational probabilities (e.g., knowledge of an opponent’s typical actions) are important in a variety of contexts, but they are likely to be especially important in situations where a player is required to initiate a response in absence of time to perceive an opponent’s movement as a whole, as is the case with penalty kicks for goalkeepers in football (Dicks et al., 2011) (for reviews on anticipation in sports, see Abernethy et al., 2018; Cañal-Bruland & Mann, 2015).

Anticipation of opponents’ movements, based on perception of preparatory movements and contextual information on typical behavior of opponents, allows athletes to produce appropriate responses to actions even under severe temporal constraints (Abernethy et al., 2018)<sup>32</sup>. Similarly, advanced anticipation of future events can facilitate sight-reading by increasing the eye-hand span (i.e., the distance between the fixated note and the currently played note). The eye-hand span

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32 According to Clarke (1988), anticipation and planning of future events are critical for improvising musicians, because they “must construct a representation for at least a short sequence of events in advance, and cannot operate at speed or with any fluency on an event-to-event level” (p. 7). Similarly, Brown et al. (2015, p. 61) argued that the “manner of planning [in segments rather than one note at a time] may allow experts’ working memory to keep pace with the high speeds of real time music performance.” Therefore, whenever the possibility to prepare future events in advance is blocked (e.g., as when one is unaware of upcoming chord changes), performance may become less fluent.



in sight-reading tasks can be measured in several ways: temporal distance (the time index), the number of notes (the note index), or the number of beats (the beat index) between the fixated note on a musical score and the currently played note (Furneaux & Land, 1999; Lim et al., 2019). Professional musicians apply larger eye-hand spans in terms of the note index compared to amateur musicians, but such skill-related differences do not seem to exist in terms of the time index (Furneaux & Land, 1999). Regarding the complexity of stimuli, Lim et al. (2019) found that the eye-hand span (both in beats and seconds) was smaller with complex stimuli. In contrast, Huovinen et al. (2018) found that sight-reading of more complex local musical events was associated with earlier fixation and longer saccades compared to less complex musical stimuli. Previous studies have provided mixed results regarding the relationship between the eye-hand span and performance tempo. According to Furneaux and Land (1999), the time index was reduced at a fast tempo and increased at a slow tempo. However, Lim et al. (2019) did not find statistically significant differences in the eye-hand span (neither in beats nor seconds) due to performance tempo among professional pianists.

Anticipation of future events is closely related to the notion of action planning and related concepts such as motor planning, movement planning, motor programming, and decision-making. To explain the notion of action planning, it is helpful to discuss the notions of intentional action and action goal for a start. Intentional action refers to a goal-directed movement, whereas action goal refers to “the desired product of an action, to the final state that should be attained through the action” (Hommel et al., 2016, p. 47). Voluntary control of actions is established by the development of sensory-motor associations, in which expected perceptual consequences are linked with movements involved in achieving the desired perceptual consequence (Hommel, 2009; Maes et al., 2014)<sup>33</sup>. Action goals can be rather vague, and they can be attained through various movements. For instance, consider a simple reaching movement in which the task is to reach an object in a specific location. This action goal can be attained using either the left or the right hand, or either the left or the right foot. In addition, the way the action goal is attained depends on body posture prior to the movement onset. Therefore, even if sensory-motor associations have been developed for a given action, not all aspects of actions are necessarily held in long-term memory.<sup>34</sup> Detailed and variable properties of actions (e.g., the precise speed of an action) are not usually stored in long-term memory and they are also difficult to learn (Hommel, 2009, p. 516).

According to Pfordresher et al. (2007), (action) planning is defined as “the preparation of to-be-produced events prior to their production” (p. 64). Note that this definition does not distinguish between selection and preparation of actions.

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33 Similarly, unplanned actions can be defined as unintentional, arbitrary movements without knowledge of their perceptual consequences.

34 On the other hand, action plans do not necessarily lead to intended behavioral consequences. One can plan to go to the beach the next day, but if it rains all day one might decide to do something else. Similarly, because of some mistake or action slip, one may fail to achieve a desired action goal in which case one’s behavior does not match with the intended action plan.

For the present purposes, action planning is considered to include both the selection of an action goal (i.e., decision-making) and any process used to specify how to achieve the desired action goal. As a result, action planning is defined here as the selection and preparation of actions prior to movement initiation at any timescale. In other words, action planning refers to the selection of action goals and any process related to preparing actions prior to movement initiation (regardless of whether planning occurs within months or milliseconds in advance).

As noted in the previous paragraph, action planning can occur at different timescales. For instance, one can plan a holiday trip months or years in advance. However, motor planning usually refers to short timescales only<sup>35</sup>. According to Wong et al. (2015), motor planning commonly refers to “any process related to the preparation of a movement that occurs during the reaction time prior to movement onset” (p. 385). In another study, Orban de Xivry et al. (2017) defined motor planning broadly as “the process of selecting a goal and the appropriate motor commands to achieve this goal” (p. 117). As a replacement for this broad definition, Wong et al. (2015) proposed that the definition of motor planning should include only such processes that follow the identification of a motor goal and are related to specifying how the desired motor goal should be attained<sup>36</sup>.

Action planning is an important precondition for fluent execution of rapid action sequences because it reduces the overall duration of performing an action (Hommel et al., 2016, p. 161). On the other hand, action planning has cognitive costs particularly on working memory capacity. According to Hommel and his colleagues, “the more extensive the plan, the higher these costs are which, given the severe limitations of working memory, can have serious consequences for other cognitive processes that need to be carried out while maintaining the plan” (Hommel et al., 2016, p. 162). However, if fast action sequences were produced one element at a time, “the production of each element and the perception of its results would cost time (of about the order of magnitude of an average reaction time) so that the next action element can be performed no earlier than about one reaction time after the previous one” (Hommel et al., 2016, p. 149).

There are two extreme views of how action sequences are retrieved from memory in skilled action. At one extreme, each element is thought to trigger the next one in an associative chaining process<sup>37</sup>. The sheer speed of consecutive

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35 Most decision-making occurs subconsciously within very short timescales. For instance, attention is directed to a new visual target two or three times every second when one is awake and requires making a choice between visual targets. (Carpenter, 1999.)

36 Wong et al. (2015, p. 386) defined motor planning as “the set of processes that describe how a motor goal will be achieved.” In their view, motor planning “involves specification of the movement trajectory for the desired action, a description of how the end-effector will produce such an action, and finally a description of the full set of the joint trajectories or muscle activations required to execute the movement” (Wong et al., 2015, p. 395).

37 In his classic paper, Lashley (1951) argued against the reflex chain theory of behavior (according to which each element in a sequence is triggered by the previous element). In his view, the reflex chain theory was a consequence of the generally acknowledged (but incorrect) conception of the nervous system, according to which the direction of nerve conduction is always from sense organs to muscles and where all actions are

movements at a fast tempo (up to 20-30 notes per second in skilled pianists), however, makes it impossible to plan upcoming movements at the level of single events. At the other extreme, all action sequences (regardless of their length and complexity) are expected to be memorized and retrieved as a whole. (Palmer & van de Sande, 1995, p. 947.) In between these two extremes, action sequences are assumed to be retrieved incrementally. Incremental planning refers to temporally distributed retrieval of sequences where only a portion of sequence elements are accessible at any given time (Palmer & Pfordresher, 2003). In skilled performance, the retrieval process occurs within shifting temporal windows, where the active region of mental representation is constantly moving and mental representations of long and complex music are “only partially activated” at any time (Clarke, 1988, p. 4)<sup>38</sup>. Such a planning strategy uses cognitive resources economically since “it minimizes the amount of information that must be maintained in working memory until it can be executed” (Beaty et al., 2022, pp. 912-913).

According to the range model of planning (Palmer & Pfordresher, 2003; Pfordresher et al., 2007), music performances are planned incrementally where only a portion of sequence elements are accessible at any point of time. The range of planning (which refers to the span of simultaneously accessible elements at any given time as indicated by the distance between the present position in a musical score and the location of unintended events in that score) is constrained by production rate and age-related differences in working memory. When production rate decreases, errors become less frequent, and they indicate a larger range of planning. A larger range of planning is also related to increasing age.

The range of planning may also increase with skill level (Drake & Palmer, 2000). For instance, Palmer and Drake (1997) found that intermediate child pianists showed larger range of planning, increased anticipatory behavior, and faster identification and correction of errors compared to beginning child pianists, which suggests that planning and monitoring abilities improve with skill level. Interestingly, increased range of planning (as measured by the number of events) did not correspond with a larger time span of planning (in milliseconds) since the time span of planning was similar between intermediate and beginning child pianists.

There is also some evidence that experts may play more easily accessible and less difficult sequences first to allow more time to plan more difficult sequences. Beaty et al. (2022) recently investigated whether expert jazz musicians play less difficult melodic sequences at the beginning of phrases. Difficulty was measured in terms of interval variety, pitch variety, the number of changes in melodic direction, the length of interval patterns without changing the melodic direction, and the relative frequency of interval patterns. Difficulty was also

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consequences of sensory stimuli (Lashley, 1951, p. 114). More recent research has provided further evidence on Lashley’s arguments (see Rosenbaum et al., 2007).

38 According to Clarke (1988), only low-level connections may be active in the middle of a phrase since higher-level structural information may be of little use for the performer in such situations. However, higher-level structural information (e.g., knowledge about the overall structure of a musical piece or the relationship between subsequent phrases) may be important in phrase boundaries. (Clarke, 1988, p. 4.)

measured in terms of interval size and maximum interval size, but these measures were excluded due to outliers. In accordance with their hypotheses, sequences at early phrase positions were less difficult, which indicates that “the substantial physical, temporal, and psychological constraints of spontaneous creativity can be mitigated by first producing less complex and easily accessible melodic sequences” (Beaty et al., 2022, p. 918).

According to Drake and Palmer (2000), there seems to be a strong relationship between advanced planning skills and “progressive mastering of temporal constraints,” which suggests that planning and mastering of temporal constraints “are reflections of the same underlying cognitive processes” (p. 27). As noted by these authors, musical performance is characterized by strong temporal constraints because of which additional processing time cannot be acquired simply by stopping the performance. In addition, skilled performance requires that the execution of current events must occur at the same time as upcoming events are planned. In contrast to skilled performers, a novice performer is likely to obtain additional processing time by making a stop from performing and continue to perform only after planning of upcoming events has been completed. (Drake & Palmer, 2000, pp. 27-29.)

#### **2.3.4 Transfer of learning**

Performance of complex and long musical works makes huge demands on memory. Professional musicians may need to memorize thousands of pitch events in a specific order (Finney & Palmer, 2003) and to produce individual events as quickly as 20-30 notes per second (Palmer & van de Sande, 1995). It is also necessary that musicians are capable of transferring acquired knowledge to new situations. This is an essential part of musicianship since without flexibility of movements, additional practice would be required to perform any alternative interpretation of a familiar musical work. (C. Palmer, 2012, p. 50.)

Transfer of learning refers to “our use of past learning when learning something new and the application of that learning to both similar and new situations” (Haskell, 2001, p. xiii). According to another and often-cited definition, “transfer of learning occurs when learning in one context or with one set of materials impacts on performance in another context or with other related materials” (Perkins & Salomon, 1992, p. 3). In the early 20th century conception of transfer of learning, the dominant view among psychologists and educators was the so-called doctrine of formal discipline. According to this doctrine, studying subjects like Latin and geometry is useful because of their influence on general faculties of the mind (e.g., attention, reasoning, and observation), which can be improved much the same way as one can improve muscles. It was thought that the content of exercises was not important. Instead, psychologists and educators stressed the level of effort, which also explains why Latin and geometry were thought to be so important. (Singley & Anderson, 1989, pp. 2-3.)

As a response to the doctrine of general faculties, Thorndike proposed a theory of identical elements, according to which:

One mental function or activity improves others in so far as and because they are in part identical with it, because it contains elements common to them. Addition improves multiplication because multiplication is largely addition; knowledge of Latin gives increased ability to learn French because many of the facts learned in the one case are needed in the other. (Thorndike, 1906/1916, p. 243.)

In other words, Thorndike proposed that skills acquired by training an activity can be transferred to other activities only to the extent that they share common elements. In accordance with Thorndike, recent evidence suggests that expertise in one skill may have little benefits in unrelated skills (e.g., Sala & Gobet, 2017). On the other hand, Thorndike's theory of identical elements ignores that transfer can occur in the absence of a shared surface structure when the two skills or tasks have similarities on a more abstract level. For instance, we could measure the similarity of two melodies based on the number of shared notes. Such an analysis would give no attention to underlying similarities on a more abstract level and could not notice such obvious similarities as that the two melodies may share an identical interval structure even though they do not have any shared notes. (Singley & Anderson, 1989, p. 9.) Thorndike's emphasis on common stimulus-response connections also precludes the significance of any kind of adaptation and transformation of knowledge, which is often required in transfer situations (Singley & Anderson, 1989, p. 5).

Transfer of learning is among primary aims of music education and education in general (Forrester, 2018). There has been considerable interest in transfer of learning in music research since the 1990's. Many of these studies have discussed questions such as whether listening to music and playing a musical instrument have cognitive and academic benefits. However, much less research has been conducted on issues regarding near transfer. It is also noteworthy that the ability to compose and improvise music has received little scientific interest compared to the study of music perception and memory in music (Thompson, 2015, p. 290), even though psychological research on composition and improvisation has increased in recent years. Although more research on composition and improvisation is needed, it should be noted that research on music perception provides useful information not only concerning perceptual processes in both musicians and non-musicians, but it also increases knowledge about processes associated with composing and improvising. Auditory processing is no less important to composers and improvising musicians than it is to non-musicians.

Only a small fraction of studies related to transfer of learning investigate transfer to new contexts in music performance, composition, and improvisation. The few studies have typically used an experimental setting in which participants first learn a task and then their easiness or difficulty in performing a novel task is measured. Whenever a novel task is performed with ease, positive transfer of learning is indicated. (C. Palmer, 2012, p. 42.) For example, Palmer and Meyer (2000) asked participants (adult and child pianists) to practice a melody and then asked them to perform another melody. The second melody was the same as the first one or differed from the first one either by its motor sequence (hand and finger movements), pitch sequence, or both. Transfer of learning was most successful for adult pianists when pitch sequences remained the same regardless of

whether motor sequences were also retained. In contrast, novice child pianists only showed transfer of learning when pitch sequences and motor sequences were both similar to the first melody. With more experienced child pianists, transfer of learning was indicated when either pitch sequences or motor sequences were similar to the first melody. According to the authors, these findings suggest that action plans become increasingly abstract and independent from required movements with increasing skill level.

## 3 CREATIVE COGNITION IN EXPERT JAZZ IMPROVISATION

### 3.1 Memory for music and motor actions

#### 3.1.1 Memory for melodies

Even non-musicians have little difficulty in recognizing familiar melodies based on interval structure (Jäncke, 2019, p. 240), which suggests that melodies are memorized in terms of abstract relations between pitch categories (Levitin, 1999, p. 215). Changes in key, tempo, timbre, loudness, or location of sound source do not change the identity of a melody and disrupt melody recognition except when those changes are so extreme that the melody becomes unrecognizable (e.g., when tempo is extremely slow or extremely fast) (Levitin, 1999, p. 214). In addition to memory for interval structure, which is the primarily used melodic encoding strategy among both adults and infants (Plantinga & Trainor, 2005), a surprisingly good memory for absolute pitch is also widespread (Halpern, 1989; Levitin, 1994; Frieler et al., 2013; Schellenberg & Trehub, 2003). For example, adults with little or no musical training can identify whether instrumental theme songs from familiar television programs were played in the original key (Schellenberg & Trehub, 2003). Many of them can also sing familiar songs from memory in the original key (or close to it) (Levitin, 1994; Frieler et al., 2013).<sup>39</sup>

In addition to interval structure and absolute pitch, melodic contour also plays an important role in recognition of melodies as indicated by that the recognition of both well-known melodies (Idson & Massaro, 1978) and recently learned melodies (Massaro et al., 1980) is severely disrupted when melodic contour and

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39 Naturally, non-musicians may have difficulties in labelling pitch categories when labels such as “E-flat” have no meaning to them (Levitin, 1999, p. 220). Therefore, the requirement for being able to label pitch categories correctly may distort estimated prevalence of absolute pitch in general population.

tone height are both violated while tone chroma (octave-independent name of a tone, e.g., C) is preserved. However, recognition of melodies is not influenced by violations in tone height when melodic contour and tone chroma are preserved (Idson & Massaro, 1978; Massaro et al., 1980). Compared to interval structure, melodic contour may play a more important role in discrimination tasks (where subjects are asked to respond whether two melodies are same or different) after short delays (1-5 seconds) but not longer delays (Dowling & Bartlett, 1981; DeWitt & Crowder, 1986).

Recognition memory for melodies is surprisingly good and resistant to intervening melodies and temporal decay. Discrimination of original melodies from similar melodies improves over time due to continued encoding and feature binding process when listeners continue to listen to the same music (Dowling et al., 2002; Tillmann et al., 2013; Dowling et al., 2016). However, Herff et al. (2018) found that the recognition accuracy of novel melodies did not decrease with increasing number of intervening melodies (which differed from the original melody) or because of increasing time in-between target melodies. Similarly, Schellenberg and Habashi (2015) showed that the ability to recognize previously unfamiliar melodies did not decrease during a one-week intervening period between initial exposure and test situation.

Familiar songs can be distinguished from unfamiliar songs very rapidly in about 100-300 milliseconds from the onset of the sample (Jagiello et al., 2019). Nevertheless, recognition of familiar songs becomes difficult if the inter-onset interval between subsequent tones is either too small or too large (Warren et al., 1991; Andrews et al., 1998). Dowling et al. (2008) made similar findings in a study, where participants listened to pairs of familiar and unfamiliar melodies and responded whether the two melodies were the same or not. In each case, the second melody was either the same as the first melody (exact repetition) or slightly altered (two notes changed). Melodic contour was always preserved. Recognition accuracy with familiar melodies was best with moderate tempos. However, similar effect was not observed with unfamiliar melodies which indicates that “it is not the effect of tempo per se that leads to worse performance for fast and slow stimuli; rather, it is whether the tempo of a well-known song deviates from its usual, familiar tempo” (Dowling et al., 2008, p. 500). Dowling et al. (2008) also found that musicians outperformed non-musicians in their recognition scores with both familiar and unfamiliar melodies regardless of tempo. However, musicians’ superiority in recognition tasks is not always apparent. For example, musicians can recognize familiar songs faster than non-musicians (with fewer notes), but the difference is small (Dalla Bella et al., 2003).

An important feature of memory is that its accuracy depends on whether events of interest can be categorized. Categorical perception refers to a “mode of perception wherein things are perceived as belonging to categories with boundaries” (Snyder, 2000, p. 256). Categorical perception increases efficiency in mental processing by ruling out unimportant differences between perceived objects (Snyder, 2000, p. 256). In contrast to primary parameters of sound (e.g., pitch, harmony, rhythm), secondary parameters of sound (e.g., loudness, tempo, timbre)



are difficult to divide into “clearly recognizable categories” (Snyder, 2000, p. 196). As a result, most people find it difficult to identify the similarity between two levels of loudness, for example, separated in time (Snyder, 2000, pp. 196-198).

### 3.1.2 Cognitive schemata in music

Schemata (i.e., schemas) represent knowledge of the world based on regularities that one has perceived in his/her environment in the past (Snyder, 2000, p. 95). They represent the world as it usually is (Snyder, 2000, p. 99) and serve as identification systems that activate appropriate knowledge for each situation (Rumelhart, 1980). Schemata have a significant role in memory as they constrain the amount of information to be memorized and avoid the need to remember a vast number of details for every object of perception (Snyder, 2000, p. 95). As another important function, schemata control one’s expectations of the world and thus allow to direct attentional resources to unusual and atypical information (Mandler, 1984, p. 105).

There are various concepts related to the notion of schema. For instance, scripts are “appropriate sequences of events in a particular context,” which are “made up of slots and requirements about what can fill those slots” (Schank & Abelson, 1977, p. 41). Similarly, templates consist of a core (which refers to stable properties of the template and conditions for its use) and slots (information which may vary from one situation to another) (Gobet, 2016, p. 54; see also Gobet & Simon, 1996). Frames represent stereotyped situations, and, like scripts and templates, they consist of fixed parts and variable slots (Minsky, 1988, p. 156). Finally, a musical gist refers to “a memory representation for schematically consistent tones – a general abstraction that lacks full detail of the original stimulus” (Agres, 2018, p. 174).

Schema research in jazz scholarship started in the 1970’s when researchers started to search for recurring formulas and formulaic systems in jazz solos. Yet, jazz researchers have shown little interest in schema analysis and related methods like Schenkerian analysis in recent years. Nevertheless, some interesting studies have appeared. For example, Love (2012) analyzed recurring melodic schemata and phrase structures in Charlie Parker’s blues improvisations (39 solos with a total of 156 choruses from 1944 to 1953) and found four recurring melodic schemata and five recurring phrasing schemata (recurring templates for phrase structure). Melodic schemata were defined as “recurring stepwise paths, spanning around one to eight measures, which a melody seems to follow” (Love, 2012, para. 4.1).

Love (2012, para. 4.16) did not claim that those melodic schemata revealed in his study necessarily represented Parker’s own thinking. To deal with this problem (the psychological existence of proposed schemata), Gjerdingen (1988) offered a set of guidelines for schema validation in music research. According to these guidelines, schemata can be validated either by psychological testing, finding evidence for shared features in a number of musical scores, or analyzing variations of a musical phrase (Gjerdingen, 1988, p. 34). For example, Gjerdingen argued that “the existence of slight variations in repetitions or restatements of a

musical phrase can lead to insights concerning what is central or peripheral to its underlying schema" (Gjerdingen, 1988, p. 34). However, schema validation can be highly difficult because of the limits of variation problem: it is difficult to say much a piece of music can change and still be an instantiation of the same schema (Gjerdingen, 1988, pp. 68-70). Another problem is that hierarchical structures may have limited psychological significance to listeners. As a result, listeners may have difficulties in perceiving similarity between original music and reductions of that music. According to Serafine et al. (1989), listeners' ability to match foreground and middleground reductions with the original music was only slightly above the chance level (64% for foreground reductions and 59% for middleground reductions). In another study, Dibben (1994) found that listeners were able to successfully match hierarchical structures with the original piece of music with tonal music but not with atonal music. In addition, Cook (1987) found that tonal closure (return to the original key) had little effect on listeners' aesthetic ratings except with very short musical works, which indicates that large-scale hierarchical structures in music may have little perceptual validity for listeners. These problems also concern formula analysis (the topic of the next chapter).

### 3.1.3 Formulas and formulaic systems

The concept of 'formula' dates to the theory of formulaic composition in oral poetry originally formulated by Milman Parry. According to this theory, oral poets use their knowledge of well-learned word combinations (i.e., formulas) to recreate songs in performance (Parry, 1930). More recently, Wray (2002) defined formulaic sequence as "a sequence, continuous or discontinuous, of words or other elements, which is, or appears to be, prefabricated: that is, stored and retrieved whole from memory at the time of use, rather than being subject to generation or analysis by the language grammar" (p. 9). Much of the everyday use of language is formulaic, as evidenced by frequently used word combinations (Siyanova-Chanturia & Martinez, 2015).<sup>40</sup>

The first applications of formula theory to music analysis were Leo Treitler's article *Homer and Gregory: The transmission of epic poetry and plainchant* (Treitler, 1974), Thomas Owens's (1974) dissertation on Charlie Parker's music, and Lawrence Gushee's (1991) analysis of four recordings of *Shoe Shine Boy* by Lester Young (originally presented as a conference paper in 1977). In his article, Treitler (1974) discussed transmission of plainchant before the use of musical notation and argued that singers used their knowledge of formulaic systems and standard formulas to reconstruct the music at each performance. Treitler used the notion of formulaic system to "refer to the system of constraints of a melody or a phrase," while he used the notion of formula to refer to standard patterns (Treitler, 1974, p. 352). Note that the notion of 'formulaic system' resembles the notion of 'schema.' Whereas the notion of schema is often used to refer to abstract

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40 The relationship between the theory of formulaic composition in oral poetry and its applications in music research deserves a profound analysis. However, a detailed discussion about this subject matter is beyond the scope of the present study.

knowledge structures typically in the form of a core and variable information, the notion of 'formulaic system' refers to constraints that allow to perceive similarities between different musical works, for example.

In his extensive study of about 250 Charlie Parker solos, Owens (1974) found ninety-seven recurring melodic patterns (or motives, as he called them), which formed sixty-four melodic pattern categories. Approximately one quarter (17/64) of these melodic pattern categories accounted for the most recurring melodic patterns. According to Owens, Charlie Parker used recurring melodic patterns (which may vary in terms of size, frequency of use, and application in different harmonic contexts) as building blocks of his improvisations. Shorter recurring melodic patterns were often used in a large variety of harmonic contexts. Longer recurring melodic patterns, however, often had specific harmonic implications and they were used less often.

Owens did not mention formula theory (nor did he use the term formula), but his use of the term 'motive' corresponds to the concept 'formula' as presented in the works of early advocates of formula theory (Finkelman, 1997, p. 160). In addition to an analysis of repeated melodic patterns, Owens also moved towards schema analysis by proposing ways of how pre-learned melodic patterns can take different forms in improvisations. According to Owens, melodic patterns can be "varied by means of metric displacement, augmentation and diminution, addition and subtraction of notes, and altered phrasing and articulation. In addition, they are juxtaposed in many different ways and are often connected by newly invented melodic material" (Owens, 1974, p. ix). In addition, Owens applied Schenkerian analysis to uncover larger and more abstract aspects in Charlie Parker's solos.

Gushee's (1991) paper, originally presented as a conference paper in 1977, was the first explicit application of formula theory in the context of jazz studies. Gushee's definition of formulaic system and formula resembles Treitler's use of these terms. According to Gushee (1991, p. 239), formulas are "more or less literal motive or phrase repetitions," whereas a formulaic system refers to "a more generalized structural outline embracing many specific formulas." However, Gushee's use of these terms is not consistent throughout the paper. He identified seven types of "formulas," many of which were actually rather abstract musical ideas that may appear in various forms (as evident in their titles: degree progression which is characterized by a descending chromatic stepwise motion, Gmaj7 arpeggio with emphatic F#, flattening the sixth, etc.) and therefore (except for the category of 'blues clichés') they should be labelled as formulaic systems.<sup>41</sup>

In line with Owens (1974), several more recent studies have emphasized that repeated melodic patterns play an important role in jazz improvisation (Berliner, 1994; Weisberg et al., 2004; Norgaard, 2014; Norgaard et al., 2016; Love, 2017; Norgaard & Römer, 2022). According to Owens (1995), learning a large

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41 According to Brownell (1994), formula theory was misunderstood by many music researchers except Treitler (1974). For further discussion on this matter, see Chapter 4.1.3: Motor-generated ideas.

knowledge base of melodic patterns is also a necessary condition to improvise fluently at fast tempos<sup>42</sup>.

Parker, like all important improvisers, developed a personal repertoire of melodic formulas that he used in the course of improvising. He found many ways to reshape, combine, and phrase these formulas, so that no two choruses were just alike. But his “spontaneous” performances were actually precomposed in part. This preparation was absolutely necessary, for no one can create fluent, coherent melodies in real time without having a well-rehearsed bag of melodic tricks ready. (Owens, 1995, p. 30.)

Previous research also indicates that even if some expert-level jazz musicians use pre-learned melodic patterns in their improvisations to a substantial extent, there seems to be considerable variation in the rate of repetition of pre-learned melodic patterns among expert jazz musicians. For instance, Weisberg et al. (2004) found 3,395 recurring melodic patterns with different length in six solos by Charlie Parker, 797 recurring melodic patterns in four solos by Lester Young, and 308 recurring melodic patterns in a single solo by Jaco Pastorius. Moreover, they found that the average proportion of notes captured by recurring 4-interval melodic patterns was 90% (in Charlie Parker’s solos), 74% (in Lester Young’s solos), and 51% (in Jaco Pastorius’s solo). In another study, Norgaard (2014) found that 82.6% of notes started a recurring 4-interval melodic pattern in a corpus of forty-eight solos by Charlie Parker, and 99.3% of notes were part of some recurring melodic pattern with at least three intervals. More recently, Norgaard and Römer (2022) found that 88.4% of all notes in the Weimar Jazz Database (which consists of 456 solos by seventy-eight jazz musicians) started a recurring 4-interval melodic pattern. However, when they analyzed the solos of eight musicians with ten or more solos in the Weimar Jazz Database, the relative frequency of notes that started a recurring 4-interval melodic pattern ranged from 42% to 63% (Norgaard & Römer, 2022, p. 19)<sup>43</sup>.

In comparison, Owens (1974) found 97 recurring patterns in about 250 solos. Although Owens’s work was based on a huge number of solos, the rate of repeated melodic patterns was much lower compared to Weisberg et al. (2004) and Norgaard (2014). More recently, Frieler (2019) found that the so-called X atoms (i.e., short pre-learned melodic patterns that did not belong to any other categories of basic melodic elements in jazz improvisation) comprised 18.5% of all melodic atoms in a sample of 456 jazz solos by seventy-eight jazz musicians. As a subgroup of X atoms, links (X atoms with the length of one interval only) comprised an additional 20.6% of all melodic atoms, which means that X atoms and links accounted for about 40% of all melodic atoms. In addition, Frieler found

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42 This claim indicates that a very large repertoire of pre-learned melodic patterns explains the creativity and behavioral flexibility (the ability to adjust to changing situations) of expert jazz musicians. According to this view, “behavioral flexibility might be achieved by having a very large repertoire of responses that are themselves individually inflexible” (Christensen et al., 2019, p. 697).

43 The relative frequency of notes that started a recurring 4-interval melodic pattern was 62.0% (in Michael Brecker’s solos), 41.6% (in Steve Coleman’s solos), 63.4% (in John Coltrane’s solos), 60.3% (in Miles Davis’s solos), 51.2% (in David Liebman’s solos), 55.8% (in Charlie Parker’s solos), 48.8% (in Sonny Rollins’s solos), and 46.4% (in Wayne Shorter’s solos) (Norgaard & Römer, 2022, p. 19).

that melodic atoms followed each other in an almost random way. According to him, these findings indicate a high level of variability in the sample.

Stehr (2016) investigated the number of repeated melodic patterns in six solos by Charlie Parker, four solos by Lee Konitz, and three solos by Warne Marsh. He found forty-four melodic patterns (with five or more notes) that were played in all six solos of Charlie Parker. In comparison, the number of melodic patterns that were played in all four solos by Lee Konitz was nine, and the number of melodic patterns that were played in all three solos by Warne Marsh was only one. The number of melodic patterns that were played in two solos by Warne Marsh was forty-eight. The number of melodic patterns that were played in three solos by Lee Konitz was sixty-five and the number of melodic patterns that occurred in five solos by Charlie Parker was 204. Stehr's findings indicate that pattern use is not a necessary part of playing bebop or learning to play it and that "licks, and specifically the licks of Parker, are not an essential aspect [of] the bebop language" (Stehr, 2016, p. 104). Stehr also argued that even if Konitz and Marsh's playing was less formulaic compared to Parker, "the use of licks is in part what allows Parker to sound more spontaneous [compared to Konitz and Marsh]. [...] By deemphasizing the extemporaneous creation of melodic content, Parker is able to focus on other issues, such as tone, style, articulation and coherence which aids in boosting the excitement and perceived spontaneity in his playing." (Stehr, 2016, p. 103.)

There are several possible reasons for the diversity of these results. First, there are large differences in the sample sizes of these studies. Owens (1974) used a sample of about 250 solos by a single musician. Although Owens did not report the total number of bars (or notes) in each solo or the overall number of bars (or notes) in the sample, a search through his research material shows that the shortest solos included only twelve bars. Weisberg and his colleagues used six solos by Charlie Parker (median length: about 400 notes; maximum length: 1,270 notes), four solos by Lester Young (range of length: 137 to about 900 notes), and one solo by Jaco Pastorius (length: 642 notes) (Weisberg et al., 2004, Musical materials section). Similarly, Stehr's (2016) sample consisted of six solos by Charlie Parker, four solos by Lee Konitz, and three solos by Warne Marsh. Stehr did not report the total number of bars in each solo, but the total number of bars in all solos was 799 for Parker's solos, 523 for Konitz's solos, and 261 for Marsh's solos (Stehr, 2016, p. 80). Norgaard (2014) used a sample of forty-eight solos by Charlie Parker. The total number of bars (or notes) in each solo or the overall number of bars (or notes) in the sample was not reported.

In most of these studies, a recurring interval sequence was defined as an interval sequence that occurred at least twice in the corpus of solos. As a result, the proportion of repeated melodic patterns is expected to increase with the number of solos in the corpus. On the other hand, it also makes sense to argue that the shorter the improvisation, the easier it is to reach a high proportion of novel melodies and thus the proportion of repeated melodic patterns is expected to decrease with the length of the improvisation. Note that the latter prediction is related to the length of a single improvisation, whereas the former prediction is

related to the size of a corpus of improvisations. Also note that the number of identified pre-learned melodic patterns may be inflated, at least to some degree, if accidental repetitions of melodic patterns are not ruled out. Accidental repetition of melodic patterns refers to the situation where a particular melodic pattern is not actually retrieved from long-term memory during performance, but it is invented anew in several performances. It should be noted that all these studies also used a very low threshold level to identify pre-learned melodic patterns. All melodic patterns that occurred at least twice were categorized as pre-learned melodic patterns.

Second, it is possible that the high proportion of repeated melodic patterns in Weisberg et al. (2004) and Norgaard (2014) was caused by that harmonic context was disregarded in both studies. Harmonic context was also disregarded in Stehr (2016). Harmonic context constrains what note choices are appropriate. As a result, the number of recurring melodic patterns is likely to increase when harmonic context is disregarded, because the same interval sequence is appropriate in a number of harmonic contexts. It is also noteworthy that Weisberg and his colleagues ignored all rests, and all analyzed improvisations were also based on the same chord progression, both of which may have exaggerated the proportion of recurring melodic patterns in this study (as noted by Norgaard, 2014, p. 274). In addition to Weisberg et al. (2004), also Stehr's (2016) sample consisted of improvisations based on a single chord progression. Note that Stehr's data consisted of sequences of pitch events (e.g., C, D, E) instead of interval sequences and he ignored the melodic contour of these sequences and calculated the repetition of melodic patterns using data where all pitch events were transformed to occur in a single octave.

Third, melodic patterns that function as chunks must have a specific beginning and ending. In case this issue is not considered, identified melodic patterns may have no perceptual relevance and there is no evidence that these melodic patterns were retrieved from memory as a single unit. This problem may occur when repeated melodic patterns are identified at any metrical position regardless of whether identified melodic patterns form plausible musical units with a beginning and end or not. In contrast to Owens (1974), segmentation of melodic patterns based on psychologically relevant segment boundaries was ignored in Weisberg et al. (2004), Norgaard (2014), Norgaard & Römer (2022), and Stehr (2016).

Finally, note that even if Norgaard (2014) removed overlapping patterns that started at the same note, this procedure was not used in Weisberg et al. (2004) and Stehr (2016). The decision not to remove overlapping melodic patterns may exaggerate the average length of melodic patterns and overestimate the number of repeated melodic patterns. For instance, consider the following example. Figure 3 shows a simple artificial melody with a repeated 3-interval melodic pattern [+2, +2, +1], first in C major (repeated 4 times) and then in D major (repeated 3 times). In this example, 18% (7/39) of notes started a repeated melodic pattern. When overlapping melodic patterns were not removed, there were three repeated melodic patterns: [+2, +2] (7 occurrences), [+2, +1] (7 occurrences), and

[+2, +2, +1] (7 occurrences). In this case, 54% (21/39) of notes started a repeated melodic pattern.



FIGURE 3 Overlapping melodic patterns in an artificial melody (example 1)

Figure 4 shows yet another simple artificial melody. In this case, there are four repeated melodic patterns: [0, 0, 0, 0] (bars 1-4) (4 occurrences), [+2, -2, +2, -2] (bars 5-8) (4 occurrences), [+2, +2, -4] (bars 9-11) (4 occurrences) and [+2, +2, +1, -5] (bars 13-16) (4 occurrences). As a result, 27% (16/60) of notes started a repeated melodic pattern. When overlapping melodic patterns were not removed, there were 101 recurring melodic patterns (range of intervals in each pattern: 2-15; range of frequency: 2-15) in this simple melody when the minimum length of patterns is two intervals, and the minimum number of occurrences is two. In this case, 95% (57/60) of notes started at least one repeated melodic pattern.



FIGURE 4 Overlapping melodic patterns in an artificial melody (example 2)

### 3.1.4 Schema theory of motor skills

According to Schmidt's (1975) schema theory of motor skills, a single motor program can be used to produce a number of variations of a particular movement (e.g., throwing a ball) by setting different specifications for the movement (e.g., throwing a ball with a different speed or different force) (Schmidt, 1975, p. 232).

Since a limited number of motor programs can be used to produce a large variety of actions, which implies that each movement does not require a separate motor program, Schmidt used the term ‘generalized motor program’ for a motor program for a particular class of movements. Schmidt’s notion of generalized motor program is mentioned in several studies on the psychology of jazz improvisation (e.g., Pressing, 1988; Norgaard, 2014; Norgaard et al., 2023). For instance, Pressing (1988, p. 153) argued that “it is schemata for action that are triggered, not precise movement details, and subsequent motor fine tuning based on feedback processes goes on after each time point.”

According to Schmidt (1975), four types of information are stored when an individual makes a goal-directed movement: “(a) the initial conditions, (b) the response specifications for the motor program, (c) the sensory consequences of the response produced, and (d) the outcome of that movement” (Schmidt, 1975, p. 235). These four types of information are used to form two types of schemata: recall schemata and recognition schemata. The recall schemata are formed by information on initial conditions, actual outcomes, and response specifications. The recognition schemata are formed by information on initial conditions, actual outcomes, and sensory consequences. (Schmidt, 1975, p. 237.)

A major advantage of Schmidt’s notion of generalized motor program is that it helps to circumvent the problem of storage demands: if there should exist a distinct motor program for each movement or a similar number of references to which actualized movements are compared to, the number of learned movements would produce a severe storage problem (Schmidt, 1975, p. 229). According to Schmidt, his theory is also able to explain the generation of novel movements. The same generalized motor program can be used to produce a number of movements by using different movement specifications. Since these specifications may not have been used before, the actual movement may be novel and never tried before. (Schmidt, 1975, p. 236.)

According to Schmidt, movements can be slightly modified even within the timescale of some tens of milliseconds. However, whenever a motor program must be replaced by another after it has been initiated, the course of action cannot be changed until the motor program has “run its course for approximately 200 msec,” or more likely for nearly 400 milliseconds depending on response type (Schmidt, 1975, pp. 232-233). In contrast to slow movements, rapid movements do not “allow feedback to be used while the movement is in progress” (Schmidt, 1975, p. 241). If the speed of movements is fast enough, action monitoring and error detection must rely on predictive feedforward control mechanisms instead of sensory feedback (Maidhof et al., 2009, p. 5). For instance, rapid finger movements of musicians are too fast to be controlled based on sensory feedback (Lashley, 1951, p. 123). However, it is easy to find activities in which motor programs cannot be successfully executed in absence of sensory feedback. For instance, downhill skiing becomes incredibly difficult if one’s eyes are closed. (Hommel et al., 2016, p. 130.)<sup>44</sup>

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44 The role of sensory feedback in jazz improvisation is discussed in more detail in Chapter 4.1.5: The role of sensory feedback in idea generation.



The notion of generalized motor program (or a scaleable response structure, to use Shea and Wulf's terminology) as an abstract structure that shares a set of invariant features (e.g., invariant order of submovements) and enables to produce a number of actions with different movement specifications, continues to be useful although some parts of the theory need revision in order to conform with recent empirical findings (Shea & Wulf, 2005).

## 3.2 Theories and models on jazz improvisation

### 3.2.1 Pressing's cognitive theory of improvisation

Pressing argued that improvisations consist of series of non-overlapping sections, which he called event clusters (Pressing, 1988, pp. 152-153)<sup>45</sup>. Event clusters are often, but not always, separated from each other based on various musical cues (e.g., pause, phrase boundary, or any another cue that sets a musical boundary) (Pressing, 1988, p. 153). In addition to musical cues, motor cues (e.g., fingering, hand position) and cognitive cues (e.g., knowledge of performer's musical style) may also be useful in setting boundaries between event clusters (Pressing, 1987, p. 161). Unfortunately, Pressing was not specific in his principles to segmentation of event clusters.

Another important aspect of Pressing's theory is that all event clusters can be considered from different points of view (aspects): as it is heard (acoustic aspect), as it is represented in terms of musical concepts (musical aspect), in terms of motor actions, timing, touch, and proprioception (movement aspect), as it is seen (visual aspect), and as it is emotionally experienced (emotional aspect). Other relevant aspects may also exist. (Pressing, 1988, p. 154.) Event clusters can be further divided to three types of components (which Pressing called "arrays"): objects (e.g., a chord or motif), features (e.g., loudness or duration), and processes (e.g., making a quotation of a well-known musical work) (Pressing, 1988, pp. 154, 156; Pressing, 1998, p. 56)<sup>46</sup>. Continuity and discontinuity between event clusters

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45 Pressing's emphasis on event clusters indicates that he regarded action control at the level of event groups to be especially important in improvised music. Action control at the level of event groups means that note choices are made in groups and thus each note is not chosen separately. Pressing defined event cluster as "an integrally conceived motoric and musical unit consisting of one or more events [e.g., a single note or a sequence of notes]" (Pressing, 1987, pp. 159-160).

46 Pressing's distinction between objects and processes is presented most clearly in Pressing (1984). In this paper, Pressing wrote: "the musical improviser typically practices in two rather distinct ways. One method is to practice the execution of specific forms, motives, scales, arpeggios or less traditional musical gestures, so that such musical objects and generalized representations of them are entered into long-term 'object memory' [i.e., declarative memory] in conceptual, muscular and musical coding. A second method is to practice the 'process' of compositional problem-solving: transitions, development and variation techniques, and methods of combining and juxtaposition are practiced in many musical contexts and with many different referents. This experience (along with actual performance) forms the basis for long-term 'process memory' [i.e., procedural memory]." (Pressing, 1984, p. 355.)

is achieved by associative and interrupt generation. Continuity between two event clusters means that event clusters must share some property in any of the three types of arrays (object, feature, process). (Pressing, 1988, p. 155.) In other words, continuity can be achieved at the level of note duration (e.g., continued use of eighth notes), intervals (e.g., continued use of perfect fourths), note choices (e.g., continued use of the notes E, G, and B), key (e.g., continued use of notes from the key of C major), and so on (Pressing, 1988, pp. 162-164). Besides building continuity between event clusters, improvisers may also interrupt the associative stream of event clusters by abandoning the current musical direction (interrupt generation) (Pressing, 1988, p. 155).

The referent and the knowledge base are also key concepts in Pressing's theory. Pressing defined the referent as "an underlying formal scheme or guiding image specific to a given piece, used by the improviser to facilitate the generation and editing of improvised behaviour on an intermediate time scale" (Pressing, 1984, p. 346). In jazz, the referent is most often the song form (including melody and chord progression) (Pressing, 1998, p. 52). The referent has several roles in music performance. For instance, it gives identity to a musical piece and guides expectancies in musical improvisation. The use of referent also increases processing efficiency because it provides pre-learned material for the improviser<sup>47</sup> and thus makes it possible to decrease cognitive demands on the selection and generation of actions and reduces the amount of decision-making in music performance. Also, a shared referent makes it possible to allocate less attention to other musicians' actions. (Pressing, 1998, p. 52.) In addition to the referent, an expert improviser also has an extensive knowledge base to increase his/her fluency in improvisation. The knowledge base consists of "musical materials and excerpts, repertoire, subskills, perceptual strategies, problem-solving routines, hierarchical memory structures and schemas, generalized motor programs, and more. It is a cauldron of devices collected and fine-tuned on the basis of optimizing improvisatory performance" (Pressing, 1998, pp. 53-54).

Pressing (1988, p. 152) suggested that all theories of musical improvisation must not only explain "how people improvise," but also how they learn to improvise, and what is the origin of novel actions. However, there is very little discussion in Pressing (1988) about the second and the third topic. The second topic (how people learn to improvise) is only discussed for two pages. According to Pressing, there are three cognitive changes that occur with the development of improvisational skills: (1) increased memory for objects, features, and processes, (2) increased accessibility of long-term memory, and (3) increased attunement to perceptual information (Pressing, 1988, p. 166). Pressing argued that practice allows to recognize redundancy in sensory information which leads to reduced cognitive load (Pressing, 1984, p. 355; Pressing, 1988, p. 167). Practice also helps to focus on relevant sensory input (Pressing, 1988, p. 167), to execute motor actions with increasing economy (Pressing, 1984, p. 355), and to reach a level of

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47 According to Pressing (1984, p. 346), improvising musicians cannot avoid using pre-learned materials and respectively no musician can avoid making at least small variations to the music.

musicianship where variable and novel actions can be produced through automated use of motor programs (Pressing, 1988, p. 140). The third topic (the origin of novel actions) is discussed briefly and in a vague way. Pressing identified three sources of novel actions: “the evolution of movement control structures for newly discovered objects, features and processes, [...] the motor enactment of novel combinations of values of array components, [...] and] distorting aspects of existing [actions]” (Pressing, 1988, pp. 161-162).

According to Pressing’s (1988), automation allows to attend higher levels of musical expression (e.g., dynamics, emotion)<sup>48</sup>. Attention to higher levels of music also plays a role in musical creativity. According to Chaffin et al. (2006), creativity in a highly automated performance depends on the use of higher-level performance cues<sup>49</sup>. Performance cues are defined as “the landmarks of the piece that a musician attends to during performance, carefully selected and rehearsed during practice so that they come to mind automatically and effortlessly as the piece unfolds, eliciting the highly practised movements” (Chaffin et al., 2006, pp. 201-202). Performance cues also provide locations in music that can be directly retrieved without the need to rewind the whole musical piece from the beginning to find a particular location (Chaffin et al., 2006, p. 202). Jazz musicians too use this memorization strategy when they are learning new musical works (Noice et al., 2008).

Creativity in performance is most likely to occur if attention is focused on expressive cues (the highest level of performance cues), which “allows the artist to adjust the performance to the unique opportunities and demands of the occasion to achieve the maximum possible impact on the audience” (Chaffin et al., 2006, p. 215)<sup>50</sup>. Creativity in performance is less likely to occur if attention is focused on lower levels of performance cues (basic cues and interpretive cues) (Chaffin et al., 2006, p. 215)<sup>51</sup>. This claim has received some support from recent qualitative studies. For example, one of Norgaard’s (2011) interviewees reported that he often starts to improvise with a general plan like: “start the solo with sparse melodic material, develop this material in subsequent choruses building to an emotional peak in the second to last chorus, and finally ‘wind down’ in the last chorus” (Norgaard, 2011, p. 122). Similarly, Wilson and MacDonald (2016) found that free improvisers’ “choices suggest a focus on larger structural aspects

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48 According to Pressing (1988), increased automation allows performers to attend “almost exclusively to a higher level of emergent expressive control parameters [...] like form, timbre, texture, articulation, gesture, activity level, pitch relationships, motoric ‘feel’, expressive design, emotion, note placement and dynamics” (p. 139).

49 Cuing refers to a process where activation of a memory automatically activates other memories that are associated with it (Snyder, 2000, p. 70).

50 This claim is not far from Berliner’s conception of improvisation. According to Berliner (1994, p. 241): “improvisation involves reworking precomposed material and designs in relation to unanticipated ideas conceived, shaped, and transformed under the special conditions of performance, thereby adding unique features to every creation.”

51 Similarly, Pressing (1984, p. 359) claimed that a strategy where attention is directed to a general overview of the music “is normally considered to produce better music” compared to a strategy where attention is focused on details and lower levels of musical hierarchy.

of the music as it emerged, such as overall texture or need for, and rate of, change” (p. 1039).

Pressing’s theory of improvisation is among the most, if not the most cited theory of improvisation. It has influenced much of the later improvisation research since the publication of his landmark works in the 1980’s. Pressing’s theory is useful for understanding some fundamental aspects of improvisation and some of his articles (Pressing, 1984, 1988, 1998) are still excellent sources for a multifaceted discussion on a variety of topics related to improvisation. However, Pressing did not provide any explicit predictions that could be tested. In addition, Pressing did not provide sufficiently specific principles of how to partition event clusters. In terms of predictive power, I agree with Clarke (2005) who argued that:

[Pressing’s theory] identifies a considerable number of abstract processes and kinds of data that may be involved in producing an improvised performance, but despite the rather intimidating appearance of its formalism, it is actually not formal enough to be implemented as a testable working model. It seems to be more like an attempt to indicate as many as possible of the components that might be involved in improvising [...], but with no sense of how these categories really work in any particular instance. (Clarke, 2005, p. 170.)

### 3.2.2 Johnson-Laird’s computational model of jazz improvisation

According to Johnson-Laird (2002), decision-making would be too slow if working memory for intermediate results was a crucial component in jazz improvisation (p. 424). As evidence to this claim, Johnson-Laird referred to an experiment carried out by him and Ivor Holloway, where they found out that cognitive load “had no adverse effects on improvisation” (Johnson-Laird, 2002, p. 439). Together with Rich Feit, Johnson-Laird also designed a computer program that was able to produce plausible jazz bass lines without storing intermediate results except for the previous note. In their view, the results were “at the level of a moderately competent beginner,” (Johnson-Laird, 2002, p. 438) but they claimed that the results could have been easily improved by using a larger knowledge base of contours and passing notes. (Johnson-Laird, 2002, pp. 437-439.)

Johnson-Laird identified three types of algorithms that could be used to model creativity in jazz improvisation. In neo-Darwinian algorithms, creative products are first created arbitrarily and then evaluated. The second type of algorithm, neo-Lamarckian algorithm, has a set of genre-specific criteria to allow a set of possibilities from which the algorithm makes an arbitrary choice. The third type of algorithm has a set of constraints for decision-making and another set of criteria for evaluation. Johnson-Laird concluded that the generation of chord progressions in jazz is likely based on similar processes as the third algorithm, whereas the generation of novel melodies is likely a result of similar processes as the neo-Lamarckian algorithm. (Johnson-Laird, 2002, p. 439.)

Another central aspect of Johnson-Laird’s model is that both composition of chord progressions and improvisation of melodies are based on rules instead of previously learned patterns (Johnson-Laird, 2002, pp. 439-440). Johnson-Laird claimed that note choices in improvisation are determined by two rules (or constraints). The first constraint determines which scale is appropriate based on the

current chord. The second constraint determines the appropriate melodic contour based on the context. (Johnson-Laird, 2002, p. 436.) These constraints reduce the number of options in each musical context, but the final choice among different possibilities is arbitrary (Johnson-Laird, 2002, p. 437).

Research on algorithmic expert systems is a natural framework in which to evaluate Johnson-Laird's claims. Many current expert systems are based on Markov-based models, where future events are "only determined by the current state (or the N last current states, depending on the chosen order)" (Pachet, 2012, p. 139). In other words, an event is determined by the probability of alternative possibilities based on N previous events (except in zeroth order Markov chains where previous events are disregarded). As such, low-order Markov models implement the idea of no-memory like Johnson-Laird. However, the application of some improvisational techniques (like side-slipping technique) requires the memory of previous phrase, which is contradictory to the idea that working memory is futile in improvisation (Pachet, 2012, p. 143).

According to Norgaard (2011), Johnson-Laird's focus on rules may offer a one-sided view of improvisation. In his view, pre-learned patterns (emphasized by Pressing, 1988) and internalized rules (emphasized by Johnson-Laird, 2002) are both used at different times to create improvised melodies in jazz. Evidence for this claim was provided from interviews, where participants reported that their choices were based on both pre-learned patterns and harmonic/melodic rules. (Norgaard, 2011, pp. 121-122.) In another study which investigated pattern use in a corpus of 48 solos by Charlie Parker, Norgaard (2014) found that 82.6% of notes started a recurring 4-interval melodic pattern and 99.3% of notes were part of some recurring melodic pattern with three or more intervals. Norgaard concluded that these findings support Pressing's (1988) theory of improvisation (according to which the use of pre-learned patterns plays an important role in improvisation) in contrast to Johnson-Laird's (2002) emphasis on the importance of rule-guided decision-making.<sup>52</sup>

### 3.2.3 Love's ecological model on jazz improvisation

According to Love's (2017) ecological model (or ecological description to use his preferred term) on jazz improvisation, improvisation is learned by developing perception through trial and error. Learning takes place when a person becomes more sensitive to affordances (i.e., possibilities for action) that exist in the

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52 Note that even if Johnson-Laird claimed that it would be impractical to rely on a large number of pre-learned melodic patterns instead of creating novel melodies (Johnson-Laird, 2002, p. 430) and argued that no one, possibly except for beginners, depends on pre-learned melodic patterns all the time (Johnson-Laird, 1988, p. 211), he acknowledged that musicians often repeat the same melodic patterns in their improvisations. In fact, Johnson-Laird (2002) was quite explicit on this matter: "jazz musicians can generate long-term relations in their improvisation without using working memory. They can make repeated use of a motif or a phrase throughout an improvisation because it is in long-term memory. [...] But, when musicians extemporize a striking phrase, they are likely to store it in long-term memory and perhaps to improvise variations on it. [...] There is no need for a working memory of intermediate computational results" (Johnson-Laird, 2002, p. 423).

relationship between a person and his/her environment. Love emphasized that perceptual learning is not the same as memory. In his view, repetition in improvisation does not require memory but it is a consequence of perceiving familiar affordances in the environment. (Love, 2017.) Love also argued that even if rules can be used to describe appropriate actions, they cannot explain these actions and claimed that “the psychological processes underlying expert improvisation do not depend on rules at any level” (Love, 2017, p. 34).

The term ‘affordance’ was introduced by Gibson (1977), who used it to refer to properties of the environment, whose meaning is related to what they offer. In Gibson’s words: “the affordances of the environment are what it offers animals, what it provides or furnishes, for good or ill” (Gibson, 1977, p. 68). For instance, sharp and rigid objects afford cutting, certain kinds of surfaces that are at the right height afford the possibility to sit on it, air affords breathing and so on (Gibson, 1977, pp. 68, 71, 75). Usually (but not always), affordances can be perceived directly, which means that perception of affordances often does not require substantial learning and that properties of a perceived object are specified in the structure of that object and hence its affordances already exist in the object (Gibson, 1977, pp. 79-80, 82). Moreover, affordances are not subjective nor objective properties of things since the meaning of an object (i.e., what kind of actions it makes possible to a person or an animal) does not depend on the observer and things do not afford anything if they are considered as objects of the outside world independent from the observer (Gibson, 1977, pp. 69-70).

Love’s use of the term ‘affordance’ is quite different. In his view, affordances are both objective and subjective. They are objective in that “the referent and style offers up the same affordances to every improviser, and improvisers succeed or fail to the extent they play inside these lines” (Love, 2017, p. 34). For example, jazz compositions offer the same basic song form and chord progression to all improvisers. According to Love, affordances are also subjective in the sense that the number of affordances for any referent is “practically infinite” and “for any particular passage, each improviser experiences a unique set of affordances, and these affordances usually appear before the improviser’s perception unmediated by rules” (Love, 2017, p. 34). In contrast to this view, Gibson’s affordances are “facts of the environment” (Gibson, 1977, p. 70). According to Gibson (1977, p. 81), a person can fail “to perceive what is present in the environment” and perceive something that is “not present in the environment,” because “either the available information is inadequate or, if not, the process of information pickup is deficient.” The possibility of misperceiving the environment is not in conflict with the view that affordances are independent from the observer.

Love’s approach has significant strengths in that it offers new ways of understanding psychological processes involved in improvisation. Also, it offers explicit predictions unlike Pressing (1988), for example. First, Love predicted that when soloists improvise on unfamiliar musical works, their initial actions (regardless of their quality or appropriateness) are unwittingly repeated from one chorus to the next. The explanation is that if improvisers do not have any previous experience of improvising in a specific context, their initial actions

“constitute the whole of their experience in this environment” (Love, 2017, p. 42). Second, Love predicted that musicians repeat the same patterns more often compared to what has been suggested in previous research and fast “attention-taxing tempos will not inhibit this repetition, as it does not depend on acts of recall” (Love, 2017, p. 42). Third, Love predicted that new affordances will spontaneously emerge as time goes by. Fourth, Love predicted that soloists make familiar-path errors<sup>53</sup> when a musical work deviates from stylistic norms (e.g., when a musical work is based on unordinary chord progression). Such familiar-path errors are caused by misperceptions of familiar affordances. (Love, 2017, p. 42.)

### 3.2.4 Goldman’s theory of improvisation

According to Goldman (2016), musicians from different musical traditions differ in their ways of knowing musical structures. For instance, there are many ways to understand what a C major chord is: it may be known in terms of haptics, proprioception, the way it sounds, how it is physically produced, or what it looks like on notation (Goldman, 2016, para. 3.2). By investigating differences between musicians from different backgrounds, Goldman proposed a research program to “compare perceptual and cognitive processes, and structural and functional neuroscientific features, between *kinds* of musicians” (Goldman, 2016, para. 4.2).

As the basis of his theory, Goldman (2016) noted that there are several concepts (e.g., novelty, spontaneity, and freedom) which have been widely used in improvisation studies. However, he argued that these are culturally contingent terms and relative to what musical parameter (e.g., melody, rhythm, harmony) is focused, because of why it is problematic to define improvisation using these concepts. Moreover, Goldman claimed that the measurement and identification of novelty, spontaneity, and freedom depends on the person who does it and that “there is no objective way to claim that a given performance really has those features, and to what extent it has them” (Goldman, 2016, para. 1.10). Finally, Goldman noted that both improvisation and non-improvisation can produce the same result, because of why one cannot distinguish between improvisation and non-improvisation based on the final product. As an alternative way to define improvisation and to distinguish between improvisation and other forms of musicianship, Goldman suggested that improvisation could be defined as ways of knowing that are specific to improvisation (Goldman, 2016, para. 8.1).<sup>54</sup>

Goldman’s (2016) proposal to investigate differences in knowledge between improvisers and other kinds of musicians offers a promising way to acquire new

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53 As also noted by Love (2017), the concept of error is problematic in improvisation, where it is impossible to identify errors based on comparing a performance of music with pre-written notes in a score. Despite of this problem, errors certainly exist in improvisations too (e.g., in the form of an unintended arrival to a strong beat or chord change too early, false perceptions of the written chord progression, and making mistakes in memory recall of the song form or chord progression).

54 Note that Goldman (2016) did not claim that concepts like novelty, freedom, and spontaneity should be rejected in improvisation studies. In fact, if we are interested in aspects of improvisation that are appreciated by improvising musicians themselves, these concepts cannot be fully ignored.

insights on cognitive processes underlying jazz improvisation. There are already a few studies that have investigated these differences. In a study by Bianco et al. (2018), a group of classical pianists and jazz pianists were shown photos of one-hand chord sequences and they were asked to play these chord sequences with a muted piano. Half of the chord sequences were typical in terms of classical harmony and fingering, but the other half contained violations to conventional classical harmony and/or fingering. The chord sequences also differed in key and length. According to the results, jazz pianists executed incongruent chords faster than classical pianists, which indicates that jazz pianists were quicker to reprogram their action plans and they were more flexible in handling harmonic violations. On the other hand, classical pianists displayed fewer fingering errors compared to jazz pianists, but they “experienced higher cognitive effort to resolve conflict in response to the unexpected chord” (Bianco et al., 2018, p. 392). The authors concluded that “generative jazz training coincides with a higher flexibility to deal with harmonic possibilities, whereas interpretative classical training enhances the preparedness to accurately set fine movement parameters” (Bianco et al., 2018, p. 392).

In another study, Goldman et al. (2020) asked their participants to listen to chord progressions and to respond as quickly as possible if they noticed anything unusual in them. Participants were also instructed to respond only if they were certain that there was something unusual in the chord progression. According to their results, participants with more experience in improvisation perceived deviant chord progressions more quickly and more accurately when the deviant chord was from a different functional category compared to when the deviant chord was from the same functional category, which indicates that experienced improvising musicians are sensitive to functional categories of chords. (Goldman et al., 2020.) Greater sensitivity to unexpected chords among jazz musicians has also been shown by Przysinda et al. (2017).

Nichols et al. (2018) investigated six working memory tasks under cognitive load. Jazz musicians outperformed classical musicians, when participants were asked to recall arpeggiated triads played on piano and to play them accurately. Regarding the other working memory tasks, no differences between the groups were found. Finally, Vuust et al. (2012) and Tervaniemi et al. (2016) found that specialization in a particular musical style influences musicians’ perceptual skill. According to Vuust et al. (2012), jazz musicians were more sensitive to changes in auditory stimuli compared to classical and rock/pop musicians, especially regarding pitch and pitch slides. These results can be explained by the fact that ear training plays a significant role in jazz schools and the complexity of chord progressions, chords, and rhythms in modern jazz places great demands on musicians’ auditory skills. (Vuust et al., 2012.) In another study, Tervaniemi et al. (2016) found that experience in classical music was associated with enhanced sensitivity to violations in tuning compared to non-musicians. Experience in jazz was associated with better auditory skills regarding timbre compared to rock musicians. Both classical and jazz musicians were more sensitive to violations in timing compared to non-musicians.



### 3.3 Other perspectives on musical creativity

#### 3.3.1 Implications from expert systems research

Expert systems are computer algorithms designed to imitate human expertise (Gobet, 2016, p. 236). They can be divided to at least four broad and non-exclusive categories based on their design: evolutionary algorithms (also known as genetic algorithms and neo-Darwinian algorithms), rule-based algorithms (also known as grammar-based algorithms), probabilistic algorithms, and artificial neural network-based algorithms (also known as connectionist algorithms).

Evolutionary algorithms are based on random generation of ideas from which some of the ideas are selected for further elaboration. As described by Johnson-Laird (1988), “its first stage consists of a procedure that combines elements at random to generate a potentially vast number of putative products, and its second stage uses a set of constraints to filter out the products that are not viable” (p. 217). Jazz musicians spend a vast amount of time rehearsing their skill “offline,” trying new ideas and evaluating their goodness. To the extent that these new ideas have a random origin, evolutionary algorithms are consistent with the way jazz musicians create new ideas. On the other hand, there is an important weakness in evolutionary algorithms. Random generation of initial sequences may produce outcomes that are not viable, which makes these systems inefficient (Johnson-Laird, 1988, p. 217) and forces to use manual editing (Pachet, 2012, p. 127). As a solution to this problem, Brown (2004) combined features of evolutionary and rule-based algorithms to decrease the influence of inherent weaknesses related to these types of algorithms. After a careful selection of settings, Brown was able to produce melodies which displayed not only well-formedness but also some aesthetic value and novelty.

As an alternative to evolutionary algorithms, many expert systems have adopted rule-based search strategies to select appropriate musical choices. As a particularly interesting example, Ramalho et al. (1999) created an expert system called *ImPact*, which can produce jazz bass lines based on reusing fragments from a database, application of production rules (if-then rules), and context information (e.g., chord progression of the musical work, previous note choices). Most production rules represented knowledge at the level of abstract musical properties (e.g., “play syncopated phrase during this last section”) (Ramalho et al., 1999, p. 11). All fragments were derived from six bass lines played by Ron Carter for the Jamey Aebersold play-along multimedia. The authors reported that their bass lines were rated by professional jazz bassists as “much better than a human beginner’s bass lines” (Ramalho et al., 1999, p. 19).

Rule-based systems can be highly complex. For example, the total number of rules in *ImPact* was eighty-four (Ramalho et al., 1999), but some rule-based expert systems are based on much larger sets of rules. In comparison, *CHORAL* used about 350 rules to harmonize four-part chorales in the style of J. S. Bach (Ebcioğlu, 1990). The definition of rules is also a laborious process if done manually (Fernández & Vico, 2013, p. 522). In addition, the requirement to define all

possibilities beforehand with if-then rules may lead to descriptions that are too complex for practical use (e.g., for teaching the musical style of classical composers).

As an example of probabilistic algorithms, Norgaard et al. (2013) created a pattern-based algorithm that can produce improvisations in any style based on Markov chains and without using any rules. Chord progressions and their function as constraints for note choices were not considered in this design. As noted by the authors, however, it is possible that rules are a necessary part of algorithms that aim to produce improvisations based on pre-defined chord progressions (Norgaard et al., 2013, p. 251). According to Fernández and Vico (2013, p. 536), probabilistic algorithms based on low-order Markov chains can produce unsuccessful results with lack of direction whereas the use of high-order Markov chains may lead to mere repetition of patterns from the training data. As one solution to this problem, Pachet (2012) used variable-order Markov chains with a maximum order of two to ensure “an optimal compromise between similarity and creativity” (p. 129).

Most recent work on expert systems in music has used artificial neural networks and deep learning approaches (Civit et al., 2022). These approaches have turned out to be highly successful in passing musical Turing tests (where success refers to evaluators’ inability to distinguish between works produced by humans and computer algorithms) (Briot, 2021, pp. 40-41). However, artificial intelligence is still underutilized in creativity research (Gobet & Sala, 2019). According to Gobet and Sala (2019), artificial intelligence could be highly useful in testing existing theories of creativity, developing new theories, providing tasks that are more complex and ecologically valid compared to those typically used, identifying domain-specific creativity, and training creative abilities in people.

There are some common problems related to expert systems in general. According to Jordanous (2011), expert systems have lacked a standard evaluation system to assess the creativity of their outputs. In addition, the creativity of these systems has often not been evaluated at all. In a sample of seventy-five creative expert systems, only a third of expert systems were evaluated on the creativity of their outputs. (Jordanous, 2011.) Another problem is that expert systems can perform complex tasks merely “by force of accumulated data” without the need to have any knowledge of how such tasks are performed in the real world (Miller, 2020, para. 1.7). The ability to imitate a desired behavior does not yet prove that the model functions in the same way as humans do, but it does provide an “adequate hypothesis which can then perhaps be tested in more direct way (for example, through experimental work)” (Temperley, 2007, p. 6).

### **3.3.2 Neuroscience of musical improvisation**

A recurring finding in the neuroscientific research on musical improvisation is that “brain networks involved in musical improvisation perform domain-general processes that are recruited for the spontaneous generation of music” (Erkkinen & Berkowitz, 2019, p. 513). For example, in a study which compared positron emission tomography (PET) data during improvised generation of vocal

melodies and spoken sentences, Brown et al. (2006) found that both tasks were associated with almost the same brain regions. In another study, de Manzano and Ullén (2012) showed a considerable overlap of neural substrates between musical improvisation and the generation of pseudo-random motor responses.

As another common finding in the neuroscience of musical improvisation, several studies have shown that motor regions of the brain play an important role in improvisation (Bashwiner & Bacon, 2019). For example, in a study which involved an extraordinarily large number of participants ( $N = 239$ ), experience with composition and/or improvisation was found to be associated with “greater cortical surface area or volume” in motor regions of the brain, the default mode network, and the limbic network (Bashwiner et al., 2016, abstract). The significant role of motor regions in musical improvisation and other forms of human creativity is not surprising, since the only way to produce musical improvisations and any other creative products is through motor actions (Erkkinen & Berkowitz, 2019, p. 515). Nevertheless, human creativity may also require the motor system in a non-trivial sense. Anic et al. (2018) compared the effects of inhibitory versus excitatory transcranial direct current stimulation (tDCS) to the primary motor cortex (M1) in jazz improvisation. According to their results, excitatory tDCS to M1 increased creativity in jazz improvisations as indicated by expert ratings. An additional music analysis also revealed that excitatory tDCS increased the variety of notes, the number of notes, and pitch range in comparison to inhibitory tDCS. These findings indicate that the M1 may not be only responsible for the execution of actions, but it might contribute to creative actions in other ways too (Matheson & Kenett, 2020, p. 3). According to Matheson and Kenett (2020, p. 4), the larger motor regions in musicians’ brains (compared to non-musicians) may not only facilitate fine motor control but may also allow “improvisors to generate a greater array of potential musical motoric actions to select from, therefore functionally contributing to an improvisor’s ability to be creative.”

Overall, there are several brain areas involved in the planning and execution of actions, including the dorsolateral prefrontal cortex (DLPFC), primary motor cortex (M1), lateral premotor cortex (LPMC), supplementary motor area (SMA), anterior cingulate cortex (ACC), orbitofrontal cortex (OFC), and cerebellum (Hommel et al., 2016, p. 18). Along with these brain regions, musical improvisation is also associated with bottom-up networks involved in auditory processing and output monitoring (which operate at fast timescales) and top-down networks involved in flow states and social aspects of improvisation (which operate at slow timescales) (Faber & McIntosh, 2019). In the following discussion, I will focus on interaction between the executive control network and the default mode network, the latter of which is associated with spontaneous internally oriented processes such as mind wandering and task-independent thought (Andrews-Hanna, 2012).

In one of the first studies on the neuroscience of musical improvisation, Limb and Braun (2008) compared functional magnetic resonance imaging (fMRI) activation patterns in professional jazz musicians. Participants were asked to play a C major scale, improvise melodies using the notes of this scale only, play

a pre-learned melody of a jazz composition, and improvise freely based on the chord progression of that musical work. Both improvisation settings showed increased activity in the frontal polar cortex (a portion of the medial prefrontal cortex) and simultaneous decreased activation throughout the lateral OFC and the DLPFC. Most brain regions showed opposite patterns of activation when participants were playing pre-learned musical sequences.

This pattern of decreased activity of the DLPFC and increased activity of the medial prefrontal cortex (MPFC) is associated with deactivation of the executive control system and activation of the default mode regions (Beatty, 2015, pp. 111-112). In accordance with Limb and Braun (2008), Berkowitz (2010) proposed that expert-level improvisation is characterized by a state of “letting go,” where improvisers allow automated processes to operate at lower levels of abstraction (e.g., the note-to-note level) and where they direct their “conscious attentional resources to higher-level musical processes” (p. 125). In his view, improvising musicians are only aware of a small portion of what processes are involved in their improvisations. Since many of these processes are only witnessed by improvising musicians, Berkowitz used the name ‘the creator and witness phenomenon’ to describe this issue. (Berkowitz, 2010, p. 125.)

The DLPFC is associated with top-down processing, attention to external cues, and executive functions such as working memory (Erkkinen & Berkowitz, 2019, p. 514). Decreased activation in the DLPFC during musical improvisation has been reported in several studies (Limb & Braun, 2008; McPherson et al., 2016; Tachibana et al., 2019). In addition, Liu et al. (2012) found decreased activation in the DLPFC during freestyle rap. However, Tachibana et al. (2019) did not find consistent support for deactivation of the DLPFC during improvisation tasks. These authors also found that subjective positive feelings regarding the creativity of their performance were associated with decreased activation in the DLPFC, whereas subjective feelings of formulaic performance were associated with increased activation in the DLPFC (Tachibana et al., 2019). In another study, McPherson et al. (2016) found that the expression of positive emotions through improvisations was associated with more pronounced deactivation in the DLPFC compared to the expression of negative or ambiguous emotions.

However, the role of the DLPFC in musical improvisation is controversial as several studies (Bengtsson et al., 2007; de Manzano & Ullén, 2012; Donnay et al., 2014; de Aquino et al., 2019) have reported increased activation in the DLPFC during musical improvisation, not the other way around. One explanation for these contradictory findings regarding the role of the DLPFC in musical improvisation is that increased demands on attention and memory may contribute to increased activation in the DLPFC (Liu et al., 2012, p. 6). Similarly, Donnay et al. (2014, p. 8) argued that the increased activation of the DLPFC may have been caused by the social context involved in duo improvisations and the higher demands on working memory in duo improvisation compared to solo improvisation. Loui (2018, p. 139) proposed that the decreased activity in the DLPFC in Limb and Braun’s (2008) study may have been caused by lower demands on working memory in the improvisation task compared to the control task in which participants were required

to recall and produce novel melodies. In addition, Pinho et al. (2016) found that the activity of the DLPFC may depend on task constraints. When they asked their participants to improvise with loose task constraints (either happy or fearful emotional content), the DLPFC was less activated compared to when participants were asked to improvise with a pre-defined set of notes.

Several studies have also suggested that the DLPFC may have a different role for more experienced musicians versus less experienced musicians, and that different processing modes (in accordance with dual-processing models) may have a different role for musicians with different levels of expertise. For instance, Beaty (2015, p. 114) noted that while Limb and Braun's (2008) participants were professional jazz musicians, participants in several other studies (e.g., Bengtsson et al., 2007; de Manzano & Ullén, 2012) were classical musicians who probably were not as experienced with improvisation as jazz musicians. Rosen et al. (2016) used anodal tDCS applied over the right DLPFC (which is associated with Type 2 processing) and found that while the quality of performance increased among less experienced musicians, the effect was reverse for more experienced musicians. Lopata et al. (2017) found that jazz improvisation (for participants with formal training in improvisation) was associated with greater frontal upper alpha-band activity compared to tasks where participants either listened to music or reproduced pre-learned melodies, and interpreted this finding "as evidence of a creative mental state characterized by spontaneous processing, and likely by a degree of top-down inhibition and internal focus of attention" (Lopata et al., 2017, p. 255). In another study, Pinho et al. (2014) found that improvisation experience was negatively correlated with activation of the DLPFC. In addition, musicians with more experience in improvisation "showed higher functional connectivity between prefrontal, premotor, and motor regions of the frontal lobe" (p. 6161). According to these authors, "skilled improvisational performance may thus be characterized by both lower demands on executive control and a more efficient interaction within the network of involved brain areas" (Pinho et al., 2014, p. 6162).

In addition to exploring the function of separate brain regions like the DLPFC, neuroscientific studies on improvisation have also been particularly interested in interactions between different brain regions. On a systems level, an interaction between the default mode network (DMN) and the executive control network (ECN) appears to play an important role in creative cognition (Beaty et al., 2015; Beaty et al., 2018) and musical improvisation (Beaty, 2015; Belden et al., 2020). For instance, Belden et al. (2020) reported that both improvising musicians and classical musicians showed higher connectivity between the ventral DMN and the bilateral ECN compared to subjects with minimal training in music. Improvising musicians showed the highest connectivity between the DMN and the ECN, whereas classical musicians showed the highest connectivity between the ventral DMN and the frontal pole.

### **3.3.3 4E cognition and dynamic systems framework**

Recent work on creativity has increasingly adopted the idea that creativity "is shaped continually, in real-time, by past, present and anticipated interactions

with the external world” (Bishop, 2018, p. 2). The 4E cognition framework (which refers to embodied, embedded, enactive, and extended aspects of cognition) consists of different but partially overlapping perspectives on cognition (Malinin, 2019, p. 2). In short, embodied cognition refers to intrinsic coupling of the mind and the body, the view that cognition emerges from interaction between the brain, the body, and the environment, and deconstruction of cognition-related dualisms such as the distinction between the brain and the body and the distinction between action and perception<sup>55</sup>. Embedded cognition refers to how cognitive activity is shaped by natural, social, and cultural environment. Enactive cognition underlines the notion of sense-making and the two-way process in which an autonomous agent shapes the environment and is shaped by it. Extended cognition refers to how cognition is extended to the world when cognition is considered not to be bound to the brain or even the body. (Wilson & Foglia, 2017; van der Schyff et al., 2018; Malinin, 2019.)

These approaches emerged as a departure from traditional cognitivist accounts, where the brain was thought to play a primary and almost exclusive role in cognition, and which ignored the importance of interactions between the brain, the body, and the environment (Gallagher, 2018). These approaches also rejected “the sequential sense-think-act processing cycle,” which had dominated the field of cognitive science (Beer, 2000, p. 97). Moreover, theories within the 4E cognition framework also appeared as a reaction to neurocentric ideals within traditional cognitive science (e.g., the idea that all psychological processes can be reduced to neuroscience and explained by neuroscientific research) and various neurocentric disciplines that have emerged in recent years (e.g., neurophilosophy, neuroeducation, and neuroaesthetics) (Gallagher, 2018).

From the perspective of embodied cognition, the brain is seen as a part of a larger system which consists of the entire human being including the body and its sensorimotor abilities. Wilson and Foglia (2017) specified three ways of how the body plays a role in cognition and cognitive processing: “the body can function as a *constraint* on cognition, as a *distributor* for cognitive processing, or as a *regulator* of cognitive activity” (Wilson & Foglia, 2017, 3 What embodied cognition is section). The body as a constraint thesis suggests that the content and type of representations are influenced by bodily characteristics. This thesis also suggests that different types of cognition are more natural to some people but difficult or impossible for others. The body as a distributor thesis suggests that cognitive processing is distributed or shared between the mind and the body. As a result, the body may take part in cognitive tasks and reduce cognitive load related to the task. Finally, the body as a regulator thesis holds that the body ensures the coordination between internal states and action through feedback. (Wilson & Foglia, 2017.)

The dynamic systems approach “describes how self-organizing, complex, systems emerge and develop over time” (van der Schyff et al., 2018, p. 8). A major

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55 The embodiment thesis holds that “the body, the brain, and the mind must be understood as one system” in which thought is not separated “from sensation or action.” Instead, “perception, thought, and action” are considered to be codependent processes. (Iyer, 2016, p. 76.)

difference between this approach and traditional views in psychology is that development is thought to be caused directly by changes in the relationship between multiple components instead of a unidirectional link between the brain and behavior (Thelen, 1995). In terms of motor actions, for example, each movement is thought to emerge from multicausal interactions between various components including body, context/environment, and task characteristics.

For infants as well as for adults, movements are always a product of not only the central nervous system but also of the biomechanical and energetic properties of the body, the environmental support, and the specific (and sometimes changing) demands of the particular task. The relations between these components is not simply hierarchical (the brain commands, the body responds) but is profoundly distributed, “heterarchical,” self-organizing, and nonlinear. (Thelen, 1995, p. 81.)

The dynamic systems approach assumes that complex systems are composed of a large number of elements that are in contact with the environment without an “executive agent or a programme that produces the organized pattern” (Smith & Thelen, 2003, pp. 343-344). As a major advantage compared to classical views, the dynamic systems approach can circumvent the homunculus problem. Homunculus refers to a theoretical concept or a system which acts as the decisive force behind actions. For instance, theories based on concepts like the will, central executive, and attentional supervisory system all suffer from this problem (Hommel et al., 2016, p. 6). The problem is that these concepts lead to circular explanations, where inhibition of actions, for example, is explained by the existence of an inhibitory system or where willed actions are explained by the existence of the will (Hommel et al., 2016, pp. 6-7).

Some researchers within the 4E cognition and dynamic systems framework have rejected the notion of mental representations in their research. Advocates of anti-representational views understate or even deny the significance of mental representations (i.e., internal models that can produce behavior independently from the world). However, theories of human behavior that ignore mental representations are faced with insuperable problems which undermine their plausibility and generality. For instance, skilled chess players can perform well even with their vision impaired (as is the case in blindfold chess), which is easy to explain with mental representations but difficult otherwise (Gobet, 2016, p. 201). Also, anticipatory behavior cannot be explained solely by an interaction between the organism and its environment because anticipation “involves internal factors beyond the immediate constraints of the environment to achieve or fulfill future needs, goals or conditions” (Wilson & Foglia, 2017, 4.2 Mental representation section). Similarly, rare medical conditions such as locked-in syndrome show that cognitive functioning can remain normal even if a person is completely unable to move his or her limbs and to interact with the environment (Paavilainen, 2020, p. 64).

To my knowledge, there are almost no empirical studies that have explored musical creativity from the 4E cognition and dynamic systems framework. As an exception, Walton et al. (2018) investigated coordination in piano duos when pianists were playing either with a swing backing track (a bass line for the jazz standard *There's No Greater Love*) or a continuous drone. According to their results,

improvised parts were more similar in terms of note combinations and key press timings when the piano duos played with a drone. The duos also produced more shared movements with drones. Based on the increased repetition of each other's actions and movements with drones, it is surprising that the musicians reported more freedom when they were playing with a drone instead of a swing backing track. The authors applied cross-recurrence quantification analysis which can be used to identify recurring states between two systems from dynamic systems perspective (see Marwan et al., 2007; Marwan, 2008; Demos et al., 2014). More specifically, Walton and his colleagues calculated the proportion of shared note combinations and key press timings and the maximum length of recurring patterns and key press timings between the two pianists. Cross-recurrence quantification analysis was also applied to movements and was supplemented by a post-session interview with the pianists. Although the authors did not directly address musical creativity in their research, their study suggests that cross-recurrence quantification analysis could be useful in creativity research.

Radical forms of the 4E cognition and dynamic systems research seem to have limited explanatory power in creativity research. For example, some aspects of musical improvisation (e.g., the repetition of melodic patterns in different solos of the same musician) are difficult to explain without the notion of mental representations. To circumvent this problem, it should be noted that the 4E cognition and dynamic systems approaches do not necessarily require to deny the notions of mental representations and preprogramming (Wilson & Foglia, 2017). If reformulated to reject an exclusive and unidirectional role of mental representations, these approaches certainly have much to offer and could provide novel insights on cognition. Finally, the 4E cognition framework offers a useful theoretical basis to investigate idea generation and the role of familiar instruments in music performance. There is little knowledge on whether musicians use different sources of idea generation when they switch from one instrument to another (e.g., when they switch from playing the trumpet to use their voice; see Chapter 4.1: Sources of idea generation in jazz improvisation). In addition, although it is well-known that musicians prefer to play concerts with familiar instruments (e.g., a familiar guitar model) whenever it is possible, a recent study did not find statistically significant differences in timing between performance of scales with three different piano keyboards (Lipke-Perry et al., 2019). Also, it could be useful to perform case studies to investigate how physical and bodily traumas might affect the role of the body as a mediator between the external world and the mind.

### **3.3.4 Experts' insights into their creative process**

Cook (2006, p. 18) warned about intentional fallacy when making inferences about composer's intentions: composer's intentions cannot be known except through an analysis of the composition, and as a result, knowledge of such intentions adds nothing to descriptions of the composition. Similarly, Brownell (1994) used the notion of 'notism' to describe research that is focused on products rather than processes. In his view, it is difficult to see how even the most detailed analysis could explain how a musical work emerged. In jazz research, however, audio



recordings and transcriptions “appear to be the best possible evidence to use, especially when studying elite expert performance” (Lehmann & Goldhahn, 2016, p. 347). With famous musicians, there are also often no alternatives to using audio recordings in data collection (Widmer, 2005, p. 17).

Another common approach to investigate processes that underlie improvisation is to ask musicians to report their experiences of improvisation process. Although such introspective reports may provide valuable information from the creator’s point of view, they may be vulnerable to bias. For example, Deliège and Richelle (2006) argued that “the more complex the processes at work, the less amenable they are to the person itself” (p. 2). It is also important to note that when musicians are asked questions in reference to particular recordings, these recordings should be recent enough to provide “accurate recollections of their thought processes at the moment of creation” (Norgaard, 2011, p. 111). Because of this problem, several studies (Hargreaves et al., 1991; Mendonça & Wallace, 2004; Fidlon, 2011; Norgaard, 2011; Wilson & MacDonald, 2016) have used a procedure, where participants are asked to think aloud either simultaneously when they are performing a task or shortly after that. However, this procedure has its own concerns, because instructions “to report cognitive processes may have induced a different mode of control than that which would be employed in typical performance” (Christensen et al., 2019, p. 699).

Although musicians’ knowledge of their craft may help researchers to ask relevant questions (McPherson & Limb, 2013) and to provide valuable criticism regarding theories of creativity (Huovinen, 2021),<sup>56</sup> qualitative studies have limited possibilities to infer what kinds of processes underlie musical improvisation<sup>57</sup>. In fact, subjective reports by expert musicians indicate that their memories of their intentions can be vague. For example, the eminent saxophonist David Liebman (1996, p. 94) claimed that if he was stopped while playing and asked to sing what he was going to play next, he could often only produce the beginning of the phrase “in terms of the pitch area, the general melodic contour, rhythmic shape and expressive setting (including dynamics, articulation and nuances).”<sup>58</sup> Similarly, Fidlon (2011) found that experienced jazz musicians’ most usual descriptions of what they were going to play next referred to pitch sketches which “did not contain specific details about the content or when events would occur” (p. 86). In addition, Norgaard (2011) found that experienced jazz musicians

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56 Regarding music students’ implicit understanding of musical creativity, Huovinen (2021) argued that “students possess a wealth of first-hand experience in musical creativity and that their theory appraisals might thus tell us something important about the scope and nature of theories of creativity” (p. 19).

57 According to Lehmann and Goldhahn (2016), although musicians may have little difficulties communicating their conscious thought processes, “they admit that the highly automatized performance often precludes conscious processing while performing” (p. 346).

58 The inability to show exactly what one was going to play next may be partly due to unpredictable interactions in group improvisation. According to Liebman (1996, p. 94), “as the line is revealed, instantaneous response to the accompaniment leads to constant revision and reinterpretation. After the outset, a line becomes truly spontaneous meaning that where it will end is also unpredictable. This is particularly true for the longer lines played.”

described their action planning in terms of “architectural elements like note density, instrument register, and harmonic structure” (p. 116).

According to Johnson-Laird (2002), cognitive processes that underlie improvisation are mostly unconscious and not accessible (for the most part) to conscious awareness. As a result, musicians may only have a limited insight into what they are doing when they improvise. Other behaviors, like spontaneous speech, are no easier in this matter - only a small proportion of processes involved in spontaneous speech are available to conscious awareness and therefore it is not a simple task to make sense of how people are able to speak fluently. (Johnson-Laird, 2002, p. 417.) Interestingly, musicians can also have major difficulties when they are asked to explain basic concepts such as groove and swing. However, it is likely that the lack of explicit knowledge on the meaning of such concepts has little or no effect on their playing.

Even experts may have a limited insight of cognitive processes that take place during an improvised performance. In fact, much of what happens during improvisation is only witnessed by the improvising musician (Berkowitz, 2010, p. 125). However, the lack of access to underlying processes of one’s actions does not mean that subjective reports about underlying processes are always incorrect. Instead of direct awareness of mental processes, subjective reports are based on a priori causal theories and beliefs about their plausibility. Depending on the accuracy of such theories, descriptions of underlying causes of actions may be either accurate or inaccurate. (Nisbett & Wilson, 1977.)

According to Dreyfus (2006), skilled actions are characterized by a lack of deliberation and reasoning as long as the situation is usual. In his view, expertise in any domain requires direct involvement with the situation and rejection of rigid context-free rules learned in an earlier phase of progress. Since expertise is typically characterized by intuitive responses without deliberation, “all reasons advanced to justify a specific action could only be retroactive rationalizations” (Dreyfus, 2006, p. 46). Similarly, Høffding (2014) argued:

In my own investigation of the phenomenology of expert musicians I have not found the issue of reason-giving to be of special importance: undertaking a phenomenological investigation of expert musicianship, I could ask a musician, ‘why are you playing this note in this exact way?’ or ‘what is the reason you played more loudly in this passage?’. Most likely, I would be met with an answer to the effect of ‘well I don’t know, that is what is written in the score’, ‘I guess I just felt like playing it like that’, or ‘that is how we agreed to do it’. In other words, asking musicians to retroactively ascribe reasons to their actions does not yield much insight into their phenomenology. (Høffding, 2014, pp. 51-52.)

On the other hand, the inability to explain the cause of actions does not mean that actions are fully automatic. In fact, completely automatic actions probably do not exist (Hommel & Wiers, 2017; see also Ericsson & Lehmann, 1996; Christensen et al., 2019).

## 4 SOURCES AND CONSTRAINTS OF IDEA GENERATION

### 4.1 Sources of idea generation in jazz improvisation

Hargreaves (2012) distinguished between three sources of idea generation in jazz improvisation: strategies, audiation, and motor programs<sup>59</sup>. Musicians may differ on what source of idea generation they mostly rely on. Musicians may also use a different source of ideas when they, for example, switch to a different instrument: a trumpet player might primarily rely on strategy-generated ideas when playing the trumpet but switch to audiation-generated ideas when singing (Hargreaves, 2012, pp. 354, 365). Such a change in the source of ideas is illustrated clearly in the following quote (for a similar example, see Hargreaves, 2012, p. 354):

My quintet was performing and the saxophonist had swiftly moved from alto saxophone to clarinet, and had just concluded a superb solo. Having worked with him for five years or so, I knew his 'voice' and noticed something. I asked him "You sound different, do you feel your ideas on clarinet come the same way?" After some deliberation and reflection, he replied, "No, it's different" but at the time he did not elaborate. I wondered if the change of instrument altered the musician's creative process. (de Bruin, 2015, p. 91.)

A discussion of different sources of idea generation is relevant to the current study because these different sources of idea generation may indicate different types of creativity. Any measure of creativity only applies to specific types of

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59 The distinction between motor-generated and audiation-generated ideas resembles the two levels of playing discussed by saxophonist David Liebman. The first level refers to playing well-learned ideas which are "immediately ready to be reproduced in a real playing situation" (Liebman, 1996, p. 31). The second level refers to "working out of a newly formed, not yet perfected idea," where the musician "may have an idea in his mind or ear but not yet under his fingers" (Liebman, 1996, p. 32). Liebman also mentioned an extremely rare third level of playing, where "the artist knows he has heard the seeds of something different" (Liebman, 1996, p. 32).

creativity. Therefore, researchers should be explicit on what types of creativity their research investigates and what kinds of creativity their research ignores.

#### 4.1.1 Strategy-generated ideas

According to Hargreaves (2012, p. 359), “strategies provide a specific plan for behaviour as a means of solving the compositional demand of improvisation.” Strategy-generated ideas do not necessarily require musicians to audiate their ideas, because of why this source of ideas can be used even by beginners whose audiation skills may yet be underdeveloped (Hargreaves, 2012, p. 360). Strategies are also useful in educational settings since they can be consciously analyzed and applied (Hargreaves, 2012, p. 363). It is noteworthy that a number of strategies used in composition can also be applied in improvised music. Such strategies include different forms of variation (e.g., transposition, augmentation, and diminution of musical ideas). However, some strategies used in composition (e.g., inversion and retrograde) are cognitively too demanding to be used in improvised music.

Norgaard (2011) interviewed seven artist-level jazz musicians to reveal their thought processes during improvisation. Each participant was first asked to play an improvised solo on a familiar key and chord progression (blues in F major). After participants completed their improvisations, they were asked to explain how they constructed their solos. As they explained their behavior, participants were introduced to recordings and preliminary transcriptions of their playing. According to the results, all musicians reported that they planned and evaluated their playing. They also reported four distinct sources of idea generation: the use of well-learned ideas, making note choices based on harmonic priority (where appropriateness of note choices in relation to the chord progression is prioritized), making note choices based on melodic priority (where attention is primarily focused on melody instead of the chord progression), and repeating ideas from previous parts of the improvisation with or without modifications.

In another study, Wilson and MacDonald (2016) investigated strategies used in free improvisation. Based on interviews with 15 musicians, the authors found two basic strategies: (1) maintaining the current direction of music, and (2) changing the current direction of the music either by making an initiative to change the current direction of the music or responding to someone else’s initiative to change the current direction of the music. The latter strategy was further divided to three substrategies: adoption (where responses are highly similar to contributions of another musician), augmentation (where responses are partly similar with contributions of another musician), and contrast (where responses are different from contributions of another musician). Other strategies reported in previous research include creating a certain mood and building a narrative (Hargreaves et al., 1991).

### 4.1.2 Audiation-generated ideas

According to Gordon (1989, p. 3), “a person audiates when he can hear and comprehend music for which the sound is not physically present.” Audiation is related to musical imagery, which refers to “a multimodal process by which an individual generates the mental experience of auditory features of musical sounds, and/or visual, proprioceptive, kinesthetic, and tactile properties of music-related movements, that are not (or not yet) necessarily present in the physical world” (Keller, 2012, p. 206). In comparison, audiation is a narrower term and limited to auditory modality. Audiation is also related to playing by ear, which refers to the ability to use internal models of “what the music should sound like” to inform what notes should be played (Woody, 2012, p. 82).

There are various benefits on audiation skills and other forms of mental imagery. For example, playing by ear is an essential skill for musicians and supports the development of various other skills including sight-reading, improvisation, playing from memory, and performing rehearsed music (for a review, see Woody, 2012). According to Pecenka and Keller (2009), auditory imagery may also facilitate action coordination in musical group performance by improving the ability to anticipate future sounds by other musicians. According to their results, participants who performed well on pitch imagery and temporal imagery tasks synchronized their tapping more precisely with stable and changing tempo. In addition, participants who performed well on imagery tasks tended to predict rather than track tempo changes.

In contrast to playing well-learned patterns, the use of audiation as a source of ideas allows musicians to use a wider range of ideas that is only constrained by what one has heard in his/her lifetime. However, using a musical instrument to produce audiation-generated ideas can be difficult even for musicians with the highest level of expertise. Performance context may affect the difficulty of producing audiation-generated ideas with a musical instrument, but there are probably several other factors that may also have an effect. According to the legendary jazz bassist Ron Carter, the ability to produce audiated sounds can be disturbed “if the room is really boomy” (e.g., a gymnasium), if “it has a really high ceiling,” or if “there is a lot of carpet in the room” (Nurmi, 2018, p. 23). In accordance with these claims, several studies have shown that delayed auditory feedback may disrupt music performance (Finney, 1997; Bartlette et al., 2006).<sup>60</sup> In addition, Keller (2001) proposed that several factors including poor acoustics, anxiety, inadequate technical skills, and distractions may influence allocation of attentional resources in music performance.

A growing body of research suggests that perception-action coupling and sensory-motor associations play an important role in music performance (for reviews, see Novembre & Keller, 2014; Maes et al., 2014), including audiation (see Keller, 2012). With its roots in the 19th century writings of ideomotor theorists, perception-action coupling refers to a view that perception and action are

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60 For a discussion on this issue, see Chapter 4.1.5: The role of sensory feedback in idea generation.

strongly intertwined<sup>61</sup>. In the words of Novembre and Keller (2014, p. 1), “given an association between movements and their ensuing effects, the perception of an effect can trigger a representation of the movement necessary to execute it. And vice versa, movement can trigger perceptual processes.” Sensory-motor associations allow to produce intentional actions based on expected sensory consequences (forward modeling) and to activate associated movements based on perceived consequences (inverse modeling) (Maes et al., 2014).

In support to theories of perception-action coupling in music performance, there is neuroscientific evidence that both auditory and motor cortex may be involved during musical imagery (Zatorre & Halpern, 2005). For instance, watching silent videos of someone playing the piano activates auditory cortex among musicians (Haslinger et al., 2005). Conversely, listening to familiar music produces involuntary activation in the motor cortex among musicians (Haueisen & Knöschen, 2001). Experimental studies have also shown that correspondence of perceived sounds (or other stimuli) and associated actions has an impact on reaction time and error-proneness. For example, Drost et al. (2005a) found that expert pianists produced requested chords faster when they were simultaneously presented a congruent auditory stimulus (the requested chord) compared to when they were presented an incongruent auditory stimulus (a different chord). In another study, these authors also found that incongruent auditory stimuli can lead to false responses (Drost et al., 2005b). In accordance with these studies, Keller and Koch (2008) found that action planning was faster when responses in a tapping task triggered congruent auditory effects (e.g., when tapping an upper key triggered a high-pitched sound) compared to incongruent auditory effects. This effect was more prominent with participants who had more musical experience, which suggests that audiation skills improve with musical experience and lead to an increased role of anticipated action effects in action planning. (Keller & Koch, 2008.)

Learning to play a musical instrument generates links between perceptual effects and corresponding motor actions. Perception-action coupling enhances the prediction of self-generated and observed actions of others (what and when will happen) and helps to entrain behavior in joint actions. (Novembre & Keller, 2014.) These functions are evident in dancing and orchestral playing, for example, both of which require ongoing comparison between self-generated actions and those generated by others (Jäncke, 2012, p. 26). Perception-action coupling also allows adaptation to novel situations (Goldman, 2016). As an example,

The action of picking up a glass of water is a different action every time depending on the size of the glass, the starting orientation of the body, the distance of the glass from the body, etc. In order to successfully interact with the world, we need this kind of

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61 According to ideomotor theorists, “human actions are initiated by nothing other than the idea of the *sensory consequences* that typically result from them” (Stock & Stock, 2004, p. 176). The execution of actions does not require any knowledge of how the motor system functions. In contrast, individuals learn what effects are linked to which actions. (Stock & Stock, 2004; for a review on contemporary ideomotor research, see Shin et al., 2010.)

coupling between sensory and motor systems in order to adapt to new situations. (Goldman, 2016, para. 4.6.)

Acquisition of sensory-motor associations explains how musicians can produce audition-generated ideas with their musical instruments. However, it is possible to imagine sounds that one is unable to produce, which indicates that contents of imagery are not fully constrained by existing associations between perception and action. In addition, one can also imagine things that one has never perceived. According to Bishop (2018), an explanation of why humans can imagine something they have never experienced may be the ability “to selectively recall elements of prior perceptual experiences and recombine them into something new” (p. 12).

It is important to emphasize that auditory-motor associations are learned (Maes et al., 2014) and their strength increases with experience (Keller & Koch, 2008; Drost et al., 2005a, 2005b). Auditory-motor associations are usually practiced by imitation and transcription (both of which develop the skill to associate sounds with corresponding movements) and by learning musical structures in all keys (which develops the ability to produce desired sounds in different contexts) (Goldman, 2016, para. 4.8). For less trained musicians, it might be difficult to produce audition-generated ideas with a musical instrument. However, transfer of audiated sounds to corresponding actions may not always be successful even for skilled musicians.

### 4.1.3 Motor-generated ideas

Motor-generated ideas refer to the use of well-learned motor programs as a basis of idea generation. In contrast to audition-generated ideas, motor-generated ideas do not require prior audition (Hargreaves, 2012, p. 362)<sup>62</sup>. This difference is illustrated in the following quote from jazz musician Harold Ousley:

Sometimes, the ideas come from my mind, and I have to find them quickly on my horn. [...] But other times, I find that I am playing from finger patterns; the fingers give it to you. (Berliner, 1994, p. 190.)

The role of motor-generated ideas in jazz improvisation has been emphasized in several studies. In fact, one of the most persistent ideas in improvisation research is that improvisation is a process of stringing together pre-learned musical materials<sup>63</sup>. As an example, Pressing (1988, p. 168) argued that improvisation is

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62 Saintilan (2015) performed a preliminary study based on nine interviews to investigate whether imagery is always used in performance of well-learned music. Most musicians reported using at least auditory imagery during performance. This finding indicates that the clear-cut distinction between motor-generated and audition-generated ideas is questionable. On the other hand, different sources of ideas may become synthesized with increasing expertise (Hargreaves, 2012, p. 365).

63 This idea should be viewed in the broader context of creativity research, where it has been long thought that novel ideas are not developed out of nothing but from combinations of pre-existing units of knowledge (e.g., Mednick, 1962; Schubert, 2011, 2021).

basically a process of stringing event clusters together<sup>64</sup>. There is some evidence to support this claim. According to Norgaard (2014), 99.3% of notes in a corpus of forty-eight solos by Charlie Parker were part of some recurring melodic pattern with at least three intervals. This finding is similar to Weisberg et al. (2004), who found that the average proportion of notes captured by recurring 4-interval melodic patterns was 90% in six solos by Charlie Parker. In another study, Norgaard (2011) interviewed seven artist-level jazz musicians and found that one of the participants “described his improvisational thinking as connecting smaller units to form longer lines” and “compared this to building with Legos, in which creation is a process of connecting pre-formed blocks” (p. 118). This idea is also common in expert systems research (Ramalho et al., 1999; Hodgson, 2006; Pachet, 2012). According to Ramalho et al. (1999, p. 6), however, jazz improvisation is not limited to reusing and stringing pre-learned musical fragments into larger units, but such a design is a successful way to construct expert systems for jazz improvisation.

There is little doubt that people often repeat their typical behaviors, and that this also holds true for improvising musicians. However, while musicians often reuse the same melodic and rhythmic patterns, and melodic contours in their improvisations, novel musical ideas often emerge too (Johnson-Laird, 2002, p. 430)<sup>65</sup>. According to Johnson-Laird (2002, p. 430), relying on a large number of pre-learned melodic patterns instead of creating novel melodies during performance would be impractical for experienced musicians.

According to Brownell (1994), improvisation as a process of stringing patterns together was already considered to be an inadequate representation of formulaic theory by its early advocates such as Treitler (1974) and Gushee (1991). As an example, consider the following citation from Treitler (1974):

If the singer has accumulated a repertory of standard formulas, each serves him when his knowledge of theme and formulaic system calls for a phrase of its characteristics. They belong to a complex of habits and associations that enable the singer to compose at high speed. [...] But this is not to say that the technique of oral composition depends on the singer's retention of a stock of standard formulas which he strings together. The formulaic analysis of an oral poem is a matter, not of making a count of recurrent phrases, but of identifying the formulaic systems that regulate the verses of the poem. (Treitler, 1974, p. 356.)

Motor-generated ideas are sometimes thought to have less aesthetic value compared to audition-generated and strategy-generated ideas. According to Poutiainen (2019, p. 25), practicing idiomatic patterns (also called formulas, clichés, licks, tricks, pet patterns, mannerisms, signature phrases, vocabulary patterns, and vocabulary phrases) is an important part in learning jazz language.

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64 However, there are very few references to this idea in Pressing's most famous articles (Pressing, 1984, 1988, 1998) and therefore it appears that the view of improvisation as basically a process of inserting pre-learned building blocks in a row may be a misinterpretation of Pressing's central claims. Pressing also noted himself that his theory has been severely misinterpreted in some cases, but unfortunately, he did not specify how it has been misunderstood (Pressing, 1998, p. 56).

65 According to Johnson-Laird (1988, p. 211), no one (except for complete beginners maybe) uses pre-learned patterns all the time.



However, improvisations where such patterns are used too frequently may have little artistic value (Poutiainen, 2019, p. 295). Despite its occasional bad reputation, even expert-level musicians sometimes fall back to merely playing their well-learned clichés (Hargreaves et al., 1991, p. 53).

#### 4.1.4 Collaborative idea generation

Jazz is most often performed in groups. As a result, collaborative forms of creativity have an important role in jazz improvisation. There are several phenomena related to collaborative idea generation, including communication, interaction, group flow, we-agency, shared cognition, and shared intentions. Importantly, collaborative idea generation is distributed across individuals instead of guided by a single person and can lead to unpredicted results “that cannot be attributed to any one person” (Bishop, 2018, p. 2; see also Sawyer & DeZutter, 2009). As another important aspect of collaborative idea generation, collaboration can also lead to results that are “greater than the sum of individual contributions” (Bishop, 2018, p. 2). These two aspects of collaborative idea generation are referred to as a phenomenon called emergence, which can be defined as follows:

A property of a system is said to emerge from the system’s parts in interaction when (a) the system property is not held by any of the parts (a commonly used example is water; water is a liquid, but hydrogen and oxygen are not); (b) the system property could not be predicted even if one held a full and complete knowledge of the parts. (Sawyer & DeZutter, 2009, p. 83.)

The notion of emergence plays an important role in dynamic system theories, where ‘emergence’ refers to “the coming into existence of new forms through ongoing processes intrinsic to the system” (Smith & Thelen, 2003, p. 343)<sup>66</sup>. Linearity and nonlinearity are also important notions in dynamic system theories. Whereas the output of a linear system is simply a sum of contributions of individual parts (Paavilainen, 2020, p. 54), nonlinear systems operate through interactions in which “small changes in one or more components of the dynamic system can lead to reorganization and to large differences in behaviour” (Smith & Thelen, 2003, p. 347). In linear systems, the outcome is the combined effect of all individual parts. In contrast, nonlinear systems can produce surprising effects that cannot be explained by properties of individual parts.<sup>67</sup>

Further research could benefit from discovering new ways to measure creativity in the context of group improvisation. As an alternative to qualitative methods to study emergence (e.g., interaction study; see Sawyer & DeZutter, 2009), quantitative methods using transcriptions and audio recordings could be

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66 Similarly, the notion of emergent property (or emergent product) refers to novelty caused by interaction between individual parts of a system (see Paavilainen, 2020, p. 31).

67 According to Sawyer and DeZutter (2009, p. 82), collaborative emergence is more likely to occur if the following four characteristics take place: the outcome is not pre-defined, each person’s contributions depend on immediately preceding actions, consequences of actions can be changed by subsequent actions, and each person’s contributions are equally important.

highly useful in improvisation studies. Recurrence quantification analysis and cross-recurrence quantification analysis could be helpful in this matter (see Marwan et al., 2007; Marwan, 2008; Demos et al., 2014).

#### 4.1.5 The role of sensory feedback in idea generation

Sensory feedback refers to a process where “visual, aural, tactile, and kinaesthetic data generated during action allows performers to assess if their intended goal is achieved” (Hargreaves, 2012, p. 357). Instrumental improvisers may use feedback from all senses, and “the design of some instruments allows more precise visual feedback and more categorical kinaesthetic feedback than others” (Pressing, 1988, p. 135). In contrast, improvising vocalists can only rely on auditory and kinaesthetic feedback (Pressing, 1984, p. 354). Performance conditions may affect the importance of sensory feedback. For instance, altered auditory feedback may be less disturbing if actual sounds cannot be anticipated (Goldman, 2013, p. 220).

Auditory feedback facilitates learning of new musical works (Repp, 1999; Finney & Palmer, 2003) and plays a major role in intonation and error correction among string players (Chen et al., 2008)<sup>68</sup>. Auditory feedback may also play an important role in music performance when playing an unfamiliar instrument or in a new environment (Repp, 1999). In addition, continuous feedback allows musicians to make changes to their action plans (Goldman, 2019). According to Goldman,

performers are continuously evaluating and re-evaluating the sounds they are making in relation to themselves and their co-performers. Feedback is continuously guiding movements, and thus they are in some sense constantly deciding what to do next. This continuous control allows improvisers to change course fluently and at almost any point in time in response to a new idea of their own or that of a fellow performer. (Goldman, 2019, p. 284.)

However, it is probably not only continuous feedback per se, which allows improvising musicians to make changes to their actions plans but also their relatively short reaction times contributes to this. According to a recent study, musicians’ simple reaction times for auditory and tactile stimuli were shorter compared to non-musicians (Landry & Champoux, 2017), which indicates that musicians may be able to use feedback to guide their choices more fluently compared to non-musicians. It is likely that expert jazz improvisers’ ability to use feedback of their own playing and their co-performers’ playing is better compared to novice jazz improvisers.

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68 In addition to sensory feedback, predictive control mechanisms also play an important role in error detection and error correction (for a review, see Maidhof, 2013). Maidhof et al. (2009) and Ruiz et al. (2009, 2011) found that expert pianists can detect erroneous notes prior to their onset and prior to the possibility of using auditory feedback for this purpose. According to these studies, incorrect notes were also executed more slowly (as indicated by increased inter-onset intervals between correct and incorrect notes) and with decreased loudness (as indicated by lower MIDI velocity). Moreover, Ruiz et al. (2009, 2011) also found that notes after incorrect notes were also executed more slowly.

Except for learning new musical works (Repp, 1999; Finney & Palmer, 2003), the absence of auditory feedback has little effect on piano performance (Finney, 1997; Repp, 1999; Finney & Palmer, 2003; Ruiz et al., 2009). In contrast to the absence of auditory feedback, delayed auditory feedback seriously impairs music performance by increasing error rates (Finney, 1997) and timing asynchrony between musicians (Bartlette et al., 2006). Both delayed and altered feedback may also disrupt the use of existing sensory-motor associations and thus prevent improvisers from using their “well-learned motor patterns in performance, which could force them to rely on some other kind of knowledge and process to generate the music” (Goldman, 2019, p. 287). On the other hand, altered auditory feedback does not disrupt musical performance when feedback is noncontextual in relation to the performed music (i.e., not part of the note sequence) (Mathias et al., 2017) or structurally dissimilar to planned actions (Pfordresher, 2005). In addition, even if future-oriented altered auditory feedback (where the next note is heard instead of the current note) disrupts the production of memorized melodies by causing a temporary slowing down, the same does not apply to past-oriented altered auditory feedback (where the previous note is heard instead of the current note) (Mathias et al., 2017). The absence of auditory feedback may have different consequences on the quality of music performance depending on whether feedback of one’s own playing or other musicians’ playing is blocked. According to Bishop and Goebel (2015), the absence of auditory feedback had negative effects on synchronization in a duo performance only when auditory feedback of the other musician’s playing was blocked. In contrast, the absence of auditory feedback had no effect on synchronization when musicians’ own playing was blocked.

Altered feedback may also have different consequences on the quality of music performance depending on modality. Expert musicians who have played together for a long time may not necessarily need visual communication or visual monitoring of other musicians’ actions to perform successfully as a group and they may rely more on auditory feedback instead of visual feedback (Salice et al., 2019, p. 203). More generally, a reduced need to monitor other musicians’ actions may be caused by shared intentions and shared mental models among a group of musicians. According to Canonne and Aucouturier (2016), “from the moment a band chooses for example *My Funny Valentine* as a basis for improvisation, they know (and know that each of them knows) that the style of music is more likely to be jazz than twelve-tone atonality; the musicians will have to follow a given chord progression and go into cycles around it; the piece is usually played in a moody and relaxed atmosphere, and so on” (p. 545)<sup>69</sup>.

There are no studies that have compared performance in normal feedback and altered/blocked feedback conditions in the context of jazz improvisation. Therefore, it is possible that altered auditory feedback may have a different effect on improvised music compared to performance of well-learned music (Goldman, 2013, p. 220), which is possible with blocked auditory feedback too.

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<sup>69</sup> According to Sawyer (2006, p. 157), “improvisation could not take place at all without some shared conventions, because otherwise communication would be impossible.”

## 4.2 Constraints in idea generation

A constraint refers to “a rule or condition that imposes limits on what is possible” due to limitations of human ability, laws of nature, or limits on what actions are acceptable or appreciated in each culture (Leman, 2008, p. 55). In addition, constraints impose limits on what actions are appropriate in a particular context. For instance, expert musicians must learn to circumvent challenges arising from the speed/accuracy trade-off, which refers to increased number of errors with decreased response time (for a review on the literature related to the speed-accuracy trade-off, see Heitz, 2014). Such a trade-off may occur when musicians “perform at the limits of their abilities” which suggests that expert musicians “are subject to the same constraints” as everyone else (Pfordresher et al., 2007, p. 85). Any musical instrument can also afford only certain possibilities (Goldman, 2013, p. 212). As a result, the development of musical instruments has played a significant role in the increase of virtuosity in Western music (Lehmann, 2012).

In addition to constraints related to response time, cultural constraints have various effects on musicians’ social status, their opportunities for employment, appreciation of musical styles, and “the status given to creative or novel musical behavior” (Pressing, 1998, p. 57). Constraints also play an important role in musical style. According to Meyer (1989), “style is a replication of patterning, whether in human behavior or in the artifacts produced by human behavior, that results from a series of choices made within some set of constraints” (p. 3). This definition resembles that of LaRue’s, who defined musical style as repetition of similar choices in different compositions (LaRue, 1992, p. ix). In line with Meyer and LaRue, Miller (2020, para. 1.13) argued that musical style is “a system of constraints within which choices are made that actually produce music.” Musical style and music-theoretical guidelines do not place strict limits on note choices. Guidelines of music theory can always be bypassed and note choices that have never been tried before can emerge in performance.

Constraints do not only impose limits on what actions are possible or appropriate in a particular context, but they may also facilitate creativity and decrease cognitive demands of performing a task. For example, Torrents et al. (2020) argued that constraints may lead to the discovery of novel action possibilities. New constraints may also release other constraints at different timescales which then allows to perform novel actions (Torrents et al., 2020). Moreover, a pre-defined chord progression may decrease cognitive demands in improvisation, because it provides pre-existing melodic material for the improviser (Laine, 2015, p. 282) and limits the number of available options in a particular context.

### 4.2.1 Constraints on memory

Human memory is limited and fallible. As an example, it is well-known that short-term memory has both capacity limitations (Miller, 1956) and temporal limitations (Peterson & Peterson, 1959). Memories are also vulnerable to changes when they are retrieved (also known as the process of memory reconsolidation)

(Alberini & LeDoux, 2013). However, memory for melodies might not be vulnerable to inference and memory decay as long as the melody was encoded successfully (Herff et al., 2018). This indicates that memory for melodies is long-lasting but depends on whether melodies can be easily encoded. For instance, the recognition accuracy for auditory stimuli is impaired when a stimulus is difficult to reproduce or to label, which indicates that such stimuli are not easily stored in long-term memory (Schulze et al., 2012).

Constraints on memory have a crucial role in music perception, music performance, and musical improvisation. Among various theories and models of working memory,<sup>70</sup> the time-based resource-sharing model of working memory (Barrouillet & Camos, 2012) is particularly interesting in the context of the present study. According to this model, working memory has two functions (temporary storage and processing of information) which share a common limited resource (attention). Attention cannot be occupied on both functions simultaneously and thus either one of these functions can only take place one at a time. As soon as attention is switched from maintenance to processing, memory traces are vulnerable to temporal decay. (Barrouillet & Camos, 2012.) As a result, tasks that require temporary maintenance of intermediary results while performing complex computations (or other complicated cognitive tasks) are difficult, because “calculations take time, and as time goes by, you may lose track of intermediary results because they fade away” (Barrouillet & Camos, 2012, p. 413). Since information processing takes time and information cannot be maintained simultaneously when it is processed, “the cognitive load of a given activity – that is, its effect on the performance of concurrent activities – corresponds to the proportion of time during which this activity occupies attention” (Barrouillet & Camos, 2012, p. 414).

Unfortunately, processing time has received little attention in research that investigates the consequences of cognitive load in different tasks. According to cognitive load theorists, there are three types of cognitive load (i.e., sources of information overload caused by excessive cognitive demands): extraneous, intrinsic, and germane cognitive load<sup>71</sup>. Extraneous cognitive load refers to

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70 The present study does not distinguish between short-term memory and working memory. According to some researchers, working memory differs from short-term memory in that the latter refers to short-term maintenance of information but not manipulation of information in contrast to working memory (Diamond, 2013, p. 143; Jäncke, 2019, pp. 237-238). In addition, short-term memory develops earlier and faster and it is associated with different neural substrates compared to working memory (Diamond, 2013, p. 143). However, there are several definitions of short-term memory and working memory, which makes it difficult to distinguish between these two concepts (Cowan, 2008). In addition, Schulze et al. (2018, p. 461) argued that a distinction between short-term memory and working memory may not be fruitful, because it is often “difficult to know whether a task needs further processing and/or manipulation in addition to the passive storage of information.”

71 According to Sweller (2010), cognitive load theory is an educational theory based on five basic principles: (1) long-term memory plays a central role in human cognition, (2) learning is a constructive process based on schema construction and automation, in which contents acquired through imitation of others and borrowing other people’s thoughts are reorganized, (3) random search processes are required when learned schemata do not exist for a present problem, (4) changes in long-term memory are slow and constrained by limitations of working memory, and (5) there are no limits of

excessive demands on working memory caused by instructional design (Kalyuga, 2010, p. 53). Intrinsic cognitive load refers to excessive demands on working memory imposed by simultaneous processing of several elements (Moreno & Park, 2010, p. 16). The third source of cognitive load, germane cognitive load refers to cognitive activities that contribute to schema acquisition and automation (Kalyuga, 2010, p. 53). Germane cognitive load differs from the other two types of cognitive load because of its positive relationship to learning outcomes (Moreno & Park, 2010, p. 17).

In music research, cognitive load has been usually investigated using a dual-task paradigm. Dual-task studies investigate how secondary tasks that occupy attentional resources affect performance of a primary task. For instance, Schendel and Palmer (2007) found that recognition accuracy for both auditory and visual sequences decreased when participants were asked either to repeatedly sing a syllable (“la”) or repeatedly say a short word (“the”) during the recognition task. Fidlon (2011) investigated how musicians with 2-42 years of experience in jazz performance performed in a dual-task condition, where they were asked to play an improvised solo based on the 12-bar blues both in a familiar and an unfamiliar key and simultaneously count the number of tactilely perceived taps. According to the results, 4 out of the 10 participants were able to perform the counting task successfully during their solos regardless of familiarity with the key. Two participants successfully performed the counting task when they improvised over a familiar key, but not when they improvised over an unfamiliar key. Other participants were not able to successfully perform the counting task either during their familiar key solos or unfamiliar key solos. Four out of the five most experienced participants were able to successfully perform the counting task during their solos regardless of key. The remaining participant performed poorly in the counting task, probably because of not paying attention to it. According to Fidlon (2011, p. 72), these findings indicate that “experienced improvisers can generate music in a way that does not call for the full engagement of their attention and working memory.” In another dual-task study, Çorlu et al. (2015) found that musicians performed a familiar piece of music with less expressivity when they were asked to simultaneously count the number of circles and triangles in a computer screen and ignore the occurrence of squares. The dual-task setting did not, however, affect performance in terms of producing accurate pitches and note durations. Floridou et al. (2017) reported that even a low cognitive load may cause a decline in the occurrence, frequency, and duration of involuntary musical imagery.

In yet another dual-task study, Norgaard et al. (2016) investigated whether musicians use more pre-learned melodic patterns “to help mitigate the cognitive demands of creating novel music in real time” (p. 562). To answer this question, the authors investigated whether artist-level pianists produced more repeated interval patterns and pitch patterns when they were asked to improvise a solo and simultaneously attend to an unrelated counting task (dual-task condition)

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how much effectively organized information from long-term memory can be processed in working memory at one time.

compared to when they were only asked to improvise a solo (single-task condition). In addition, the authors investigated how single-task and dual-task conditions affect the frequency of repeated interval/pitch patterns in situations where pianists played in a familiar key or an unfamiliar key. According to the results, participants played more repeated interval/pitch patterns when they performed in a dual-task condition compared to a single-task condition. Moreover, participants also played more repeated interval/pitch patterns in a familiar key compared to an unfamiliar key, although there was a statistically significant effect for key only with pitch patterns and a single-task condition. Based on the assumption that dual-task performance corresponds to allocation of attention to other musicians' playing in a group performance, Norgaard et al. (2016) concluded that that use of pre-learned melodic patterns may be "an essential mechanism that allows musicians to focus externally away from their own actions during improvised performances" (p. 569).

Note that there is also an alternative explanation for the above-mentioned finding. Norgaard et al. (2016) found that the frequency of repeated melodic patterns was higher when musicians simultaneously performed an unrelated secondary task as they were improvising. The authors interpreted this finding by suggesting that relying on pre-learned melodic patterns may allow musicians to focus on other musicians' playing instead of their own. Alternatively, in accordance with the association between working memory and inhibition of stereotyped actions (Bengtsson et al., 2007), it is also possible to interpret this finding by assuming that the secondary task disrupted the inhibition of repeated melodic patterns, which then caused participants to play more recurring melodic patterns. Also note that high working memory capacity may have more important consequences on the inhibition of repeated melodic patterns that occur farther apart compared to tasks where the improviser is required to maintain a memory of what he or she just played.

Cognitive load may also be increased by diverse distracting factors in the environment. For instance, performance pressure may reduce working memory capacity and decrease the quality of performance outcome depending on the task and one's working memory capacity (Beilock & Carr, 2005; Markman et al., 2006). In addition, increasing tempo and unfamiliarity with the musical work may have an important role in performance deficiencies among novice improvisers, because fast tempos may require too quick decision-making for them and unfamiliarity with the musical work may force them to direct much of their available cognitive resources to trying to remember what the next chord is.

In summary, these studies indicate that excessive demands on working memory may have a negative effect on performance outcome as indicated by redundancy of melodic patterns, loss of musical expressivity, and difficulties in involuntary musical imagery. Note that this finding appears to contradict with that expert jazz musicians rely more on Type 1 processing compared to Type 2 processing (Limb & Braun, 2008; Liu et al., 2012; Adhikari et al., 2016; Lopata et al.,

2017; Rosen et al., 2016, 2017, 2020)<sup>72</sup>. A possible explanation for these seemingly discrepant findings is that excessive demands on working memory may have considerable negative effects among less experienced musicians but not experts. In addition, note that both Type 1 and Type 2 processing are essential in expert-level improvisation (Rosen et al., 2020). As a result, additional cognitive load may affect the balance between Type 1 and Type 2 processing among jazz musicians of any level.

As a common drawback on dual-task studies, they rely on the assumption that better performance on a low rather than high cognitive load implies that the task requires working memory (see De Dreu et al., 2012, p. 658). However, as noted by Dean and Bailes (2016), a decline in performance of a task due to a simultaneous secondary task provides “a quite indirect assessment of attentional demands and [it is] even less directly related to the issue of conscious versus unconscious behaviors” (p. 43). Moreover, Hommel et al. (2016) argued that:

the commonly used comparison between single-task and dual-task performance is methodologically questionable. This comparison confounds a whole number of other variables: As compared to single-task situations, dual-task conditions require participants to keep in mind more instruction-relevant information on working memory, to process a larger number of stimuli and responses, and they are likely to exhibit a different level of motivation and stress. Any difference between single-task and dual-task performance may be affected by these factors, which limits their interpretation in terms of resource-related effects. (Hommel et al., 2016, p. 183.)

#### 4.2.2 Temporal constraints

As a modification of Leman’s (2008) definition of constraint, a temporal constraint is defined as a time-related “rule or condition that imposes limits on what is possible” (Leman, 2008, p. 55). There are at least five ways of how temporal constraints can affect jazz improvisation. First, improvised music is generated at the same time as it is performed, because of which there are limits to the amount of available time to make decisions about what to play in a particular context. Second, decision-making at the level of individual notes (i.e., the note-to-note level) becomes impossible with increasing tempo (Palmer & van de Sande, 1995; Pachet, 2012) and requires a transition from the note-to-note level to planning at higher levels of music (Pachet, 2012). According to Pachet (2012, p. 143), all major decisions in virtuoso jazz improvisations are made at higher-level properties of music instead of individual notes, which “explains how virtuosos improvise melodies satisfying so many difficult and contradictory constraints at high speed. By delegating the choice of individual notes with a beat to a non-conscious, sensory-motor level, they have enough time to focus on high-level decisions, such as influencing pitch contour, chromaticity, tonality, etc.”<sup>73</sup> Third, short-term memory

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72 Type 1 processing refers to rapid, automatic, and unconscious processing, whereas Type 2 processing refers to slow, deliberate, and conscious processing (Evans, 2008, p. 256).

73 According to Norgaard (2011, p. 122), musicians do not focus on individual notes when they improvise. Certainly, it would be highly impractical to make decisions regarding each note separately at fast tempos. However, it is likely that musicians are well capable of making decisions regarding individual notes as long as they are playing to a very slow tempo with a high inter-onset interval between subsequent notes.



has a limited duration, which affects how far musicians can remember what they have played before. Fourth, improvisers are required to maintain temporal continuity, which “reflects a requirement to produce events in a continuous fashion without hesitations or temporal interruptions” (Drake & Palmer, 2000, p. 4). Fifth, increased temporal constraints can increase redundancy in jazz improvisation. In addition to these consequences of temporal constraints in jazz improvisation, there may be others too. For example, variability of nerve conduction velocity may have some effect in jazz improvisation. In this chapter, I will focus on two temporal constraints related to jazz improvisation: reaction times and time pressures caused by fast tempos.

Reaction time reflects the required time to initiate an action in response to a stimulus and it has been widely used to investigate the length of necessary preparation times to execute actions (see e.g., Wong et al., 2017). According to a recent study, the simple reaction time for auditory stimulus (in this case, the required time to press the left mouse key after hearing a signal) was 194 milliseconds on average for musicians and 250 milliseconds on average for non-musicians. The simple reaction time for tactile stimulus was 209 milliseconds on average for musicians and 277 milliseconds on average for non-musicians. The simple reaction time for audio-tactile stimulus (i.e., simultaneous auditory and tactile stimulation) was 167 milliseconds on average for musicians and 222 milliseconds on average for non-musicians. (Landry & Champoux, 2017.) Thus, if expert-level jazz musicians were able to make note-to-note level decisions at the timescale of simple reaction times, the minimum inter-onset interval between subsequent notes would be about 200 milliseconds (e.g., as when playing quarter notes at a tempo of 300 bpm). However, reaction times increase with the number of possible responses (see Hommel et al., 2016, pp. 114-117) because of why simple reaction times underestimate reaction times (and the time needed to plan actions) in jazz improvisation (where there are a number of possible responses at any point of time). At least to my knowledge, there are also no empirical studies that have investigated the length of choice reaction times in jazz improvisation.

Several recent studies have called for reconsideration of the notion of reaction time. For example, Haith et al. (2016) proposed that after the preparation of movement has been completed, there is an involuntary delay before the prepared movement is initiated. The authors suggested that movement initiation is delayed to avoid “initiating a movement before it has been fully prepared” (p. 3013). Such delayed movement initiation allows to make decisions based on more information before the movement is initiated (Haith et al., 2016). Under time pressure, initial decision-making may also precede the possibility to consider all available information. In such cases, information processing continues after the initial decision has been made and can lead to a change of mind during the movement execution. (Resulaj et al., 2009.) In another study, Orban de Xivry et al. (2017) found that reaction times for reaching far targets were shorter compared to movements that required to reach a closer target, which indicates that movement preparation and movement execution phases may overlap. In addition, Wong et al. (2017) found that recent reaction times may influence subsequent reaction times

for other actions, which indicates that other factors in addition to the time to prepare actions may also have an effect.

As noted earlier, temporal constraints may increase the redundancy of melodic patterns in jazz improvisation. Lehmann and Goldhahn (2016) found that non-redundancy (in half bar segments from different takes of John Coltrane's *Giant Steps*) was slightly (1.35 times) more likely after longer pauses (0.5 seconds) compared to segments that did not appear after a rest. In another study, Dean (2014) found that the use of well-learned finger patterns increased in fast passages in a sample of Pat Metheny's improvisations. Consistent with these findings, Frieler (2014) found that pattern use increased at fast tempos. However, pattern use did not increase with tempo in Frieler et al. (2018).<sup>74</sup> In other areas of expertise, the scarcity of available time can increase the quantity of ideas, but this benefit comes at the expense of lower novelty and quality of ideas (for reviews, see Liikkanen et al., 2009; Karau & Kelly, 1992).

### 4.2.3 The role of context familiarity

Goldman (2013) investigated how changes in the mind-body relationship affect cognitive processing in jazz improvisation. Ten pianists improvised over a familiar chord progression (*Rhythm Changes*)<sup>75</sup> in eight conditions: familiar key (Bb major), less familiar key (B major), playing with the right hand only, playing with the left hand only, improvising a melody, and improvising a walking bass line (Goldman, 2013, pp. 214-215). The author hypothesized that improvisers would not have "access to familiar and overlearned motor patterns," when they improvised in a less familiar performance condition, and that they "would have a smaller repertoire of ideas in terms of their ability to use the range of tonal possibilities available to them in the key and in terms of more specific licks and patterns acquired over years of practice" (Goldman, 2013, p. 214). Moreover, musicians were expected to be less capable of knowing how to produce desired sounds in a less familiar condition and, as a result, they would rely more on chord notes and diatonic pitch classes (Goldman, 2013, p. 214).

As expected, the proportion of diatonic pitch classes was higher in the less familiar key (B major). Improvisations were also more predictable in the less familiar key, as measured by entropy and conditional entropy of pitch class distributions. Both entropy and conditional entropy of pitch class distributions were higher in right-hand improvisations compared to left-hand improvisations. Both entropy and conditional entropy of pitch class distributions were also higher in melody improvisations compared to walking bass lines. These results indicate that pianists were able to rely on a larger repertoire of well-learned patterns in a familiar performance condition. In a less familiar context, where they had no

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74 Unfortunately, both Frieler (2014) and Frieler et al. (2018) are unpublished and only the presentation slides of these conference papers were available.

75 *Rhythm Changes* contains no less than fifty chord changes, which makes it a difficult chord progression to be memorized. On the other hand, this chord progression is highly structured which facilitates its learning. (Laine, 2015.)

access to procedural knowledge for more complex patterns, pianists relied more on their harmonic understanding. (Goldman, 2013, pp. 216-218.)

To my knowledge, there are only two other studies that have investigated the role of context familiarity in jazz improvisation. Norgaard et al. (2016) investigated whether artist-level jazz pianists used recurring melodic patterns (either interval or pitch patterns) more often when they simultaneously attended to an unrelated secondary task. According to their results, the frequency of recurring interval/pitch patterns was higher when pianists also attended a secondary task compared to when they could solely focus on improvisation. In addition, the authors found that the frequency of recurring melodic patterns was higher when pianists improvised in a familiar key compared to an unfamiliar key. However, the difference between familiar key and unfamiliar key solos was statistically significant only when pianists did not simultaneously attend to a secondary task and when repetition of melodic patterns was measured based on the similarity of pitch class sequences instead of the similarity of interval sequences. (Norgaard et al., 2016.) In another study, Mendonça and Wallace (2004) used retrospective verbal protocols to investigate cognitive processing in jazz improvisation. Three duos of professional musicians improvised both over a common chord progression (*Rhythm Changes*) and freely without predefined chord progressions. After the improvisation task was completed, musicians were asked to report their thought processes as they occurred during performance. Contrary to their expectations, the authors did not find statistically significant differences in the proportion of verbal protocols related to temporal and creative cognition between the participants in each duo. (Mendonça & Wallace, 2004.)

#### 4.2.4 Duration of integrated units in perception and action

Successive events are automatically integrated into units with a duration of about three seconds (Pöppel, 1997; Wittmann & Pöppel, 1999), or about 2-3 seconds (Fraisse, 1984; Szeląg et al., 1996), which corresponds to the limits of working memory: “if rehearsal is not possible, the content in working memory is available for ~3 s only” (Pöppel, 1997, p. 59)<sup>76</sup>. Higher estimates on the maximum duration of integrated units have also been reported. According to Fraisse (1984, pp. 10, 30), successive events can hardly exceed five seconds in order to be organized as a unit<sup>77</sup>. However, the duration of integrated units can vary as the number of events within a given time period changes<sup>78</sup>. As the number of events per second increases, the duration of integrated units can decrease to about one second. (Szeląg et al., 1996.)<sup>79</sup>

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76 Associated with the feeling of *nowness*, this timescale is also known as the psychological present (e.g., Wittmann & Pöppel, 1999; Fraisse, 1982, 1984) or the subjective present (e.g., Pöppel, 1997).

77 Similarly, Fraisse (1982) argued that the timescale of 4-5 seconds is “an extreme limit that allows only unstable groupings” (p. 158).

78 The duration of integrated units can also vary depending on age and cognitive abilities (Szeląg et al., 1996).

79 Some authors have also argued for wider temporal limits for integrated units. According to Snyder (2000, p. 13), the duration of integrated units is in the range of 3-5

The average duration of ordinary actions may also have a role in preference for actions of certain length, which may be based on biomechanical constraints of actions (e.g., need to change posture or take a rest) (Godøy et al., 2010). For instance, composers must consider how distant events listeners can still perceive as parts of a single musical unit (Wittmann & Pöppel, 1999, p. 20). In regard to jazz improvisation, Frieler et al. (2016) investigated a sample of 140 jazz solos and found that the average duration of midlevel units<sup>80</sup> was 2.25 seconds, which (based on its similarity with the range of the psychological present) they “viewed as indirect evidence that the underlying concept of action plans is viable and might capture some ‘true’ elements of the underlying psychological processes” (Frieler et al., 2016, p. 159). In another study, Lehmann and Goldhahn (2016) found that the average length of playing bursts was 2.42 seconds in *Giant Steps (take 1)* and 3.0 seconds in the master take of the same composition. A playing burst refers to a distinct musical idea, which is separated from adjacent playing bursts based on “long-held notes, silent gaps or brief interjections” (Lehmann & Goldhahn, 2016, p. 348). According to these authors, planning the next playing burst takes place in resting places (placed in between adjacent playing bursts), where musicians have time to think and take a breath (Lehmann & Goldhahn, 2016, p. 348).

Some important implications can be drawn from these findings. Based on earlier research, action control seems to operate at a timescale of about 2-3 seconds on average, which means that the duration of playing bursts (or midlevel units) is usually about 2-3 seconds. The upper limit of playing bursts/midlevel units is about 3 seconds and the lower limit of playing bursts/midlevel units is about 1 second. Previous research also indicates that the range of planning may increase with tempo if measured by the number of events in a given time period but not necessarily if measured by the duration of integrated units in a given time period.

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seconds on average. According to Godøy (2014), “what we perceive as coherent chunks with highly significant features [is] in the very approximately 0.5 to 5 seconds range” (p. 225).

80 Midlevel units refer to non-overlapping events that represent “distinct playing ideas [and action plans] on a middle level between the level of single events (tones) and structural levels such as the underlying chord progression, single choruses or even the typical head-solo-head structure of a jazz tune” (Frieler et al., 2016, p. 145).

## 5 RESEARCH QUESTIONS AND METHODS

### 5.1 Research questions

The first main aim of this exploratory research was to investigate the relationship between temporal constraints (as operationalized by tempo and harmonic rhythm) and creativity in pattern use (as operationalized by the variability of melodic patterns) in bass line reductions of two eminent jazz bassists. As the second main aim, the research investigated whether learning a large storage of melodic patterns is a necessary requirement for creativity in the generation of jazz bass lines. In addition, the research also aimed to investigate the relationship between temporal constraints and musical creativity at the level of target notes, melodic contour patterns, approach-note patterns, and melodic complexity, and the relationship between tempo/harmonic rhythm and the length of recurring melodic patterns. Finally, several methodological issues were considered. To achieve these goals, the following research questions were answered:

- What is the relationship between tempo and the variability of melodic patterns?
- What is the relationship between harmonic rhythm and the variability of melodic patterns?
- What is the relationship between tempo and the variability of target notes?
- What is the relationship between harmonic rhythm and the variability of target notes?
- What is the relationship between tempo and the variability of melodic contour patterns?
- What is the relationship between harmonic rhythm and the variability of melodic contour patterns?

- What is the relationship between tempo and the variability of approach-note patterns?
- What is the relationship between harmonic rhythm and the variability of approach-note patterns?
- To what extent the same melodic pattern classes are repeated across different bass line reductions?
- What is the relationship between tempo and the melodic complexity of bass line reductions?
- What is the relationship between harmonic rhythm and the melodic complexity of bass line reductions?
- What is the average and the maximum length of recurring melodic patterns?
- What is the relationship between tempo and the average/maximum length of recurring melodic patterns?
- What is the relationship between harmonic rhythm and the average/maximum length of recurring melodic patterns?
- What is the average and the maximum length of recurring melodic patterns and melodic contour patterns?
- What is the relationship between tempo and the average/maximum length of recurring melodic contour patterns?
- What is the relationship between harmonic rhythm and the average/maximum length of recurring melodic contour patterns?
- How does disregarding the harmonic context influence the results?
- How does increasing the threshold level of repeated melodic patterns influence the results?
- How does disregarding the head sections influence the results?
- How does disregarding the identification of segment boundaries influence the results?

Creativity was defined as novel (i.e., unpredictable, different) and appropriate products or ideas and the ability to create such products or ideas (where the novelty of a product or an idea only requires that it is new to the creator). Despite the generality of this definition, the study focused on a single type of creativity: variability of actions, where the complete lack of repetition (i.e., where all actions occur only once) or the highest level of unpredictability (i.e., where the probability of all actions is equal) is regarded as the highest level of creativity. All measurements were also solely focused on novelty, unpredictability, and difference (measured as the variability of melodic patterns, target notes, melodic contour patterns, or approach-note patterns), whereas appropriateness was not measured. Instead, all musical works or any part of them were considered appropriate a priori. There were several reasons not to measure appropriateness. First, both Paul Chambers and Ron Carter are among the most renowned jazz bassists in the history of jazz. Among several others, they defined through their music what actions are appropriate in jazz bass playing. Second, it is unclear how appropriateness should be measured in the context of jazz improvisation (except for

considering obvious mistakes or playing unintentionally out of tune as inappropriate actions), where appropriateness of note choices partly depends on the decisions of co-performers. If other musicians did not adapt their own playing to surprising notes, such note choices would sound inappropriate and wrong. Finally, the importance of adding appropriateness to definitions of musical or artistic creativity is in my view merely to acknowledge that all actions are constrained and that completely random actions do not represent the highest level of creative achievement. Nevertheless, appropriateness may still play an important role in creativity assessment in the fields of musical and artistic creativity depending on the research question.

Note that risk-taking, the ability to surprise, and avoidance of redundancy are acknowledged as valid criteria for expert-level improvisation (Wopereis et al., 2013)<sup>81</sup>. In fact, the concept of improvisation disapproves the mere reproduction of existing performances and requires that “each improvisation must appear more or less different from the preceding one” (Sparti, 2016, p. 190). Therefore, definitions of creativity that focus on the novelty, uniqueness, or unpredictability of products and the ability to create such products are consistent with common artistic goals of expert-level jazz musicians. Of course, jazz musicians have other goals as well besides trying to avoid excessive repetition and predictability. For example, creativity in jazz improvisation may also occur as finding a personal sound or inventing original approaches to improvisation (cf. Boden’s notion of transformational creativity; see Boden, 2004, pp. 5-6). In addition, there are several factors that contribute to aesthetic evaluation of improvisation music – including emotional complexity (Huovinen & Keipi, 2022), melodic complexity, and technical excellence (Eisenberg & Thompson, 2003).

## 5.2 Research material

### 5.2.1 Selection of research material

The research was conducted by analyzing reductions of selected bass lines by Paul Chambers (1935-1969) and Ron Carter (b. 1937). Both are some of the most significant musicians in the history of jazz. Paul Chambers started as a baritone horn and tuba player but turned to double bass in 1949 and soon started to collaborate with local musicians in Detroit’s vibrant jazz scene (Feather & Gitler,

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81 According to Wopereis et al. (2013), the statement “who doesn’t like repetition, improvisation done” was considered as an important or at least quite important quality of a good improviser (mean rating: 2.50/5.00). However, two quite similar statements “who dares taking risks and who is adventurous, but not reckless” and “a good improviser should surprise” scored considerably higher ratings (mean ratings: 3.50/5.00 and 3.79/5.00, respectively) among the group of expert musicians, music teachers, and music critics who took part in this study. (Wopereis et al., 2013, pp. 228, 231.) It is also noteworthy that the aim to find surprising note choices is often noted as one of the main goals in Ron Carter’s bass lines (e.g., Ouellette, 2013). Regrettably, there are no interviews of Paul Chambers concerning his thoughts about bass playing or improvising in general, at least to my knowledge.

1999, p. 120). In the mid-fifties, Paul Chambers rose to international fame as the bassist in Miles Davis's new quintet. During his short but productive career, Paul Chambers played on more than 300 albums (R. Palmer, 2012, p. 3), including a number of critically acclaimed albums such as Miles Davis's *Kind of Blue* (1959), John Coltrane's *Giant Steps* (1959), Sonny Rollins's *Tenor Madness* (1956), and Oliver Nelson's *The Blues and the Abstract Truth* (1961), among many others. Ron Carter's career is no less prolific, and he holds the Guinness World Record for being the most recorded bass player in jazz history with 2,221 recording credits up to 2015<sup>82</sup>. Ron Carter started as a cellist at the age of ten (Feather & Gitler, 1999, p. 115), but he switched to double bass at the age of eighteen (Ouellette, 2013, p. 46). Ron Carter is especially known for his work as the bassist in Miles Davis's quintet from 1963 to 1968. In addition, he has played on many highly influential jazz albums including Wayne Shorter's *Speak No Evil* (1965), Herbie Hancock's *Maiden Voyage* (1965), McCoy Tyner's *The Real McCoy* (1967), and Freddie Hubbard's *Red Clay* (1970), to name a few.

There are certain similarities between Paul Chambers and Ron Carter in their musical style. According to Nurmi (2006, 2018), both musicians generated their walking bass lines in the 1950s and 1960s according to target note technique. This technique refers to a strategy of building improvised jazz melodies, where one of the tones of the upcoming chord is chosen as a target note and the chosen target note is approached with a suitable melodic pattern. Target notes (defined here as the first note of each bar) are emphasized using stable notes. For instance, Ron Carter often played roots, fifths, and thirds as target notes depending on harmonic rhythm in his bass lines from the 1960's (Nurmi, 2018, p. 32). If the chord changed every two bars (one chord per two bars harmonic rhythm), Carter usually played either the root or the fifth as a target note. If the chord changed in each bar, Carter usually played either the root, the fifth, or the third. If there were two chords per one bar, his usual choice of a target note was the root. (Nurmi, 2018, p. 32.)

On the other hand, Ron Carter's walking bass lines during the 1960's were sometimes highly adventurous. For example, upper structure chord notes were extensively used in some of Ron Carter's bass lines during the 1960's. The use of upper structure chord notes gives a wider range of note choices compared to using mainly roots, thirds, and fifths. In addition, Carter often avoided playing the root and other notes that clearly outline the E7alt chord in his walking bass line on *E.S.P.*, but then again, he might play roots, fifths, and thirds in the next bar (Nurmi, 2018, p. 32). Carter also used different kinds of chord substitutions extensively during this period. For instance, there are many examples of chord substitutions in his walking bass line on *Seven Steps to Heaven*. His adventurous playing is also evident in some of the Miles Davis Quintet's so-called time no changes recordings. As an example, Carter's note choices for each of the three solos on *Pinocchio* were only loosely related to the original chord progression and sometimes the original chord progression was abandoned altogether. However, Carter seems to have been constantly aware of the original form as evidenced by the fact

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82 See <https://www.guinnessworldrecords.com>.



that he occasionally played notes that outlined the original chord progression. (Nurmi, 2018.)

The research material consisted of 42 full-length bass line transcriptions (including 30 bass lines by Paul Chambers and 12 bass lines by Ron Carter) (see Table 1), which were reduced to sequences of quarter notes. I transcribed 17 out of the 42 bass lines analyzed in this study, whereas the other transcriptions were collected from various sources. The research material was selected with the aim of getting as much data as possible from each musical work. However, several relatively short transcriptions were also accepted (the total number of analyzed bars was less than 150 in ten transcriptions). In addition, some of the research data was disregarded because of methodological reasons. The overall quantity of research material was 9,335 bars of transcriptions. Bars that were disregarded in the analysis were not counted. The average length of transcriptions was 222 bars (range: 95 to 465 bars) and the average duration of transcriptions was 280 seconds (4 min 40 s) (range: 96 to 638 seconds). The median length of transcriptions was 219 bars. The median duration of transcriptions was 251 seconds (4 min 11 s).

There are at least 76 published transcriptions of Paul Chambers's solos<sup>83</sup> and at least 48 published transcriptions of Ron Carter's solos<sup>84</sup>. In addition, there are at least 24 published transcriptions of Paul Chambers's bass lines and 55 published transcriptions of Ron Carter's bass lines. However, most of these bass line transcriptions are incomplete and cover only a small part of the complete bass line. Solo transcriptions are written from the beginning to the end, but they have the disadvantage of much shorter duration compared to walking bass lines (because of why they provide less data for research purposes compared to walking bass lines). For instance, despite the large number of transcribed solos in the Weimar Jazz Database (including 456 solos in total), most of them are quite short "with a median of two choruses and a median duration of 87 s (1 min 27 s)" (Pfleiderer, 2017, p. 30).<sup>85</sup>

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83 These transcriptions of Paul Chambers's solos are published in four books by Jim Stinnett: *The Music of Paul Chambers* (1990), *The Music of Paul Chambers Vol. 2 Arcology* (1999), *The Music of Paul Chambers Vol. 3* (2005), and *Secret Chambers* (2009).

84 These transcriptions of Ron Carter's solos are published in two books: *Ron Carter Solos – Transcribed From 22 Classic Standards* (2010) and *Ron Carter Solos, Volume 2* (2010).

85 In terms of the number of transcribed solos, to my knowledge the largest database of jazz transcriptions is the DTL1000 database with 1,736 solos. For more information on this database, see <http://dig-that-lick.eecs.qmul.ac.uk/>.

TABLE 1 List of transcriptions

Musical work (Paul Chambers)	Album (recording year / release year if different from recording year)	Transcriber
A Foggy Day	Red Garland Trio: A Garland of Red (1956/1957)	P. Bierma
All of You	Miles Davis: 'Round About Midnight (1955-1956/1957)	P. Bierma
All the Things You Are	Jimmy Heath Quintet: On the Trail (1964)	J. W. Skinner
Apothegm	Kenny Clarke: Jazzmen Detroit (1956)	M. Benning
Autumn Leaves	Wynton Kelly: Wynton Kelly! (1961)	J. W. Skinner
Blues by Five	Miles Davis Quintet: Cookin' with the Miles Davis Quintet (1956/1957)	M. Nurmi
Blue Train	John Coltrane: Blue Train (1957/1958)	P. Bierma
Chamber Mates	Paul Chambers Quartet: Bass on Top (1957)	M. Benning
Chasin' the Bird	Paul Chambers Quartet: Bass on Top (1957)	M. Benning
C-Jam Blues	Red Garland Trio: Groovy (1957)	P. Bierma
Cool Struttin'	Sonny Clark: Cool Struttin' (1958)	M. Herridge
Cotton Tail	Kenny Clarke: Jazzmen Detroit (1956)	M. Benning
Crazy Rhythm	Red Garland Trio: It's a Blue World (1958/1970)	M. Benning
Excerpt	Warne Marsh: Warne Marsh (1957-1958/1958)	D. Fink
Freddie Freeloader	Miles Davis: Kind of Blue (1959)	M. Nurmi
Giant Steps	John Coltrane: Giant Steps (1959/1960)	M. Nurmi
I Can't Give You Anything but Love	Red Garland Trio: Red Garland's Piano (1957)	D. Fink
I Could Write a Book	Miles Davis Quintet: Relaxin' with the Miles Davis Quintet (1956/1958)	M. Nurmi
If I Were a Bell	Miles Davis Quintet: Relaxin' with the Miles Davis Quintet (1956/1958)	M. Nurmi
It's a Blue World	Red Garland Trio: It's a Blue World (1958/1970)	M. Benning
Milestones	Miles Davis: Milestones (1958)	M. Nurmi
Moment's Notice	John Coltrane: Blue Train (1957/1958)	P. Nabuurs
Mr. P.C.	John Coltrane: Giant Steps (1959/1960)	E. Gregor
Oleo	Miles Davis Quintet: Relaxin' with the Miles Davis Quintet (1956/1958)	J. W. Skinner
So What	Miles Davis: Kind of Blue (1959)	M. Nurmi
Syedda's Song Flute	John Coltrane: Giant Steps (1959/1960)	Jazz Bass Tr.

Musical work (Paul Chambers)	Album (recording year / release year if different from recording year)	Transcriber
Tenor Madness	Sonny Rollins Quartet: Tenor Madness (1956)	P. Bierma
The Theme	Paul Chambers Quartet: Bass on Top (1957)	M. Benning
Woody'n You	Miles Davis Quintet: Relaxin' with the Miles Davis Quintet (1956/1958)	Jazz Bass Tr.
You'd Be So Nice to Come Home to	Paul Chambers Quartet: Bass on Top (1957)	M. Benning
Musical work (Ron Carter)	Album (recording year / release year if different from recording year)	Transcriber
Autumn Leaves	Bobby Timmons Trio: The Bobby Timmons Trio in Person (1961)	J. W. Skinner
Autumn Leaves	Miles Davis: Miles in Berlin (1964/1965)	T. Kolarczyk
Dolphin Dance	Herbie Hancock: Maiden Voyage (1965)	M. Nurmi
E.S.P.	Miles Davis: E.S.P. (1965)	M. Nurmi
Israel	Kai Winding & J. J. Johnson: Israel (1968)	D. Fink
Loose Bloose	Bill Evans: Loose Blues (1962/1982)	M. Nurmi
Mo' Joe	Joe Henderson: The Kicker (1967/1968)	M. Nurmi
Oleo	Charles Bell & the Contemporary Jazz Quartet: Another Dimension (1963)	J. W. Skinner
Passion Dance	McCoy Tyner: The Real McCoy (1967)	M. Nurmi
Pinocchio	Miles Davis: Nefertiti (1967/1968)	M. Nurmi
Seven Steps to Heaven	Miles Davis: Seven Steps to Heaven (1963)	M. Nurmi
Witch Hunt	Wayne Shorter: Speak No Evil (1964/1965)	M. Nurmi

*Note.* Patrick Nabuurs's (2017) transcription of Paul Chambers's bass line on *Moment's Notice* included the bass line from the beginning to the end of the first solo. This transcription was used as the basis for my full-length transcription of this bass line. Five of my own transcriptions (Paul Chambers's *Blues by Five*, *Freddie Freeloader*, *I Could Write a Book*, *If I Were a Bell*, and *So What*) were originally written for my master's thesis (Nurmi, 2006). In addition, six of my own transcriptions (*Dolphin Dance*, *E.S.P.*, *Passion Dance*, *Pinocchio*, *Seven Steps to Heaven*, and *Witch Hunt*) were published as a part of an earlier work (Nurmi, 2018). Jazz Bass Tr. = Jazz Bass Transcriptions portal (<https://www.jazzbasstranscriptions.com/>).

The present research was focused on walking bass lines (which usually include four quarter notes in each bar). As a result, bass solos and parts of bass lines based on a repeated riff or pre-composed material (e.g., head sections in *Passion Dance*, *So What*, and *Seven Steps to Heaven*) were excluded. Sections in which the bassist played nothing (e.g., solos played without bass accompaniment) were excluded of course. In addition, all melodic patterns where one or more notes were inaudible (or contained a rest) were excluded. Pre-composed intros (e.g., the first five bars in *Witch Hunt*) and outros (e.g., the last four bars in *Giant Steps*) were excluded. Also, two-beat bass lines and other bass lines primarily based on half notes were excluded (e.g., the bass line for the head section in *E.S.P.*). Except for head sections, there were very few occurrences of half notes in any bass line.

Since some performances included walking bass lines in head sections (i.e., the theme) and others did not, all bass parts played during the head section could have been ignored for the sake of clarity. To know how head sections affect the results, I calculated the repetition of melodic patterns both when head sections were disregarded and when they were considered. The aim was to make sure that the decision to take head sections into account (whenever they included walking bass lines) had no relevant effect on the relationship between tempo and/or harmonic rhythm and the repetition of melodic patterns.

The research material was collected by selecting at least three walking bass lines from each of the four tempo categories: category 1 (100-150 beats per minute), category 2 (151-200 beats per minute), category 3 (201-250 beats per minute), and category 4 (251-300 beats per minute). An equal number of walking bass lines from each tempo category was preferred, but it turned out to be difficult to accomplish. To measure tempo, I used two online metronome tools (Szpak, n.d.; Reel, 2019), both of which allow to tap beats manually while simultaneously listening to an audio recording. Tempo in each bass line was measured three times. First, I measured tempo at the end of the first solo with both Szpak's (using the average of the last twenty beats) and Reel's metronome tools. After that, I measured tempo two more times from different parts of the bass line by using Reel's metronome tool. Based on these four measurements, the average tempo in each bass line was calculated to avoid measurement errors and to ignore tempo changes during any performance.

The research setting did not allow to collect a similar amount of research material from each harmonic rhythm category. To get an equal amount of research material from each harmonic rhythm category, the research material should consist of identical chord progressions and an identical overall length of bass lines. In practice, it is highly difficult to find performances with both the same harmonic structure and an identical overall length. Also, it can be very difficult to find such works at different tempos. As a result, at least three walking bass lines were selected from each of the three harmonic rhythm categories: medium fast harmonic rhythm (harmonic rhythm category I, where the most usual distance between chord changes is one bar), slow harmonic rhythm (harmonic rhythm category II, where the most usual distance between chord changes is at least two bars), and fast harmonic rhythm (harmonic rhythm category III, where

the most usual distance between chord changes is two beats). In one bass line (*Witch Hunt*), the distance between chord changes was occasionally six beats (E7 Eb7 / Eb7). In this bass line, Ron Carter often clearly outlined the latter chord using six-note phrases. These parts of *Witch Hunt* were considered to imply a special harmonic rhythm category distinct from the three harmonic rhythm categories mentioned above.

Table 2 shows the average tempo of bass lines, the average distance between chord changes, the proportion of bars in each harmonic rhythm category per chorus, the title of the work, and the name of the bassist playing in that recording (for raw data used to calculate the average tempo in each bass line, see Table 18 in Appendix 1). For example, 17% of the bars in *Freddie Freeloader* were based on the first category of harmonic rhythm (where the distance between chord changes is one bar), whereas 83% of the bars were based on the second category of harmonic rhythm (where the distance between chord changes is at least two bars). There were no occurrences of the third harmonic rhythm category (where the distance between chord changes is two beats) in this bass line.<sup>86</sup> Note that whenever two subsequent chords differed only slightly (e.g., in case of a sequence of a D7 chord and a D9 chord), and they shared the same root note and the same triad structure, these chords were considered to be identical. Pedal point sections were also considered to be based on a single chord. The average distance between chord changes ( $k$ ) was calculated according to the formula below, where 'a' is the total chorus length in bars, and 'b' is the total number of chord changes. For example, the chorus length was twelve bars and there were five chord changes in *Freddie Freeloader*. Therefore, the average distance between chord changes was two bars.

$$k = \frac{a}{b + 1}$$

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86 All harmonic rhythm category II sections (where the distance between chord changes is at least two bars) were disregarded in *Syeeda's Song Flute*.

TABLE 2 Tempo and harmonic rhythm in each bass line

Musical work (Paul Chambers)	Tempo (bpm)	Dist. (in bars)	Proportion of bars
Cool Struttin'	110	1.00	I (50%), II (33%), III (17%)
Freddie Freeloader	128	2.00	I (17%), II (83%), III (0%)
Autumn Leaves	132	1.03	I (56%), II (31%), III (13%)
Blue Train	133	1.71	I (33%), II (67%), III (0%)
So What	139	10.67	I (0%), II (100%), III (0%)
All of You	166	0.84	I (56%), II (13%), III (31%)
C-Jam Blues	166	2.00	I (17%), II (83%), III (0%)
You'd Be So Nice to Come Home to	167	0.97	I (50%), II (31%), III (19%)
Apothegm	171	0.84	I (44%), II (25%), III (31%)
Tenor Madness	175	1.00	I (50%), II (33%), III (17%)
Blues by Five	177	1.00	I (75%), II (17%), III (8%)
Chasin' the Bird	179	0.84	I (62.5%), II (12.5%), III (25%)
I Can't Give You Anything but Love	185	1.00	I (47%), II (34%), III (19%)
If I Were a Bell	187	0.82	I (59%), II (13%), III (28%)
Syedda's Song Flute	189	0.94	I (94%), II (0%), III (6%)
It's a Blue World	191	1.23	I (50%), II (44%), III (6%)
The Theme	211	0.64	I (6%), II (25%), III (69%)
A Foggy Day	215	1.06	I (88%), II (12%), III (0%)
Excerpt	221	1.37	I (50%), II (46%), III (4%)
I Could Write a Book	229	0.70	I (50%), II (0%), III (50%)
All the Things You Are	232	1.00	I (72%), II (17%), III (11%)
Milestones	237	4.00	I (0%), II (100%), III (0%)
Moment's Notice	244	0.61	I (37%), II (0%), III (63%)
Cotton Tail	253	0.73	I (25%), II (25%), III (50%)
Woody'n You	257	0.91	I (62%), II (19%), III (19%)
Mr. P.C.	260	1.71	I (33%), II (67%), III (0%)

Musical work (Paul Chambers)	Tempo (bpm)	Dist. (in bars)	Proportion of bars
Oleo	267	0.63	I (3%), II (25%), III (72%)
Chamber Mates	267	1.09	I (83%), II (17%), III (0%)
Crazy Rhythm	283	1.07	I (38%), II (43%), III (19%)
Giant Steps	293	0.62	I (37.5%), II (0%), III (62.5)
Musical work (Ron Carter)	Tempo (bpm)	Dist. (in bars)	Proportion of bars
Loose Bloose	115	0.50	I (0%), II (0%), III (100%)
Dolphin Dance	122	1.31	I (35%), II (53%), III (12%)
Autumn Leaves (1964)	133	1.07	I (69%), II (25%), III (6%)
Autumn Leaves (1961)	136	1.10	I (63%), II (31%), III (6%)
Witch Hunt	139	2.67	I (17%), II (79%), III (4%)
Israel	148	1.50	I (25%), II (67%), III (8%)
Pinocchio	212	1.38	I (33%), II (56%), III (11%)
Passion Dance	240	12.00 <sup>a</sup>	I (0%), II (100%), III (0%)
Oleo	244	0.68	I (16%), II (25%), III (59%)
Seven Steps to Heaven	286	0.78	I (69%), II (0%), III (31%)
E.S.P.	289	1.19	I (41%), II (50%), III (9%)
Mo' Joe	298	0.94	I (44%), II (25%), III (31%)

*Note.* Dist. = average distance between chord changes; Proportion of bars = proportion of bars in each harmonic rhythm category.

<sup>a</sup> one chord only (no chord changes).

### 5.2.2 Reliability of research material

All bass lines were typically transcribed or checked two bars at a time at different tempos by using the *Transcribe!* software (Seventh String Software). The accuracy of all transcriptions was verified at least twice both by listening to the recordings and by playing the bass lines simultaneously when listening to the recordings. Many of the already existing transcriptions were very good, although based on my own analysis, they also involved some errors that I subsequently corrected. Considering only the transcribed notes that were included in the analysis, the observed error rate in these previously existing transcriptions was 6%<sup>87</sup>. In addition, I made some minor modifications to chord progressions on some occasions and used the same chord progression for each chorus in all transcriptions. I also used as long transcriptions as possible to increase the reliability of the transcriptions. Because of using relatively long bass lines, I presumed that the proportion of incorrect notes was small and practically had no effect on the results of the study.

In addition to imperfect pitch discrimination skills and musicians' occasional problems with intonation, one reason why completely accurate transcriptions are so difficult to make is that Western music notation offers only a small amount of pitch categories for a large variety of sounds. In musicological research, intervals smaller than a semitone are ignored, when researchers rely on twelve categories in one octave. Categorical perception simplifies the world and the use of relatively few categories to describe music naturally leaves out many details that could be important both regarding musicians' intentions and listeners' experience of the music. On the other hand, deficiencies caused by categorical perception may not always be a bad thing. On the contrary, it would be difficult to perceive similarity in melodic patterns if every minor change in pitch was considered.

The accuracy and the quality of the research material can be increased either by removing all ambiguities (which means that all notes where the membership to a particular pitch category is not clear are removed), or by using a sufficiently large amount of research data so that possible errors could not have a significant effect on the results. In my view, removing all ambiguous parts may not necessarily increase the quality of the research material, because melodic patterns with ambiguous notes are likely to be melodic patterns that occur only rarely in the research material. Therefore, removing those parts could unduly increase the proportion of recurring melodic patterns. Because of this, ambiguous parts were removed only if it was completely impossible to infer what notes were played.

I searched for published sheet music to find accurate chord progressions for the musical works analyzed in this study. Their accuracy was assessed by the relationship between individual notes in the transcribed bass lines and the chords

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87 In my view, it is often difficult and sometimes (in case of poor sound quality) even impossible to produce completely accurate transcriptions of recorded music. Such an accuracy of transcriptions could only be achieved with the use of MIDI instruments.



proposed by the lead sheet. If the bass lines clearly outlined the chords in the published lead sheet in most cases (though not necessarily always), and especially during the head sections, I presumed that the published lead sheet was an adequately accurate representation of the original lead sheet based on which the musicians played the performance. The following sources were used to search for chord progressions: Hal Leonard's *The Real Book Volume 1* (for *Witch Hunt* and *Passion Dance*), Sher Music's *The New Real Book Volume 2* (for *Seven Steps To Heaven* and *Mo' Joe*), Sher Music's *The New Real Book Volume 3* (for *Dolphin Dance*), Keith Waters's *The Studio Recordings of the Miles Davis Quintet, 1965-68* (for *Pinocchio* and *E.S.P.*), and Pascal Wetzel's *Bill Evans Fake Book* (for *Loose Bloose*). Regarding the other bass lines, I used chord progressions as they were presented in the transcriptions (with occasional minor changes).

There are several problems related to chord analysis in the context of jazz improvisation. In my view, the aim of chord analysis in jazz research is to reveal the harmonic structure of the composition to which the musicians were relying on when they recorded the performance. However, even if the chord progression was extracted simply by emphasizing what the pianist or the guitarist is playing, the result is merely an interpretation of what the original lead sheet might have been, since jazz musicians often do not play pre-defined chords throughout the performance. Another option is to transcribe all notes that were played either simultaneously or within specific time windows to create a general interpretation of what chords are implied. This would be a highly time-consuming job, but still it would not remove the possibility of false interpretations of what the original lead sheet might have been.<sup>88</sup>

There are few photographs taken from recording sessions that could verify the accuracy of lead sheets. Yet even photographs are sometimes inadequate to represent the original lead sheet used in a particular recording session. For example, Wayne Shorter's copyright deposit lead sheets for the Library of Congress differ from recorded versions in terms of form, melody, and harmony, which suggests that these compositions were altered in the studio before they were recorded (Waters, 2011, p. xii). In addition, although some of the published sheet music in books like *The New Real Book* and others have been verified by the composer, it is not always explicit which lead sheets were verified by the composer, and whether these lead sheets are identical to the ones used in original recording sessions. Also, published sheet music may sometimes include errors and therefore they should be used with reasonable doubt. For example, some published lead sheets of Wayne Shorter's compositions have been claimed to contain inaccurate chords and even inaccurate melodies (including *Orbits*, *Pee Wee*, *Prince of Darkness*, and *Pinocchio*) (Waters, 2011, p. 8).

It is important to note that jazz musicians often make changes to predetermined chord progressions during performance in order to follow their musical goals or to respond to what other musicians are playing. However, it is necessary

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88 According to Laine (2015, p. 287), chord progressions constructed by music analysts should be viewed as hypothetical proposals if their aim is to reveal the harmonic structure to which a particular musician was relying on when he/she was improvised a particular performance.

that the analysis of recurring melodic patterns is based on a fixed chord progression, where the chord progression is identical in each chorus. The use of a fixed chord progression eliminates, at least partly, the problem of incorrect chord representations since even if a particular chord is transcribed incorrectly, the similarity between two or more melodic patterns is still noticed if they occur in the same part of the song form. However, further research is obviously needed to provide shared guidelines on lead sheet representations and harmony-based analysis of jazz improvisation.

### 5.2.3 Basic statistics of the data

A corpus-level analysis of the data was performed with *MeloSpyGUI* (Abeßer et al., 2018) (except for chordal pitch class distributions which were calculated by hand). According to corpus-level pitch class distributions (see Figure 5), G and D were the most frequently used pitch classes in both Paul Chambers's and Ron Carter's bass line reductions. Even if this analysis did not make a difference between the use of open strings and other note choices (which would require a video analysis of the original performances), the use of open strings (especially G and D) can be used to help shifting between different positions of the double bass and to overcome technical difficulties related to playing the instrument. As a result, it is likely that open strings are used often in any double bass performance. In fact, Frieler et al. (2018) found that open strings (especially the open G string) were the most frequently played notes in the analyzed bass lines.

According to chordal pitch class distributions (see Figure 6), root notes and fifths were the most frequently used chordal pitch classes in the bass line reductions of both bassists<sup>89</sup>. Target note distributions also showed that root notes and fifths were used most frequently in both bassists' bass line reductions (see Figure 7). Distributions of intervals between the last note of the bar and the first note of the next bar (see Figure 8) indicated that even though both bassists used ascending minor seconds and descending minor and major seconds most often in these situations, Ron Carter used a larger variety of intervals. The proportion of repeated notes was very small in both bassists' bass line reductions (see Figures 9 and 10). Corpus-level interval distributions are presented in Chapter 5.3.2: Basic conversion and segmentation of research material and so they are not presented here too. Nevertheless, it is worthwhile to note here that both bassists used small intervals (minor and major seconds) much more often than any other intervals.

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89 I also tested whether roots, thirds, and fifths were used more extensively in Paul Chambers's bass line reductions compared to Ron Carter's bass line reductions. The proportion of roots, thirds (including both minor thirds and major thirds), and fifths (including both diminished fifths and perfect fifths) was 62.6% in Paul Chambers's bass line reductions and 63.7% in Ron Carter's bass line reductions. This finding suggests that neither of these two bass players used significantly more upper structure chord notes or significantly less roots, thirds, and fifths in their bass line reductions compared to the other bass player.

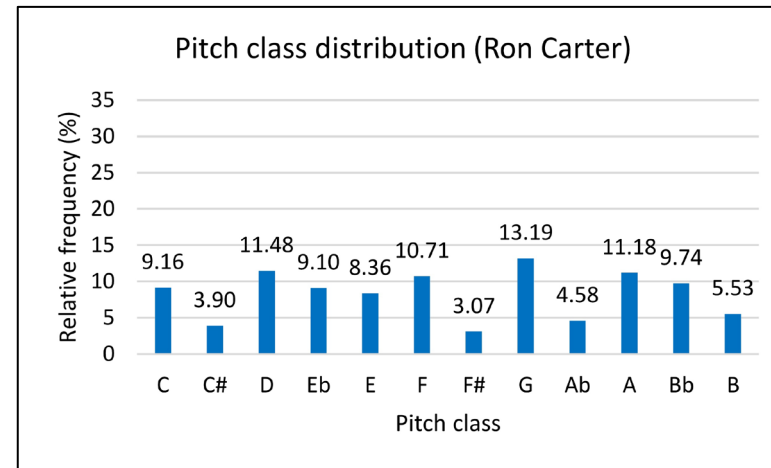
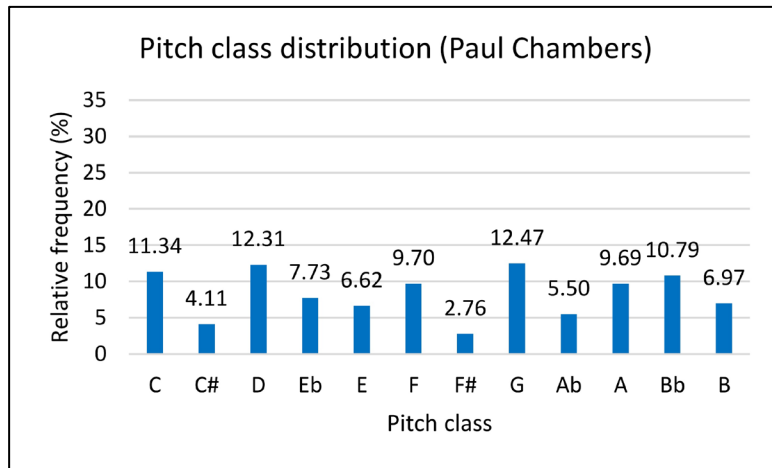


FIGURE 5 Corpus-level pitch class distributions

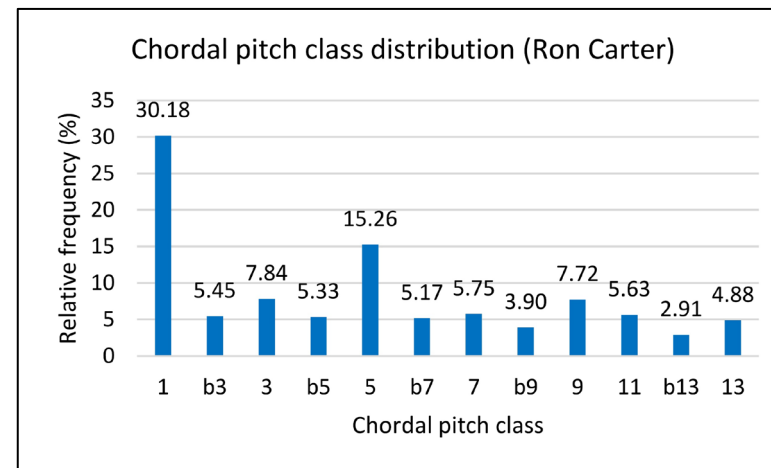
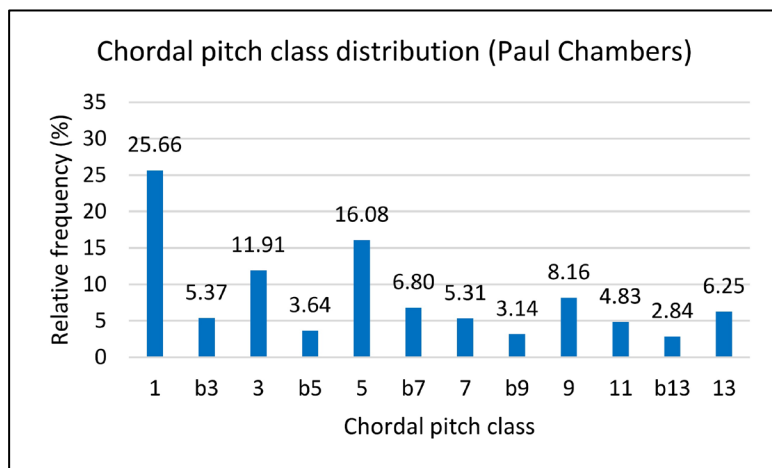


FIGURE 6 Corpus-level chordal pitch class distributions

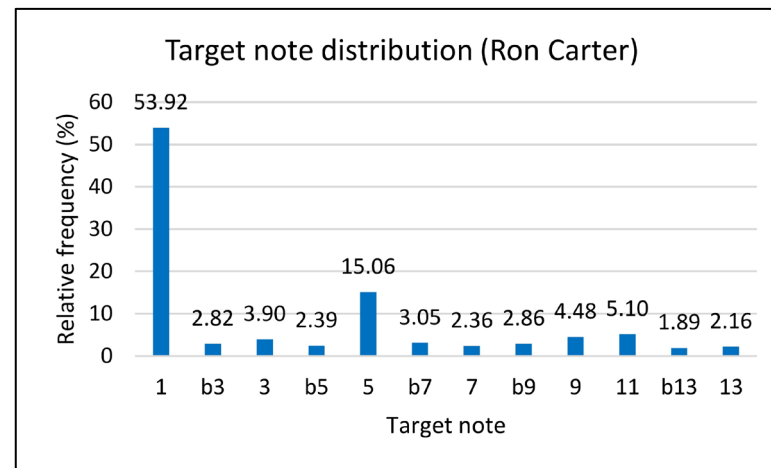
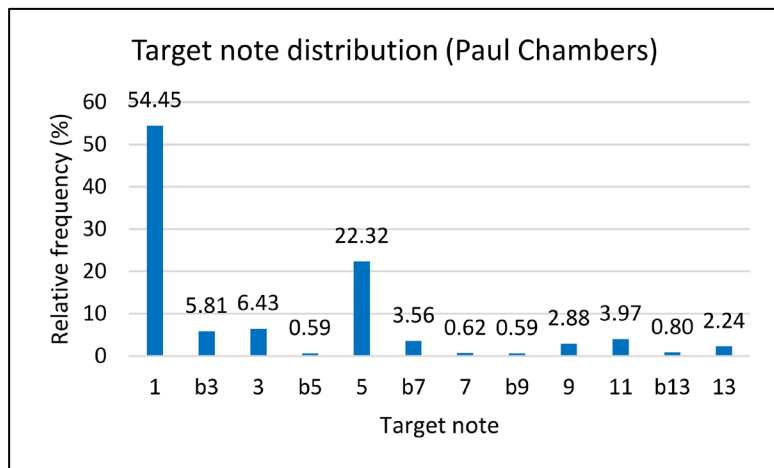


FIGURE 7 Corpus-level target note distributions

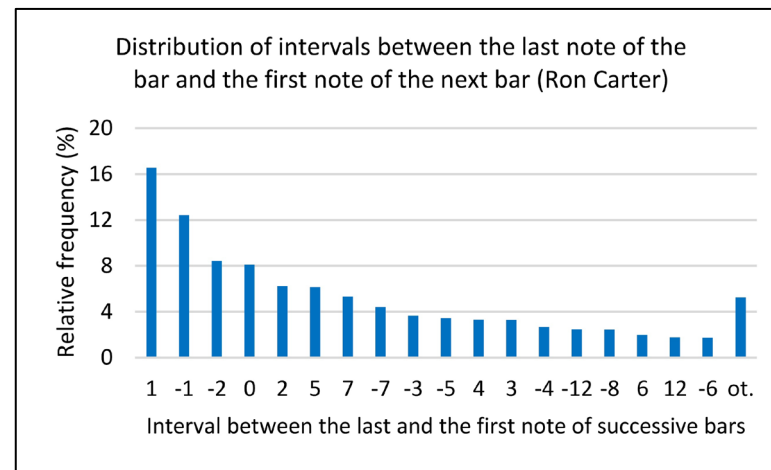
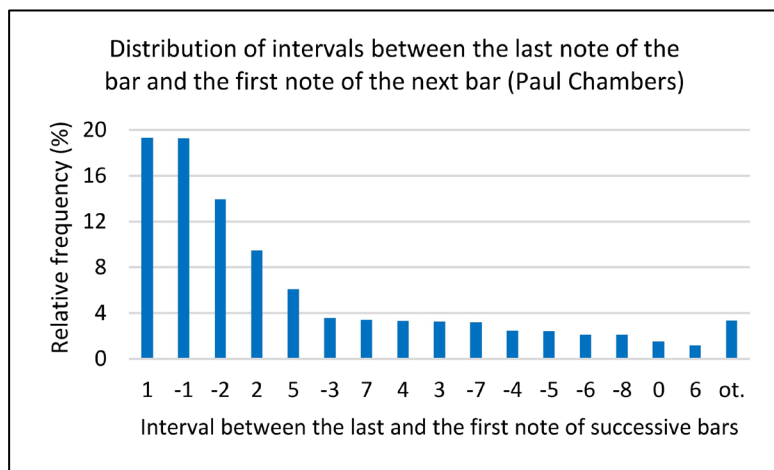


FIGURE 8 Corpus-level distribution of 2-note approach-note patterns (ot. = other intervals)

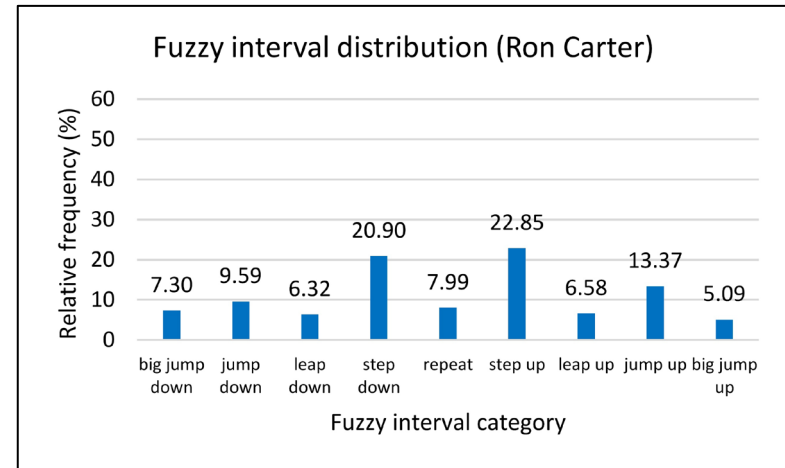
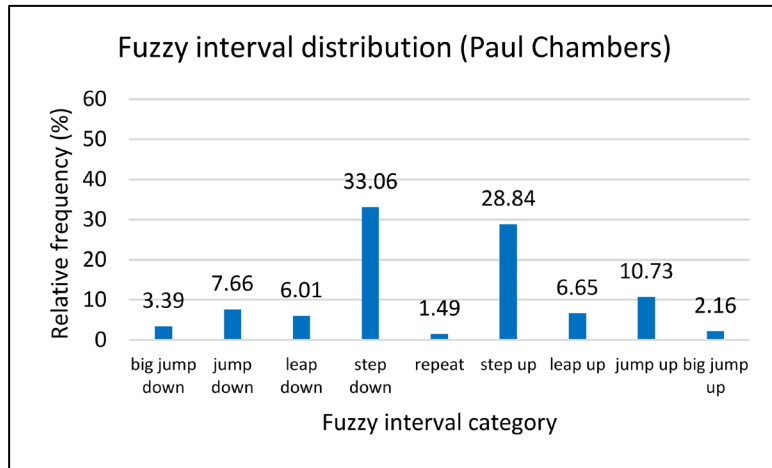


FIGURE 9 Corpus-level fuzzy interval distributions

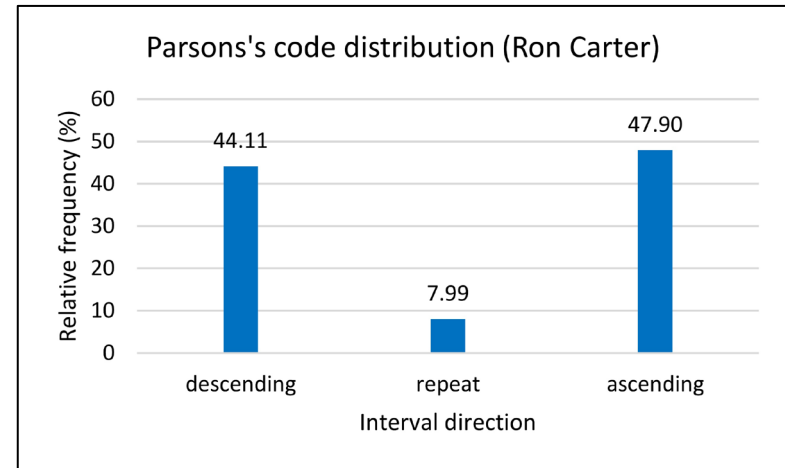
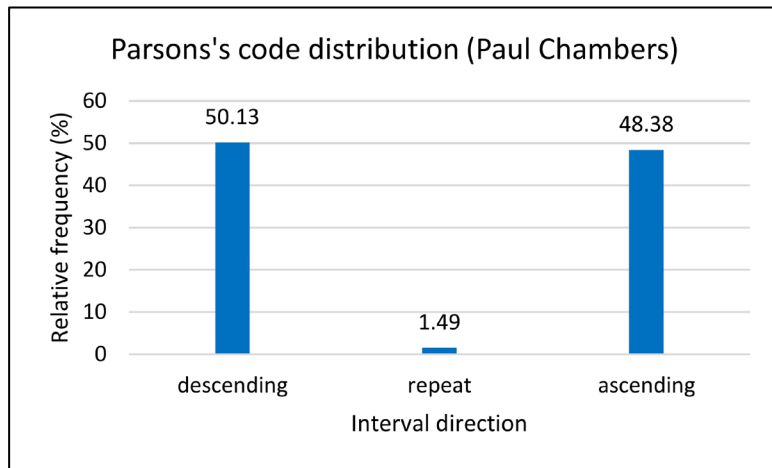


FIGURE 10 Parsons's code distributions

## 5.3 Research method

### 5.3.1 Methodological problems related to segmentation

In this chapter, my purpose is to discuss differences between melodic groupings, melodic patterns, and melodic chunks. After that, I will discuss principles of melodic grouping and their implications on the identification of melodic chunks in jazz bass improvisations. Although these considerations are methodological, they will also clarify the meaning of some of the key concepts of this study.

The term ‘melodic grouping’ is often used as a synonym with the term ‘melodic pattern.’ However, these two concepts differ from each other in that melodic groupings refer to perceptually relevant note sequences (although single note groupings may also exist, as shown later in this chapter), whereas melodic patterns refer to any note sequence that consists of at least two notes. The term ‘perceptual relevance’ refers to the existence of a stimulus to a person<sup>90</sup>. In other words, perceptually relevant stimuli refer to all stimuli that a person can perceive. Distinct from these terms, ‘melodic chunk’ refers to a note sequence that is retrieved from memory as a single unit. In the context of music performance, melodic chunks provide information about the memory structures of the musician, whereas melodic groupings describe the segmentation of music from the listener’s point of view.

Grouping is a natural human tendency to organize information into units (Snyder, 2000, p. 31). As an example, listeners perceive meaningful sequences of notes instead of individual notes that are not related to each other, and they are able to detect similarities and connections between different musical units. Grouping plays a significant role in making sense of musical works and lays the foundation for constructing more complicated understanding of a musical work (Lerdahl & Jackendoff, 1983, p. 13). Grouping is also an important ability underlying successful music performance. For instance, the phenomenon that singers tend to breathe between units rather than within them depends on their ability to group events into units (Lerdahl & Jackendoff, 1983, p. 12).

A necessary condition for all melodic groupings is that they can only exist if they are perceptually relevant. Moreover, perceptual relevance can only occur when events belonging to a group are contiguous. This condition was expressed by Lerdahl and Jackendoff as follows: “any contiguous sequence of pitch-events, drum beats, or the like can constitute a group, and only contiguous sequences can constitute a group” (Lerdahl & Jackendoff, 1983, p. 37). In other words, individual events must occur close in time to be perceived as a grouping and individual events that are distant in time cannot be perceived as a melodic grouping.

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90 Note that any stimuli may consist of a series of stimulus features (e.g., sound pressure level). According to Milne & Herff (2020), perceptual relevance of stimulus features can be defined by their effect on memory and/or evaluation (i.e., perceptually relevant stimulus features have systematic effects on tasks like recognition and liking).

There are three basic principles that influence how events are grouped together: proximity, similarity, and continuity. The principle of proximity states that events that occur close to each other in time tend to be grouped together. The principle of similarity states that similar events tend to form groupings. The principle of continuity states that a series of events with the same direction and consistent relationship between events (e.g., the same interval size) tend to be grouped together. (Snyder, 2000, pp. 39-43.)<sup>91</sup> For example, grouping boundaries (which define where a particular grouping begins and ends) can be identified by a sufficient change in auditory information (e.g., a change in loudness) (Snyder, 2000, pp. 33-34) or by searching for signs of how the composer intended his/her music to be performed (e.g., notes on articulation and phrasing in sheet music) (see Huovinen et al., 2018, p. 1). In addition, structural importance of notes can be also used to identify grouping boundaries.

Following Narmour's (1990) implication-realization model, Snyder (2000) proposed that two intervals (i.e., three notes) is a "minimum size for a typical melodic grouping" (Snyder, 2000, p. 146) and constitutes the "basic unit for the analysis of melodic grouping" (Snyder, 2000, p. 147). A maximum size of melodic and rhythmic groupings is established by constraints of short-term memory. Two events that are farther apart than 3-5 seconds are too distant to allow perceiving a relationship between them. In such cases, events do not appear to be connected and perceiving a relationship between events requires the use of long-term memory. Conversely, if two events are temporally too close to each other (closer than about 60 milliseconds), it becomes impossible to perceive them as separate events. (Snyder, 2000, p. 162.) Of course, it is easy to imagine occasions where even a single event may constitute a melodic grouping. For instance, a single pitch that continues for a considerable time and begins and ends with silence is perceived as a single grouping. Such situations are, however, quite infrequent, and marginal in music (see Lerdahl & Jackendoff, 1983, pp. 43-44).

According to Lerdahl and Jackendoff, musical groupings are perceived in a hierarchical fashion and therefore subsequent groupings cannot overlap except for shared events that function as the last event of the preceding grouping and the first event of the latter grouping (Lerdahl & Jackendoff, 1983, pp. 13-14). Lerdahl and Jackendoff also argued that there can be several grouping principles that apply simultaneously, and such simultaneously possible grouping principles may either reinforce or conflict with each other (Lerdahl & Jackendoff, 1983, pp. 39-40). The existence of possible groupings that reinforce each other lead to a stronger certainty in assessing whether a particular grouping is appropriate. The existence of possible groupings that conflict with each other lead to vague and ambiguous interpretations of appropriate groupings. (Lerdahl & Jackendoff, 1983, pp. 39-40.) The same piece of music may afford several interpretations of grouping structure. Some of these interpretations are more acceptable or more

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91 Along with these basic grouping principles, there are also other factors that can affect grouping including accent, articulation, dynamics, harmonic parallelism, motivic parallelism, and others (Lerdahl & Jackendoff, 1983, p. 43).

preferred than others but possible, nevertheless. (Lerdahl & Jackendoff, 1983, p. 42.)

Following Lerdahl and Jackendoff (1983, p. 12), it is reasonable to assume that grouping structure and metrical structure are independent components of musical organization. Therefore, grouping structure may not necessarily coincide with metrical structure as is often the case in jazz solos. Figure 11 (eight bars from Paul Chambers's bass solo on *Blues by Five*) illustrates this issue. Except for bar 269, there are no groupings that start at the strong beat.

The image shows two staves of musical notation in bass clef with a key signature of two flats. The first staff, labeled '265', contains five measures of music. Above the staff, brackets indicate groupings of notes that span across bar lines. The chords indicated above the staff are B<sup>b</sup>7, E<sup>b</sup>7, B<sup>b</sup>7, F<sup>m</sup>7, and B<sup>b</sup>7. The second staff, labeled '269', contains four measures of music. Above the staff, brackets indicate groupings of notes that also span across bar lines. The chords indicated above the staff are E<sup>b</sup>7, B<sup>b</sup>7, and G<sup>7</sup>.

FIGURE 11 Grouping structure in Paul Chambers's bass solo on *Blues by Five*, bars 265-272

It is noteworthy that previous research on jazz improvisation has focused on solos, whereas other roles of ensemble improvisation have been largely neglected. This is a pity since an analysis of walking bass lines provides an ideal approach to investigate repetition of melodic patterns, because grouping boundaries in walking bass lines are usually equivalent with the metrical structure (in contrast to solos). As a result, segment boundaries in walking bass lines can be identified mechanically and reliably. The main reason for this correspondence between grouping structure and metrical structure in walking bass lines is that blurring the metrical structure is rare in walking bass lines. Even if jazz musicians often tend to blur the metric and harmonic structure of a composition by extending the current chord over the bar line or by playing melody lines that overlap parts of the metric and harmonic structure (Tabell, 2004, p. 151), there are only a few occurrences of where a chord is implied beyond the bar line in Ron Carter's bass lines (Nurmi, 2018). Regarding Paul Chambers's bass lines, I have found no such occurrences. Instead, both Ron Carter and Paul Chambers often emphasize chord changes by playing a stable note on each first beat of a bar (Nurmi, 2006, 2018).<sup>92</sup>

In the present study, I used Lerdahl and Jackendoff's (1983) and Snyder's (2000) principles of melodic grouping to investigate melodic chunks in walking bass lines. As noted earlier in this chapter, melodic chunks refer to note sequences

92 Cross and Goldman (2021) recently found that the occurrence of repeated melodic patterns in jazz improvisation may depend on metrical location. These authors found that short repeated melodic patterns were more likely to occur on specific metrical locations than others, which indicates that metrical location is either a part of mental representations of well-learned melodic patterns or that certain melodic patterns are easier to access. Regarding the present study, these findings support the assumption that the metrical location of melodic patterns should be considered if identification of segment boundaries contributes to the reliability of the results.



that are retrieved from memory as a single unit. Following Lerdahl and Jackendoff's (1983) principles of melodic grouping, I also assumed that melodic chunks must have a specific starting and ending point, and that they cannot overlap with other melodic chunks. In addition, I assumed that even though melodic chunks may share common properties with each other, they can exist as distinct entities only if they do not overlap with each other.<sup>93</sup>

Like melodic groupings, I assumed that there is a minimum size for melodic chunks too: all melodic chunks are required to contain at least one interval (i.e., at least two notes). The basic idea is that the more repeated and longer the melodic pattern, the more plausible it is to argue that the repeated melodic pattern is a melodic chunk which is memorized and retrieved as a single unit. If a repeated note sequence is very short or it is repeated only once, there is little evidence to show that this particular note sequence was memorized as a single unit or that it was retrieved from memory as a single unit. It is important to note that this reasoning of how to measure the quantity of learned melodic chunks differs from how vocabulary size is measured in language studies (see Brysbaert et al., 2016). The major difference is that the identification of melodic chunks often requires to search for note sequences that are repeated at least twice by the same musician. Also, the amount of repetition adds to the plausibility of claiming that a particular note sequence was retrieved from memory as a single unit (as opposed to invented during the performance or by chance). Repetition of words, however, is not required in estimations of vocabulary size. Even a single occurrence of a particular word in a text indicates that the author knows at least that such a word exists.

### 5.3.2 Basic conversion and segmentation of research material

There are two advantages of using walking bass lines as research data in jazz improvisation research compared to solos. As discussed in the previous chapter, segmentation of music provides less problems with walking bass lines compared to solos. In addition, time values in walking bass lines are usually less varied compared to solos. As a result, the inter-onset intervals between subsequent notes are more stable compared to solos. However, it turned out to be very difficult to use only note sequences where the inter-onset intervals between subsequent notes were completely stable. Only six bass lines (Paul Chambers's bass lines on *Chamber Mates*, *Excerpt*, *Milestones*, *Mr. P.C.*, and *Oleo*, and Ron Carter's bass line on *Mo' Joe*) were completely based on quarter notes. In addition, both bassists used a much larger variety of note durations at slow tempi compared to fast tempi. The decision to remove all melodic patterns that consisted of time values other than quarter notes was discarded, since such a decision would have

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93 As will be shown in Chapter 5.3.3.4: Average length of recurring melodic patterns, it is impossible to remove all overlapping melodic patterns from the research data. However, these remaining overlapping melodic patterns were at least partly caused by an overlap between the last note of the previous melodic pattern and the first note of the next melodic pattern.

caused a significant loss of research data. Instead, a mild form of reduction was preferred.

Reductions have long been used in music analysis, where they are useful to reveal common features in different musical examples. In the present study, the original bass lines were reduced to sequences of quarter notes to remove all temporal differences between melodic patterns if they shared the same underlying interval structure at the beat level. As a result, it was possible to examine whether melodic patterns played at slow tempi (based on a variety of note durations) shared the same underlying interval structure compared to melodic patterns played at fast tempi (usually based on quarter notes).

Note reductions were implemented in the following way. When two-beat bass lines (i.e., bass lines that mainly consist of half notes), bars with whole notes, and rests with a minimum duration of a quarter note were removed, all notes shorter or longer than a quarter note were converted to quarter notes based on applying the following rules: (1) For dotted eighth notes followed by sixteenth notes (which is in the context of jazz usually notated as two-note triplets with a quarter note followed by an eighth note), disregard the second note (see Figure 12); (2) For eighth note triplet sequences with three notes, disregard the second and the third note; (3) Convert half notes to two quarter notes; (4) Convert dotted half notes to three quarter notes; (5) For syncopations (including quarter note triplets), disregard the note farther away from the beat; (6) For double-stops, disregard the lower voice<sup>94</sup>. As a result, the research material consisted of only quarter notes in 4/4 meter. Figure 12 shows a typical example of how note durations were removed from data. Figure 13 shows less typical examples of reduction of note durations.

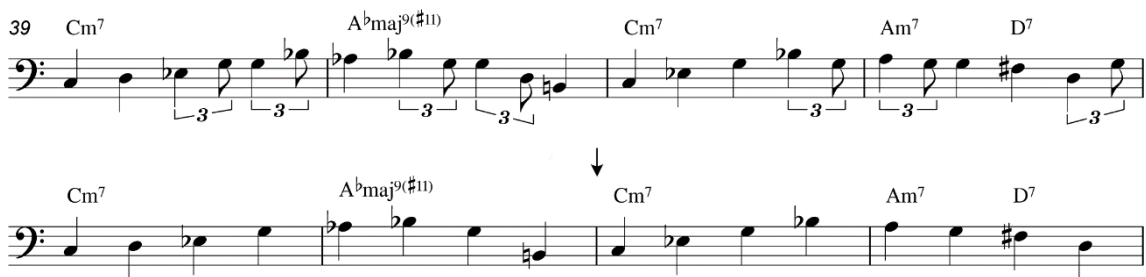


FIGURE 12 Reduction of note durations in Ron Carter's bass line on Dolphin Dance, bars 39-42

94 Conversion of double-stops caused some difficulties, since it was not perfectly clear which note should be regarded more important compared to others. Although it is a common practice to emphasize the highest voice in music analysis (e.g., Gjerdingen, 1988), and even if the highest voice is more salient for the listeners (Fujioka et al., 2005), the function of bass lines is to provide the bottom line for all other simultaneous voices and thus it would make sense to regard the lowest voice as the most important voice in bass lines. The highest voice was considered more salient and therefore the lower notes were removed. Again, it should be noted that double-stops were very rare in my research material. Therefore, this problem with double-stops had practically no effect on the results.

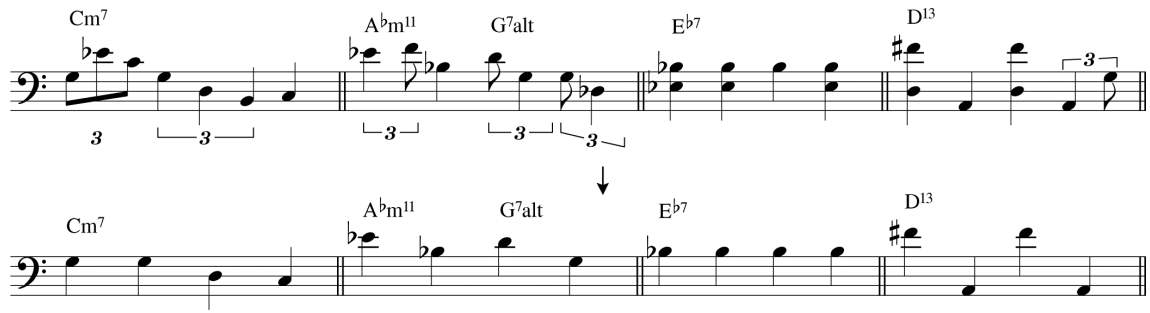


FIGURE 13 Less typical reductions

Note that the present approach avoids problems that occur when all notes are equally important. Figures 14 and 15 illustrate this issue. In both examples, the first line shows four bars from the original bass line, whereas the second and the third line represent two ways to reduce note durations. In the second line, all notes are treated as equal. In the third line (the approach used in this study), all notes with onsets between the beats (instead of onsets at the beat) are removed. Obviously, the third line sounds more similar compared to the original bass line, compared to aural similarity between the second line and the original bass line.



FIGURE 14 Reduction of note durations in Ron Carter's bass line on Witch Hunt, bars 78-81

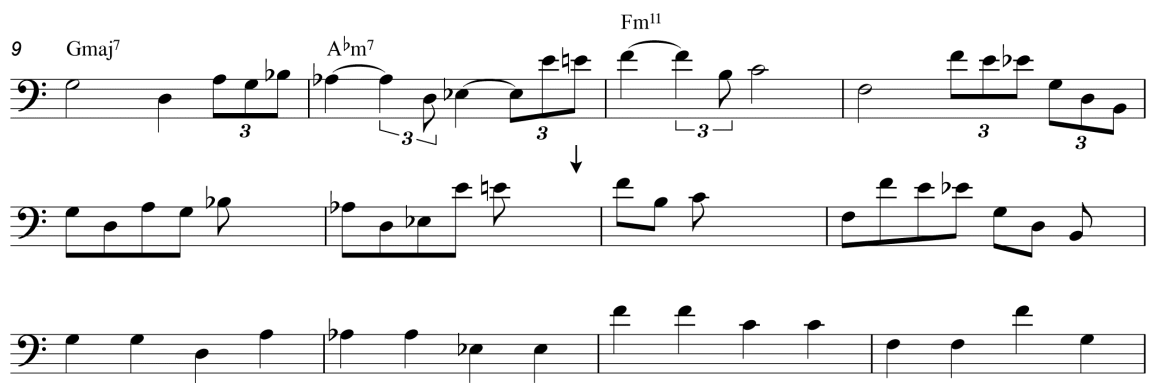


FIGURE 15 Reduction of note durations in Ron Carter's bass line on Dolphin Dance, bars 9-12

After all note durations were converted to quarter notes, the research material was converted to melodic patterns in two different ways. The first conversion method considers both the direction of melodic movement and harmonic context. Note that harmonic context is a fundamental constraint to what notes sound consonant in each situation. However, a method of analysis that takes harmonic context into account becomes problematic in situations with atypical or ambiguous chord substitutions, or when the relationship between melody and underlying chord is unclear because of some other reason. Also, it is often difficult to distinguish between the use of chord substitutions (which refer to common ways of using alternative chords as substitutes to original chords) from taking of liberties in relation to the current harmonic context.

Figure 16 represents four 4-note melodic patterns with the same chordal pitch classes but different melodic direction.



FIGURE 16 Change of melodic direction

In Figure 17, '1' refers to the root of the chord, '+' refers to an ascending interval, '-' refers to a descending interval, '+3' refers to an ascending interval leading to the third of the current chord, and so on.

FIGURE 17 Conversion method 1 (Paul Chambers's bass line on If I Were a Bell, bars 41-48)

In addition to this conversion method, all bass lines were also converted to MIDI files, where harmonic context was disregarded. In this case, the data represents the size of consecutive intervals and the direction of melodic movement but does not provide any information about the relationship between notes and underlying chords. Ignoring the harmonic context makes it possible to avoid problems with chord analysis, but the classification process of melodic patterns is also less stringent compared to conversion method 1. For example, the melodic pattern Bb-B-C-E in the second bar (bar 42) (see Figures 17 and 18) is also often found in the harmonic context of Bb major. When harmonic context is considered, the notes would be classified as [1-b2-2-b5] in Bb major and [b7-7-1-3] in C major. If harmonic context is disregarded in the classification of the melodic patterns, each of these melodic patterns would belong to the same category [+1, +1, +4]. In this

example, the numbers refer to interval size (e.g., '1' refers to one semitone, '2' refers to two semitones, etc.), and the plus and minus signs refer to direction of melodic movement.

In Figure 18, '1' refers to the root of the chord, '+' refers to an ascending interval, '-' refers to a descending interval, '+3' refers to an ascending interval leading to the third of the current chord, and so on.

The figure shows two staves of music in bass clef with a key signature of one flat (B-flat). The first staff (bars 41-44) has chords G7, C7, and Fmaj7. The second staff (bars 45-48) has chords Am7b5, D7, G7, and C7. Interval numbers are written below the notes to indicate the relationship between consecutive notes. Bar 41: G7 chord, notes G, Bb, D, Eb with intervals -5, -2, -1. Bar 42: C7 chord, notes C, Eb, G, A with intervals -1, +1, +1, +4. Bar 43: Fmaj7 chord, notes F, Ab, C, Eb with intervals +1, -8, +5, -1. Bar 44: Fmaj7 chord, notes F, Ab, C, Eb with intervals -1, +7, -2, +5. Bar 45: Am7b5 chord, notes A, C, Eb, F with intervals -1, -2, +5, +1. Bar 46: D7 chord, notes D, F, Ab, B with intervals +1, -12, +2, +2. Bar 47: G7 chord, notes G, Bb, D, Eb with intervals +1, +2, +1, -8. Bar 48: C7 chord, notes C, Eb, G, A with intervals +5, -9, +2, -8. A triplet of notes (Eb, G, A) is marked with a '3' and a bracket in bar 48.

FIGURE 18 Conversion method 2 (Paul Chambers's bass line on *If I Were a Bell*, bars 41-48)

Once the research material was transformed according to these two conversion methods, all note sequences were segmented into 4-note melodic patterns, 3-note melodic patterns, and 2-note melodic patterns. Melodic patterns of each length were analyzed separately. Except for approach-note patterns, the first note of all patterns was always the one that occurred at the first beat of the bar. As previously mentioned, jazz bassists frequently emphasize the first beat of each bar by playing stable notes on these occasions. Note that there are virtually no pauses in walking bass lines or subsequent identical melodic patterns that could allow other grouping principles to be applied. As a result, playing stable notes on the first beat of each bar appears to be a fundamental grouping mechanism in walking bass lines.

Even if reduction of note durations is a useful method to reveal similarities between melodic patterns, there are some problems with this approach that need to be considered. For example, the need to define what is 'a small variation' may lead to considerable difficulties<sup>95</sup>. In addition, it is possible that important information is lost when the proportion of note reductions increases too much. As another problem with reductions, when a small part of the complete musical work is used to investigate the creativity of the whole musical work, it is possible that a high proportion of disregarded information may decrease the reliability of the results. In the present study, the proportion of disregarded information was at its greatest in the analysis of target note use (where only the first note in each bar was considered). However, although the proportion of disregarded information is particularly high in case of target notes, much of the original data must be disregarded if the researcher aims to analyze this type of musical creativity at all.

95 In the present study, a small variation in melodic patterns was defined as any difference between melodic patterns that still shared the same underlying interval structure at the beat level.

Also note that even if reduction allows to remove rhythmical variation and to uncover melodic patterns that are only slightly different from each other, other types of slight variation of melodic patterns may also exist. Figure 19 shows two excerpts from Ron Carter's bass line on *E.S.P.* The first five bars are from the beginning of the first chorus of Herbie Hancock's piano solo and the next five bars are from the beginning of the second chorus of Herbie Hancock's piano solo. These two five-bar excerpts are almost identical with only slight differences in bars 294 and 326 until the first note of the fifth bar, even though there is no rhythmical variation in these examples. However, this type of slight variability of melodic patterns is quite rare, at least in the present data.

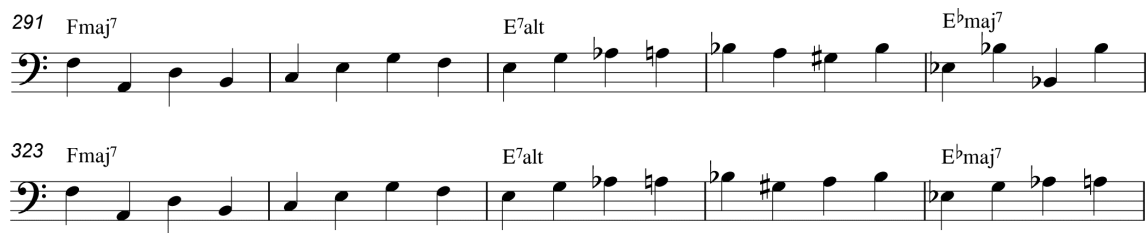


FIGURE 19 Slight variability of melodic patterns in Ron Carter's bass line on *E.S.P.*, bars 291-295 and 323-327

In the present study, the overall number of converted bars was 1,854 (19.9% of all bars in the research material). However, the average proportion of bars that included at least one reduced note was much higher in Ron Carter's bass line reductions ( $M = 45.7\%$ , range: 0% to 89.4%,  $SD = 32.5$ ). Moreover, the proportion of bars that included at least one reduced note was 50% or more in 6 out of the 12 Ron Carter's bass line reductions (this proportion was 80% or more in 3 bass line reductions). In Paul Chambers's bass line reductions, the average proportion of bars that included at least one reduced note was 12.7% (range: 0% to 42.4%,  $SD = 13.8$ ). Except for four bass line reductions (*Cool Struttin'*, *Freddie Freeloader*, *Blue Train*, and *C-Jam Blues*), the proportion of bars with at least one reduced note was less than 30% (for proportion of bars that included at least one reduced note in each bass line reduction, see Table 19 in Appendix 1). As the proportion of bars with at least one reduced note was high in many of Ron Carter's bass line reductions, it is possible that much relevant information was lost during the reduction process. To avoid this problem, further research could use more sophisticated reduction methods where the loss of information is minimized or use both reductions and original transcriptions to fully understand the effects of the reduction process. In some cases, it could also be a good idea to avoid reductions completely. For example, it might be sometimes useful to restrict the range of tempos to make sure that all notes in the original bass lines are quarter notes instead of using reductions. Also, sometimes it could be useful to measure the variability of melodic patterns without considering pattern lengths (e.g., by considering all notes that are played in a bar as a single pattern) with or without reductions.

Corpus-level interval distributions were visually examined to find out whether the reduction process influenced these distributions. Since most target

variables in this study were based on either interval patterns or chordal pitch class patterns, it might have been useful to also investigate whether chordal pitch class distributions differed between bass line reductions and original bass lines. However, due to the considerable amount of work required to perform such an analysis, differences between these distributions were not analyzed. Visual examination of interval distributions did not indicate notable differences between distributions from bass line reductions and original bass lines except for note repetitions. The proportion of note repetitions was larger in the original bass lines compared to bass line reductions, which was especially obvious in Ron Carter's bass lines and bass line reductions. This finding suggests that even if the reduction process causes loss of information, the interval distributions of the original bass lines were preserved (at least approximately) except for the proportion of note repetitions. Interval distributions in both original bass lines and bass line reductions are presented in Figure 20. For clarity, all intervals larger than eight semitones with the same direction are combined into a single category ('others').

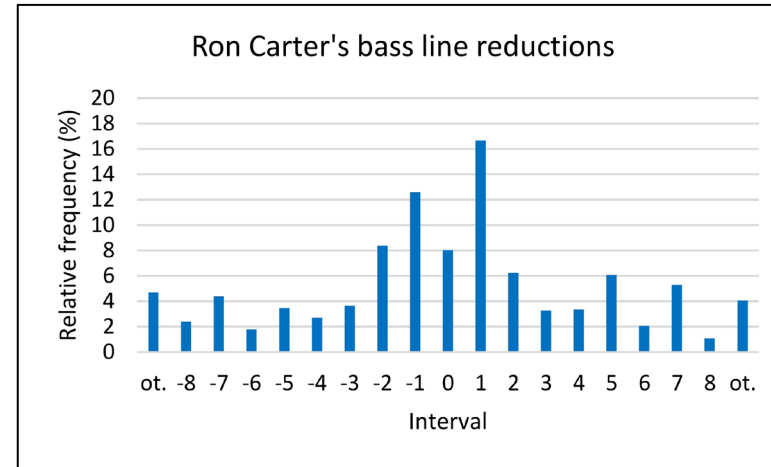
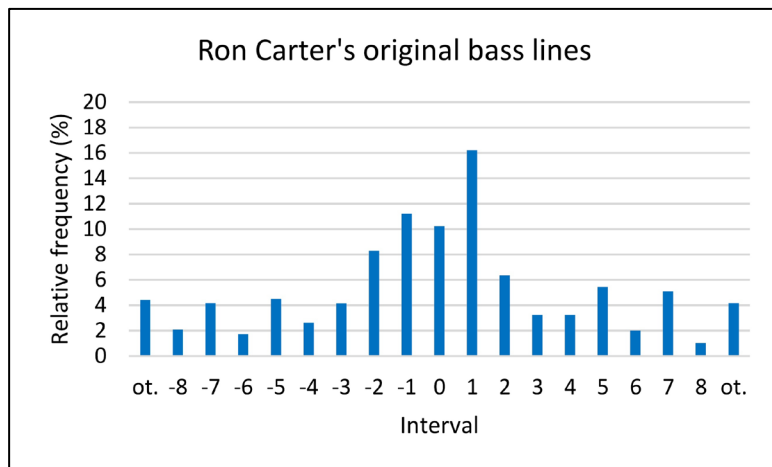
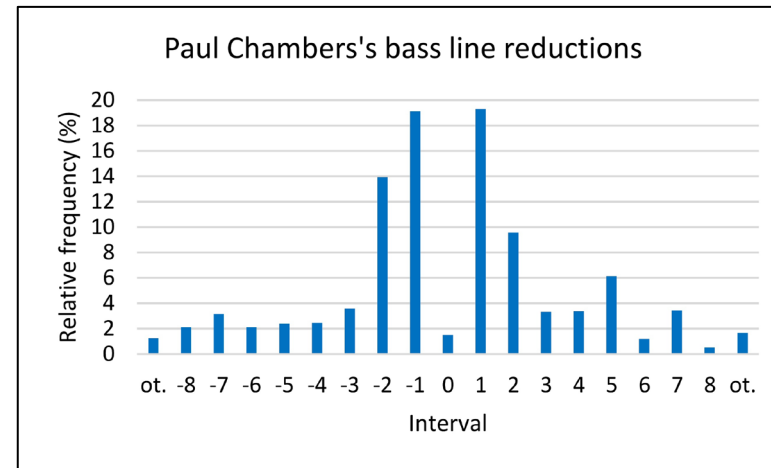
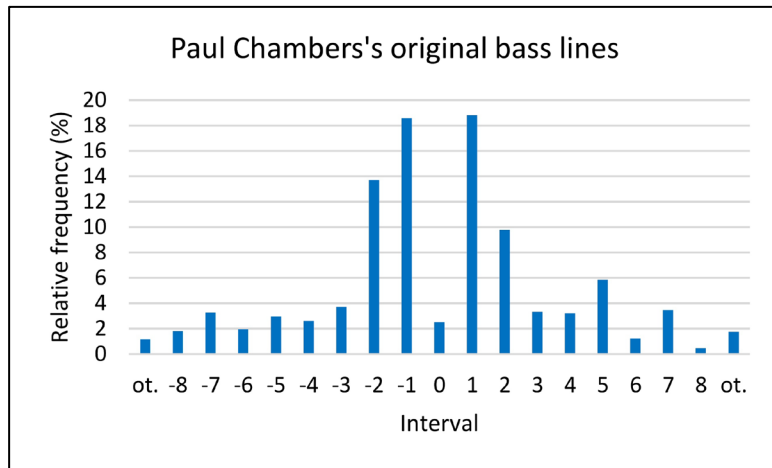


FIGURE 20 Corpus-level interval distributions in original bass lines and bass line reductions (ot. = others)



Despite of these above-mentioned problems, note reductions have an important role in the present study. As an important advantage, the use of note reductions removes small differences between melodic patterns. As a result, the threshold of how much difference between two or more melodic patterns is required to consider them different was tightened. Also note that the reduction method allowed to remove all differences between melodic patterns with dotted eighth notes followed by sixteenth notes (or two-note triplets with a quarter note followed by an eighth note), which are often used in walking bass lines (see Figure 21)<sup>96</sup>. Ignoring small variations of melodic patterns makes it more difficult to create walking bass lines with a very high amount of variability. In addition, if very small variations of melodic patterns were not removed, it would be more difficult to identify differences between the creativity of walking bass lines from highly distinguished musicians.



FIGURE 21 Dotted eighth notes followed by sixteenth notes in Paul Chambers's bass line on Freddie Freeloader, bars 205-212

Finally, note that the occurrence of pedal point sections in bass lines (where the bassist often plays the same note repeatedly for an extended duration) may increase the relative frequency of recurring melodic patterns. The same applies to prewritten parts of bass lines. As a result, bass lines where pedal point sections are common (or where there are prewritten parts) may appear to be less creative compared to bass lines where pedal point sections do not occur (or where there are no prewritten parts). Thus, all clearly prewritten bass parts (e.g., in *Milestones* and *Moment's Notice*) including all clearly prewritten pedal point sections were disregarded from the analysis. However, pedal point sections in bass lines can also occur spontaneously, which means that these sections are not prewritten or preplanned parts of the composition. Whenever pedal point sections were not exactly (or almost exactly) repeated in each chorus, they were not considered to be prewritten and thus they were not removed. As an example, Ron Carter's bass line on *Israel* contains several lengthy pedal point sections, but all of these appear to be spontaneously played (in contrast to being prewritten sections).

96 In the present research material, the most frequent note durations (apart from quarter notes) were eighth notes, dotted eighth notes followed by sixteenth notes (or two-note triplets with a quarter note followed by an eighth note), and eighth note triplets with two or three notes.

### 5.3.3 Methods of measurement

#### 5.3.3.1 Entropy of melodic pattern classes

Entropy has been widely used as a measure of information content,<sup>97</sup> novelty, and unpredictability in comparative studies on musical style (e.g., Youngblood, 1958; Knopoff & Hutchinson, 1983; Snyder, 1990; Manzara et al., 1992) and studies on music cognition (e.g., Goldman, 2013; Pinho et al., 2014; Daikoku, 2018). As an example, Loui and Guetta (2019, p. 277) suggested to define creativity based on the information content of products and encouraged to search for “biomarkers of creativity by having rigorously defined outcome measures and relating these outcome measures to data from the brain” (p. 278).

Entropy of melodic patterns was calculated according to the formula below, where ‘n’ is the number of melodic pattern classes (melodic pattern class is an abstract object to which all occurrences of the same melodic pattern belong), and ‘p<sub>i</sub>’ is the probability of each melodic pattern class. For instance, in a melody with 4 occurrences of melodic patterns (A, A, A, and B), there are 2 melodic pattern classes (A and B).<sup>98</sup>

$$H = - \sum_i^n p_i * \log_2(p_i)$$

In music, there is an almost infinite number of different ways to combine notes together. For instance, if a musician is restricted to using only two different notes, these notes can be used to create 2<sup>4</sup> (i.e., sixteen) different 4-note melodic patterns. In a standard piano keyboard with 88 keys, there are 88<sup>4</sup> (i.e., nearly 60 million) different ways of how to combine whatever four notes in a row. The average range of notes in double bass is from low E to high c<sup>2</sup>. In other words, there are 33<sup>4</sup> (more than one million) different possibilities for how to combine four notes in a row (note that the number would be higher if micro-intervals were also considered). Since real music never comes even close to such complexity, a better way to measure maximum entropy for the purpose of the present study is to define maximum entropy as a situation where the probability of all melodic pattern classes is equal. For instance, in a melody with one hundred bars (where each bar may either contain one novel melodic pattern or one melodic pattern that occurs more than once in the same melody), the maximum number of different melodic pattern classes is 100. In this case, the maximum entropy is 6.64.

It is important to note that the number of input values affects the rate of entropy and therefore the entropy of two sets of data cannot be compared directly

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97 Entropy was originally designed as a measure of information content in messages. Information was defined as the logarithm of possible choices: “if one has available say 16 alternative messages among which he is equally free to choose, then since  $16 = 2^4$  so that  $\log_2 16 = 4$ , one says that this situation is characterized by 4 bits of information” (Shannon & Weaver, 1949/1964, pp. 9-10).

98 For convenience, I will use the term ‘entropy of melodic patterns’ instead of ‘entropy of melodic pattern classes’ to avoid the use of confusing terminology like ‘normalized entropy of chordal pitch class pattern classes’ when harmonic context is considered.

if their quantity of input values is not the same (e.g., Snyder, 1990, p. 134). As a result, to compare musical works with a different number of input values, the normalized entropy of melodic patterns was also calculated. In addition, an analysis of how the normalized entropy of melodic patterns varies with pattern length was also performed.

Normalized entropy is “the ratio of the actual [entropy] to the maximum entropy” (Shannon & Weaver, 1949/1964, p. 13), where maximum entropy refers to the highest possible information content in a message with  $N$  symbols<sup>99</sup>. Normalized entropy ( $H_0$ ) was calculated by using the following formula (e.g., Frieler, 2017, p. 65), where ‘ $H_0$ ’ can range from 0 to 1 and where ‘ $N$ ’ is the total number of melodic patterns.

$$H_0 = \frac{H}{H_{max}} = \frac{H}{\log_2 N}$$

### 5.3.3.2 Relative frequency of non-recurring melodic patterns

I used two different methods to calculate the relative frequency of non-recurring melodic patterns. According to the first method (calculation method 1), the relative frequency of non-recurring melodic patterns was calculated according to the formula below, where ‘ $a$ ’ is the total number of non-recurring melodic pattern classes<sup>100</sup> in a particular musical work (instead of the sub-corpus of all bass line reductions of Paul Chambers or the sub-corpus of all bass line reduction of Ron Carter) and ‘ $m$ ’ is the total number of melodic pattern classes in a particular musical work.

$$f_1 = \frac{a}{m} \times 100$$

According to the second method (calculation method 2), the relative frequency of non-recurring melodic patterns was calculated according to the following formula, where ‘ $a$ ’ is the total number of non-recurring melodic pattern classes in a particular musical work and ‘ $n$ ’ is the total number of all occurrences of melodic patterns in a particular musical work. Using this calculation method,  $f_2 = 30\%$  means that non-recurring melodic pattern classes covered 30% of all occurrences of melodic patterns in particular musical work.

$$f_2 = \frac{a}{n} \times 100$$

To illustrate the difference between these calculation methods, consider the following sequence of melodic patterns: A, A, A, B. In this sequence, there are four occurrences of melodic patterns (A, A, A, B), two melodic pattern classes (A, B),

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99 Shannon and Weaver (1949/1964) used the term ‘relative entropy’ instead of normalized entropy.

100 As noted in the previous chapter, the term ‘melodic pattern class’ refers to an abstract object to which all instances of the same melodic pattern belong.

three occurrences of the melodic pattern class A, and one occurrence of the melodic pattern class B. Using calculation method 1, the relative frequency of non-recurring melodic patterns is 50%, because there is only one non-recurring melodic pattern class and two melodic pattern classes in total. Using calculation method 2, the relative frequency of non-recurring melodic patterns is 25%, because there is only one non-recurring melodic pattern class (B) and there are four occurrences of melodic patterns in total (A, A, A, and B). When combined, these results show that the relative frequency of non-recurring melodic patterns was 50% and these non-recurring melodic patterns covered 25% of all occurrences of melodic patterns.<sup>101</sup>

Following Norgaard (2014) and Norgaard and Römer (2022), I also calculated the relative frequency of notes that started a recurring interval pattern at any metrical location. In contrast to these studies, however, the relative frequency values were calculated separately for each musical work instead of the sub-corpus as a whole (which includes all analyzed improvisations by the same musician). The relative frequency of notes that started a recurring interval pattern at any metrical location was calculated according to the formula below, where 'b' is the number of notes that started a recurring interval pattern at any metrical location in a particular musical work and 'c' is the total number of notes in a particular musical work. Overlapping interval patterns that started at the same note were removed. Analysis was limited to 4-note interval patterns.

$$f_m = \frac{b}{c} \times 100$$

Note that even slight differences in the number of melodic pattern classes may have a considerable effect on the results if the total number of all occurrences of melodic patterns in a particular musical work is small. For example, if the total number of non-recurring melodic pattern classes in a particular musical work is 5, the total number of recurring melodic pattern classes is 3, the total number of melodic pattern classes is 8, and the total number of all occurrences of melodic patterns is 11, the relative frequency of non-recurring melodic patterns (using calculation method 1) is 62.5% and the relative frequency of non-recurring melodic patterns (using calculation method 2) is 45.5%, even if the difference between the number of non-recurring melodic pattern classes and the number of recurring melodic pattern classes is only two.

The relative frequency of non-recurring melodic patterns was calculated both when harmonic context was disregarded and when harmonic context was considered. Following Frieler (2017), all melodic patterns where harmonic context is disregarded are called interval patterns and all melodic patterns where harmonic context is considered are called chordal pitch class patterns. All relative frequency values for interval patterns were calculated with *MeloSpyGUI* (Abeßer

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101 As with entropy values, I will use the term 'relative frequency of non-recurring melodic patterns' instead of 'relative frequency of non-recurring melodic pattern classes' to avoid the use of confusing terminology like 'relative frequency of non-recurring chordal pitch class pattern classes' when harmonic context is considered.

et al., 2018), whereas all relative frequency values for chordal pitch class patterns were calculated manually.

### 5.3.3.3 Variability of target notes

Variability of target notes (the term 'target note' was defined here as the first note of each bar) was analyzed in two stages. First, the occurrence of different types of target notes (e.g., root notes, major thirds, perfect fifths, etc.) was calculated in each bass line. Then, the normalized entropy of target notes, the relative frequency of root notes, and the relative frequency of consonant target notes (root notes, major thirds, minor thirds, and perfect fifths combined) were calculated. As with the normalized entropy of melodic patterns, the maximum entropy of target notes was defined as the equal probability of different target note classes in a single bass line. Note that the lower the relative frequency of root notes or consonant target notes, the higher the creativity of the bass lines in terms of target notes.

### 5.3.3.4 Average length of recurring melodic patterns

To investigate whether expert jazz improvisers compensate increasing time pressures by using larger melodic chunks at fast tempos compared to slow tempos, I calculated the average length of recurring melodic patterns and the maximum length of melodic patterns in each bass line reduction, when harmonic context was disregarded. In this analysis, overlapping melodic patterns were removed in three stages. (1) Since melodic patterns were considered to always start at the first beat of the bar, melodic patterns that started at any other location were disregarded. (2) Overlapping melodic patterns that started at the same location were removed except for the longest melodic pattern. These overlapping melodic patterns are caused by the fact that for every recurring melodic pattern with  $n$  elements, there are always  $n-1$  overlapping recurring melodic patterns with fewer elements (see Norgaard, 2014, p. 278). As an example, for every recurring 8-interval melodic pattern, there is an overlapping recurring 7-interval melodic pattern that starts at the same location, an overlapping recurring 6-interval melodic pattern that starts at the same location, and so on. (3) Recurring melodic patterns that were part of a larger recurring melodic pattern and contained five or more notes were removed. Since only those recurring melodic patterns that started at the first beat of the bar were considered, all recurring melodic patterns with twelve notes, for example, were removed if a 16-note recurring melodic pattern with the same notes had started at the first beat of the previous bar (except for the first four notes of the larger melodic pattern, of course).

Note that this process does not remove all overlapping melodic patterns from the research data. For instance, the process does not remove overlapping of the last note of a melodic pattern and the first note of the next melodic pattern. However, these overlaps were accepted. See Figure 22 for an example of overlapping melodic patterns that remain in the research data after the three-stage removal process.

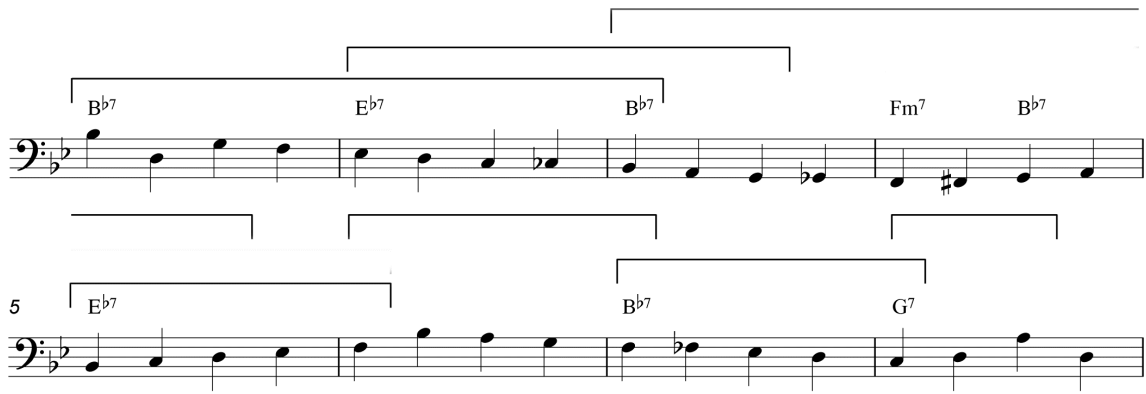


FIGURE 22 Overlapping melodic patterns after stage three in Paul Chambers's bass line on *Blues by Five*, bars 1-8

The average length of recurring melodic patterns was reported both as the number of intervals and approximate duration in seconds. The approximate average duration of recurring melodic patterns (in seconds) was calculated by the following formula, where 'L' is the average length of recurring melodic patterns (in intervals), and 'T' is the approximate tempo of the bass line.

$$D = L * (1/(T/60))$$

### 5.3.3.5 Melodic complexity

Although distinct from musical creativity (e.g., Eisenberg & Thompson, 2003), I also investigated the melodic complexity of the bass lines to find out whether increasing technical demands at fast tempos influence expert jazz musicians' note choices. To answer this question, two methods were used: entropy of interval distribution and pitch proximity (see Eerola, 2016). I hypothesized that expert jazz musicians' note choices are technically less demanding (as implied by lower melodic complexity) at fast tempos compared to slow tempos, which facilitates the generation of novel melodic patterns at fast tempos. I also investigated whether Paul Chambers used roots, thirds, and fifths more extensively in his bass lines compared to Ron Carter. In melodic complexity literature, a similar method is tonal ambiguity, which is measured by calculating the number of unstable notes (Eerola, 2016).

The entropy of interval distribution was calculated by using the `ivsizedist1` function in *MIDI Toolbox* (Eerola & Toiviainen, 2004). This function calculates interval size distribution (i.e., probability for each interval size), where interval direction is discarded. Note that the `ivsizedist1` function transforms all intervals that are larger than an octave to intervals within an octave, which may undermine the frequency of large intervals in some bass lines. Also note that the number of possible intervals is very limited when all intervals larger than an octave are disregarded and interval direction is disregarded. The maximum entropy of interval distribution was defined as the equal probability of input values in a bass line. Pitch proximity (where occurrence of larger intervals implies complexity)

was calculated as the average interval size in each bass line as suggested by Eerola (2016, p. 4). The average interval size was calculated by using the `abs_int_mean` function in *MeloSpyGUI* (Abeßer et al., 2018).

#### **5.3.3.6 Transfer of melodic patterns between bass line reductions**

Transfer of melodic patterns was examined by investigating whether the same chordal pitch class patterns were repeated in at least two different bass line reductions by the same musician. Since repetition of melodic patterns may also occur by chance, the plausibility that a particular melodic pattern was retrieved from memory was assessed by using two additional threshold levels: (1) a particular melodic pattern was considered to be retrieved from memory if the same melodic pattern occurred at least three times in at least two bass line reductions, and (2) a particular melodic pattern was considered to be retrieved from memory if the same melodic pattern occurred at least twice in at least three bass line reductions. The higher the threshold level, the higher the plausibility that a particular melodic pattern was retrieved from memory. In addition, it was assumed that the longer the recurring melodic pattern, the higher the probability that it was learned. The analysis was restricted to 2-note, 3-note, and 4-note chordal pitch class patterns.

#### **5.3.3.7 Shared melodic contour patterns**

In addition to reduction (see Chapter 5.3.2: Basic conversion and segmentation of research material), contour analysis provides an easily applicable method to search for underlying similarities in melodies. In addition to their importance in music perception and memory for melodies, melodic contours can function as templates of melody that can be used as a source of idea generation in the process of improvisation.

Four types of melodic contour were considered for their applicability to the present study. Fuzzy intervals analysis encodes the interval structure based on nine categories: descending interval with more than 7 semitones, descending interval with 5-7 semitones, descending interval with 3-4 semitones, descending interval with 1-2 semitones, repetition, ascending interval with 1-2 semitones, ascending interval with 3-4 semitones, ascending with with 5-7 semitones, and ascending interval with more than 7 semitones (Frieler, 2017, p. 67). Parsons's code, originally introduced as a classification system to index musical themes, encodes the interval structure based on three categories: ascending melodic direction, descending melodic direction, and repetition of previous note (Parsons, 1975/2008). Huron's (1996) classification system consists of nine contour types. However, its reliance on the mean values of mid-phrase notes (i.e., notes that occur between the first and the last note in a phrase) makes it an unnecessarily complex method regarding the present study. Narmour's (1990) classification of basic melodic structures has the advantage that it was designed to analyze both very short melodic patterns and larger hierarchically organized melodic structures. Narmour's aim was to present a theory of melodic implication that applies to all people and all musical styles. The theory predicts what kind of melodic continuations any

given interval implies to the listener and how such lower-level implications affect melodic implications at higher levels of music.

According to Narmour's theory, there are several basic melodic structures (i.e., contour types): process (P) (continuity of same-size intervals and melodic direction), intervallic process (IP) (continuity of same-size intervals but change in melodic direction), registral process (VP) (continuity of melodic direction but change in interval size; small to large), duplication (D) (repeated note), intervallic duplication (ID) (repeated interval), reversal (R) (change in melodic direction and interval size), intervallic reversal (IR) (continuity of melodic direction but change in interval size; large to small), registral reversal (VR) (change in melodic direction and interval size; large to even larger), registral return (aba) (return to the same pitch), and near registral return (aba') (a' is within one or two semitones from a) (Narmour, 1990, pp. 96, 435-437) (see Figure 23).

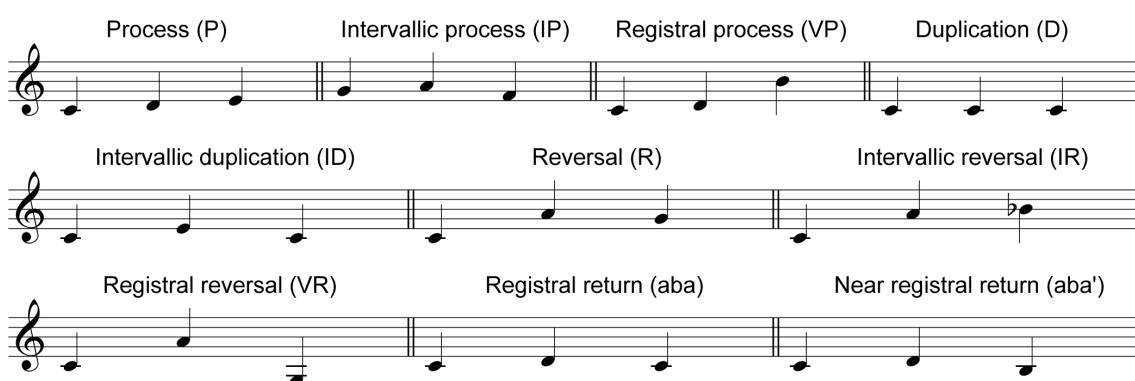


FIGURE 23 Narmour's basic types of melodic contour

Narmour's contour types can be analyzed by using an available pattern recognition tool, *MIDI Toolbox* (Eerola & Toiviainen, 2004). However, an analysis of Narmour's contour types provides little additional information compared to an analysis based on fuzzy intervals and Parsons's code. Therefore, an analysis of Narmour's contour types was abandoned.

Melodic contour analysis (based on fuzzy interval patterns and Parsons's code patterns) was performed with *MeloSpyGUI* (Abeßer et al., 2018). Only melodic contour patterns that started at the first beat of the bar and consisted of 4 notes (i.e., 3 intervals) were analyzed. Harmonic context was not considered. The term 'fuzzy interval pattern class' refers to an abstract object to which all occurrences of the same fuzzy interval pattern belong. The term 'fuzzy interval pattern' refers to all fuzzy interval patterns regardless of their similarity with other fuzzy interval patterns. Similarly, 'Parsons's code pattern class' refers to an abstract object to which all occurrences of the same Parsons's code pattern belong and the term 'Parsons's code pattern' refers to all Parsons's code patterns regardless of their similarity with other Parsons's code patterns.



### 5.3.3.8 Variability of approach-note patterns

The following four ways to reach a desired target note are extensively used in Paul Chambers's bass lines: the interval between the previous note and the target note is either a minor second, a major second, a descending fifth, or an ascending fourth (Nurmi, 2006). Longer approach-note patterns are also common: two minor seconds (e.g., B $\flat$  and B if the target note is C) and a changing note pattern (e.g., G and D if the target note is C). An extensive use of approach-note patterns may decrease cognitive resources required in the generation of novel melodic patterns by decreasing the number of elements to be selected. In addition, pre-learned approach-note patterns may also give additional time to prepare upcoming note choices.

To investigate the variability of approach-note patterns (which refer to short melodic patterns that are used to move towards the next target note), I calculated the normalized entropy of interval patterns that started either at the third beat or the fourth beat of the bar. Interval patterns that started either at the third beat or the fourth beat were also compared to interval patterns that started at the first beat of the bar with the same pattern length, in order to find out whether the relative frequency values and the normalized entropy values were influenced not only by pattern length but also by the metrical location of the patterns (i.e., whether patterns either started at the beginning of the bar or at beat 3/beat 4). In both cases, the length of analyzed interval patterns was fixed: the length of interval patterns that started at the third beat and ended at the first beat of the next bar was always two intervals (i.e., three notes). Similarly, the length of interval patterns that started at the fourth beat and ended at the first beat of the next bar was always one interval (i.e., two notes). Harmonic context was disregarded in these analyses.

As with melodic, fuzzy interval, and Parsons's code patterns, the term 'approach-note pattern class' refers to an abstract object to which all occurrences of the same approach-note pattern belong. The term 'approach-note pattern' refers to all approach-note patterns regardless of their similarity or difference from other approach-note patterns.

### 5.3.3.9 Familiarity with the chord progression

Subjective familiarity with a chord progression was assessed based on the following assumptions. First, a chord progression was considered familiar if it was based on one of the two most widely used chord progressions in jazz (the blues or the *Rhythm Changes*). Second, a chord progression was considered familiar to the bassist if the musical work was written or co-written by him. Third, a chord progression was considered familiar if the musical work had appeared previously in at least one recording featuring the same musician. For example, *You'd Be So Nice to Come Home to* (a popular musical work written by Cole Porter) was recorded for Paul Chambers Quartet's album *Bass on Top* (1957), but it was also recorded for Art Pepper's album *Art Pepper Meets the Rhythm Section* several months earlier and for Cannonball Adderley's 1955 album *Julian "Cannonball" Adderley*. Therefore, this musical work was thought to be already well-known to

Paul Chambers when he recorded the album *Bass on Top. Fourth*, a musical work was considered familiar if it was often featured on the band's regular live set list. The relationship between familiarity with the chord progression and musical creativity was assessed by investigating whether the average normalized entropy of chordal pitch class patterns differed between original or unusual chord progressions and chord progressions which were likely well-known to the musician.

### 5.3.4 Correlation analysis

Since most of the data were proportions, non-parametric correlation analysis was used to investigate the relationship between the variables as it makes no assumptions on distributions (Williamon et al., 2021, p. 366). As an alternative strategy, non-parametric methods to investigate differences between groups could have also been used. However, due to the small sample sizes of the present study (especially regarding Ron Carter's bass line reductions), correlation analysis was preferred over these methods. Among the most common non-parametric correlation methods (Spearman's rho and the different versions of Kendall's tau), Kendall's tau-b was preferred due to the small sample sizes (especially in regard to Ron Carter's bass line reductions) and the large number of tied ranks with harmonic rhythm data (which represent the average distance between chord changes)<sup>102</sup>. Since the length of analyzed bass line reductions varied considerably (which can lead to a situation where the variability of melodic patterns decreases, at least partly, simply due to increased length of analyzed bass line reductions), Kendall's tau partial correlation analysis was used to remove the influence of the length of the analyzed bass line reductions.<sup>103</sup>

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102 Although Kendall's tau is the recommended choice for small sample sizes with a large number of tied ranks by some researchers (e.g., Williamon et al., 2021, p. 366), some have argued instead that Spearman's rho is a better choice with tied ranks (Puth et al., 2015). However, Kendall's tau has an important advantage as it provides narrower confidence intervals compared to Spearman's rho (Puth et al., 2015). Also, it should be noted that many of the variables in the present study did not contain ties.

103 The length of analyzed bass line reductions ranged from 95 to 465 bars ( $M = 224.9$ ,  $SD = 96.9$ ) in Paul Chambers's bass line reductions and from 104 to 310 bars ( $M = 215.8$ ,  $SD = 69.1$ ) in Ron Carter's bass line reductions. To find out whether the variability of melodic patterns decreases, in part, due to the length of analyzed bass line reductions, I used Kendall's tau correlation analysis with Bonferroni correction to determine the relationship between the length of analyzed bass line reductions and the variability of melodic patterns with the same 19 measurements as used to assess the relationship between tempo/harmonic rhythm and the variability of melodic patterns. After Bonferroni correction, the alpha level for statistical significance was adjusted to .003 (.05/19). The results indicated a moderate negative correlation between the length of analyzed bass line reductions and the variability of melodic patterns in both Paul Chambers's bass line reductions (mean absolute tau-b = .40, all  $p$ -values were equal or smaller than .013, range: .32 to .55,  $SD = 0.07$ ) and Ron Carter's bass line reductions (mean absolute tau-b = .34, range: .24 to .52,  $SD = 0.08$ ). In Paul Chambers's bass line reductions, 10 out of the 19 measurements indicated a statistically significant correlation after Bonferroni correction. In Ron Carter's bass line reductions, all measurements indicated a statistically non-significant correlation after Bonferroni correction. The direction of the effect was always negative in both Paul Chambers's and Ron Carter's bass line reductions.

Correlation coefficients were interpreted with the use of Cohen's standards, which suggest that coefficients of .10, .30, and .50 indicate weak, moderate, and strong correlation, respectively (Cohen, 1988, pp. 79-81)<sup>104</sup>. To assess the strength of evidence and the precision or uncertainty of observed effect sizes, *p*-values and bootstrapped confidence intervals (with 1,000 replicates) were also reported<sup>105</sup>. Instead of analyzing the data both with and without outliers, correlation analyses were performed only with the original data since Kendall's tau is not sensitive to outliers (e.g., Wilcox, 2010, p. 179)<sup>106</sup>. Finally, Bonferroni correction was used to control the increased risk of falsely rejected null hypotheses caused by simultaneous comparisons (e.g., Pike, 2011). Multiple testing not only increases the probability of false positive findings, but it may also lead to biased confidence intervals and increased probability of extreme effect size estimates (Jeffries, 2007). Therefore, Bonferroni correction was used not only to adjust alpha levels, but also to adjust confidence intervals. All statistical analyses were performed with *JASP* (JASP Team, 2022), except for descriptive statistics which were performed with *Microsoft Excel*.<sup>107</sup>

In contrast to standard repeated measures design (where two or more subjects are observed multiple times), the present study was based on a single-

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104 Several other standards (or rules of thumb) to interpret correlation coefficients have also been proposed. For example, Russell (2018, p. 292) suggested that coefficients between 0 and .29 are weak, coefficients between .30 and .69 are moderate, and coefficients larger than .70 are strong. Williamon et al. (2021, p. 363) suggested that coefficients of .10, .30, .50, and .70 indicate weak, medium, strong, and very strong correlations, respectively. Schober et al. (2018, p. 1765) suggested that coefficients between 0 to .10 indicate negligible correlation, coefficients between .10 to .39 indicate weak correlation, coefficients between .40 to .69 indicate moderate correlation, coefficients between .70 to .89 indicate strong correlation, and coefficients between .90 to 1 indicate very strong correlation. Ferguson (2009) suggested that a coefficient of .20 represents the lower limit for a practically significant effect in social sciences, a coefficient of .50 indicates a moderate effect size, and a coefficient of .80 indicates a strong effect size. To my knowledge, there are no standards that are specifically designed for music researchers to interpret effect sizes. In recent textbooks for music researchers, both Russell (2018) and Williamon et al. (2021) used Cohen's standards with slight changes to interpret correlation coefficients.

105 The *p*-value, used to estimate the strength of evidence against the null hypothesis, indicates the probability of the observed (or more extreme) result when the null hypothesis is assumed to be true and all underlying assumptions are correct (Goodman, 2008; Wasserstein & Lazar, 2016; Greenland et al., 2016). A confidence interval gives a range of values that can be expected to include the true effect with a given level of confidence (e.g., 95% confidence) if the experiment is repeated very many times. The precision of the confidence interval is measured by the width of the confidence interval. A wider confidence interval gives a less precise estimation on the range of plausible effects compared to a narrower confidence interval. (Greenland et al., 2016.) For recent critical discussions on *p*-values and significance testing, see e.g. Wasserstein et al. (2019).

106 Outliers in the data may have a considerable influence on the results when the sample size of the study is small (Marino, 2014, p. 86) and their effect increases as the sample size decreases (Asuero et al., 2006, p. 46).

107 To avoid bloating the number of statistical tests, a single effect size method (Kendall's tau) was used in this study. In general, however, it is recommended to use several effect size methods. For example, Wilcox (2017) argued that "assuming that a single measure of effect size is adequate is a strategy that cannot be recommended. The general issue of assessing effect size in a satisfactory manner is a complex problem that might require multiple perspectives." (Wilcox, 2017, pp. 294-295.)

subject design where one person is observed multiple times (see Williamon et al., 2021, p. 217). Since all measurements were performed separately for the two bassists (in other words, all data sets contained observations on a single subject only), the fact that the data consisted entirely of statistically dependent observations was not considered to be a problem. All common correlation methods (including Kendall's tau) assume independence between observations, which means that observations (i.e., data points) should not depend on any other observations (Bakdash & Marusich, 2017, p. 2). Violations of this assumption are a problem when data consists of observations from two or more subjects and all observations are mixed in a single group or data set. The reason is that observations on the same subject tend to be more similar compared to observations on other subjects (Schober & Vetter, 2018). Similarly, the variability of observations between subjects is often greater compared to the variability of observations on a single subject (Bland & Altman, 1994, p. 896). However, this problem does not occur when only a single subject is measured or when two or more subjects are measured separately.

As a disadvantage of correlation analysis, it does not allow to estimate the size of the effect based on original units of measurement (original units often make it easier to interpret effect sizes compared to standardized effect size methods) (Baguley, 2009; Peng & Chen, 2014)<sup>108</sup>. In addition to this problem, even if standards such as those proposed by Cohen (1988) provide a simple solution to interpret correlation coefficients, they are problematic since even very small effect sizes can be important depending on the subject matter. For example, interventions that could reduce the risk of morbidity can have important practical significance even with small effect sizes. On the other hand, very small effect sizes may not be clinically relevant regardless of the statistical significance of the results (Phillips et al., 2022). Typical effect sizes can also vary between study designs and even within a discipline (e.g., there are large differences in median effect sizes between the subdisciplines of psychology), which makes it impossible to apply the same standards to interpret effect sizes in all contexts (Schäfer & Schwarz, 2019). As indicated by these examples, Cohen's standards (or any existing rules of thumb) may lead to false and misleading interpretations of effect size. Therefore, it is acknowledged that Cohen's standards should not be used blindly (e.g., Kraft, 2020). In fact, Cohen himself recommended that his standards should be used "only when no better basis for estimating the ES index is available" (Cohen, 1988, p. 25).

I deliberately avoided using the term 'lack of correlation' for correlation coefficients smaller than  $\tau = .10$ . Instead, the term 'negligible correlation' (Schober et al., 2018) was used in these situations (where  $\tau$  was smaller than  $.10$ ). The problem with the term 'lack of correlation' is that correlation coefficients that are smaller than  $\tau = .10$  only indicate that the effect is so small that it has no practical significance (however, note that the lowest meaningful effect size

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108 On the other hand, unstandardized effect sizes often do not allow to compare the results from different studies since "units of measurements are rarely identical from one study to the next" (Peng & Chen, 2014, p. 44). In contrast, standardized effect sizes allow to compare between current effect sizes and those found in relevant literature.

depends on the subject matter). Similarly, if the results are statistically non-significant, the results do not indicate the lack of effect but only that there is insufficient evidence against the null hypothesis (see Altman & Bland, 1995; Alderson, 2004).<sup>109</sup>

As noted earlier in this chapter, the sample sizes of the present study were small which has consequences for the probability of statistically significant results and the precision of effect size estimates. For example, statistically significant results with small effect sizes can only be detected with large sample sizes (Button et al., 2013). Low-powered studies (i.e., studies with inadequate “probability of rejecting a false null hypothesis”; Serdar et al., 2021, p. 3) are also more likely to produce erroneous effect size estimates and a wider range of effect size estimates compared to high-powered studies (Button et al., 2013). In addition, there is a high probability of Type II errors (where  $H_0$  is incorrectly maintained) when sample sizes are small and effect sizes are not very large (de Winter, 2013). Finally, the probability that a statistically significant result is actually true (instead of being a false positive) decreases with small sample sizes (de Winter, 2013) and small statistical power (Button et al., 2013).

Assuming that May and Looney’s (2020) calculations for Spearman’s rho and Kendall’s coefficient of concordance are approximately true for Kendall’s tau, the required sample size for each bassist to achieve a statistical power of 0.80 given an effect size of  $\tau = .30$  ( $\alpha = 0.05$ , two-tailed) is about 90, and the required sample size for each bassist to achieve a statistical power of 0.80 is about 200 given an effect size of  $\tau = .20$  ( $\alpha = 0.05$ , two-tailed) (May & Looney, 2020). By convention, 0.80 is an acceptable rate of statistical power (e.g., Serdar et al., 2021). A statistical power of 0.80 means that the probability for a correctly rejected null hypothesis is 80% (Serdar et al., 2021). Since statistical power is calculated as “1 - Type II error probability,” a power of 0.80 also indicates that the probability of a Type II error is 20% (Serdar et al., 2021, p. 3).

### 5.3.5 Consistency of effect directions

When observed effect sizes are very small, there is a high risk for false estimates on the direction of the effect. In this study, consistency of effect directions obtained from multiple measurements was used to assess the level of uncertainty in effect direction estimates. At the level of pattern use, musical creativity was measured as normalized entropy of chordal pitch class patterns, normalized entropy of interval patterns, relative frequency of non-recurring chordal pitch class patterns (using two different calculation methods), relative frequency of non-recurring interval patterns (using two different calculation methods), and relative frequency of notes that started a recurring interval pattern at any metrical

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109 Also note that it is a common misinterpretation of statistically non-significant results to claim that the most likely effect based on the data is the null effect. Instead, “the effect best supported by the data from a given experiment is always the observed effect, regardless of its significance.” (Goodman, 2008, p. 136.) As a consequence, statistically non-significant results should not be interpreted to indicate a lack of effect (unless the observed effect is exactly zero) (Greenland et al., 2016, p. 341).

location. Except for the relative frequency of notes that started a recurring interval pattern at any metrical location, all measurements were performed with three pattern lengths (2 notes, 3 notes, and 4 notes). In total, creativity in pattern use was assessed based on 19 measurements. Note that the relative frequency of notes that started a recurring interval pattern at any metrical location is a measure of redundancy of melodic patterns. As result, the higher the relative frequency of notes that started a recurring interval pattern at any metrical location, the lower the creativity of the bass line reduction.

Musical creativity was also measured at the level of target notes, melodic contour patterns, and approach-note patterns. At the level of target notes, musical creativity was measured as normalized entropy of target notes, relative frequency of root notes, and relative frequency of root notes, major thirds, minor thirds, and perfect fifths combined (in total: 3 measurements). In the case of the last-mentioned measurement, the lower the relative frequency of target notes, the higher the musical creativity. At the level of melodic contour patterns, musical creativity was measured as normalized entropy of fuzzy interval patterns, normalized entropy of Parsons's code patterns, relative frequency of non-recurring fuzzy interval pattern classes, relative frequency of non-recurring Parsons's code pattern classes, relative frequency of non-recurring fuzzy interval patterns, and relative frequency of non-recurring Parsons's code patterns when pattern length was always four notes (in total: 6 measurements). At the level of approach-note patterns, musical creativity was measured as normalized entropy of approach-note patterns, relative frequency of non-recurring approach-note pattern classes, and relative frequency of non-recurring approach-note patterns when pattern length was either 2 notes or 3 notes (in total: 6 measurements).

Since effect direction estimates are particularly prone to be false when correlations are negligible ( $\tau\text{-}b < .10$ ), all correlations smaller than  $\tau\text{-}b = .10$  were disregarded when the proportion of negative and positive correlations were calculated. In addition, it was only allowed to make conclusions on the direction of the effect if all or most measurements indicated the same effect direction. In any other case, the results did not allow to make conclusions on the direction of the effect.

Consistency of effect directions can be only used to provide tentative conclusions on effect directions. As a result, further research should consider using more sophisticated methods to make conclusions on the direction of the effect. Confidence intervals, for instance, could be used for this purpose. If all values in the confidence interval are negative (or all values are positive), it is reasonable to claim that the direction of the effect is negative (or positive) with a given confidence level. In any other case, the direction of the effect cannot be determined. However, if most values in the confidence interval have the same direction, the results could be considered as hints and interpreted with statements like the direction of the effect is "uncertain, but plausibly positive" or uncertain, but plausibly negative (Tukey, 1991, p. 103).

## 6 RESULTS

### 6.1 Methodological issues

#### 6.1.1 The role of harmonic context

When improvising to a specific chord progression, harmonic context limits what note choices are available. As a result, I hypothesized that the normalized entropy of melodic patterns and the relative frequency of melodic patterns should decrease when harmonic context is disregarded since interval sequences can be played in a variety of harmonic contexts instead of just one. As expected, the normalized entropy of interval patterns, the relative frequency of interval patterns (calculation method 1), and the relative frequency of interval patterns (calculation method 2) were almost always lower compared to chordal pitch class patterns measured with the same methods. In a few cases, however, the normalized entropy of interval patterns, the relative frequency of interval patterns (calculation method 1), and the relative frequency of interval patterns (calculation method 2) were higher compared to chordal pitch class patterns analyzed with the same methods, in contrary to what was expected.

In Paul Chambers's bass line reductions, the absolute average difference between the normalized entropy of chordal pitch class patterns and the normalized entropy of interval patterns was 0.018 for 4-note melodic patterns (range: 0 to 0.053,  $SD = 0.014$ ), 0.049 for 3-note melodic patterns (range: 0.005 to 0.112,  $SD = 0.025$ ), and 0.105 for 2-note melodic patterns (range: 0.022 to 0.206,  $SD = 0.039$ ). The absolute average difference between the relative frequency of chordal pitch class patterns and the relative frequency of interval patterns (calculation method 1) was 3.07 percentage points for 4-note melodic patterns (range: 0 to 8.89,  $SD = 2.20$ ), 4.76 percentage points for 3-note melodic patterns (range: 0.44 to 11.7,  $SD = 3.45$ ), and 19.4 percentage points for 2-note melodic patterns (range: 0 to 35.9,  $SD = 8.26$ ). The absolute average difference between the relative frequency of

chordal pitch class patterns and the relative frequency of interval patterns (calculation method 2) was 4.00 percentage points for 4-note melodic patterns (range: 0 to 9.90,  $SD = 2.87$ ), 5.82 percentage points for 3-note melodic patterns (range: 0 to 16.8,  $SD = 4.06$ ), and 9.77 percentage points for 2-note melodic patterns (range: 0.30 to 26.3,  $SD = 5.76$ ).

In Ron Carter's bass line reductions, the absolute average difference between the normalized entropy of chordal pitch class patterns and the normalized entropy of interval patterns was 0.022 for 4-note melodic patterns (range: 0.004 to 0.046,  $SD = 0.015$ ), 0.063 for 3-note melodic patterns (range: 0.005 to 0.129,  $SD = 0.036$ ), and 0.150 for 2-note melodic patterns (range: 0.032 to 0.272,  $SD = 0.062$ ). The absolute average difference between the relative frequency of chordal pitch class patterns and the relative frequency of interval patterns (calculation method 1) was 3.44 percentage points for 4-note melodic patterns (range: 0.54 to 8.38,  $SD = 2.61$ ), 9.93 percentage points for 3-note melodic patterns (range: 1.58 to 18.2,  $SD = 4.89$ ), and 27.5 percentage points for 2-note melodic patterns (range: 8.99 to 44.3,  $SD = 10.0$ ). The absolute average difference between the relative frequency of chordal pitch class patterns and the relative frequency of interval patterns (calculation method 2) was 6.70 percentage points for 4-note melodic patterns (range: 0.38 to 13.5,  $SD = 4.23$ ), 14.8 percentage points for 3-note melodic patterns (range: 1.14 to 33.7,  $SD = 8.14$ ), and 19.0 percentage points for 2-note melodic patterns (range: 3.03 to 38.4,  $SD = 9.55$ ).

According to these results, the decision to use interval patterns (instead of chordal pitch class patterns) as a measure of musical creativity had little effect on the results with 4-note melodic patterns. However, the difference between the measurements based on interval patterns and chordal pitch class patterns increased with shorter melodic patterns. This finding suggests that further studies could benefit from using interval patterns instead of chordal pitch class patterns to avoid problems with the identification of the chord progression when the length of the melodic patterns is at least 4 notes. See also Figures 24 and 25 for scatter plots, which indicate that the normalized entropies of chordal pitch class patterns were very similar to the normalized entropies of interval patterns when pattern length was 4 notes but not when pattern length was 3 notes or 2 notes. For the average difference between the normalized entropy of chordal pitch class patterns and the normalized entropy of interval patterns in each bass line reduction, see Table 20 in Appendix 2.



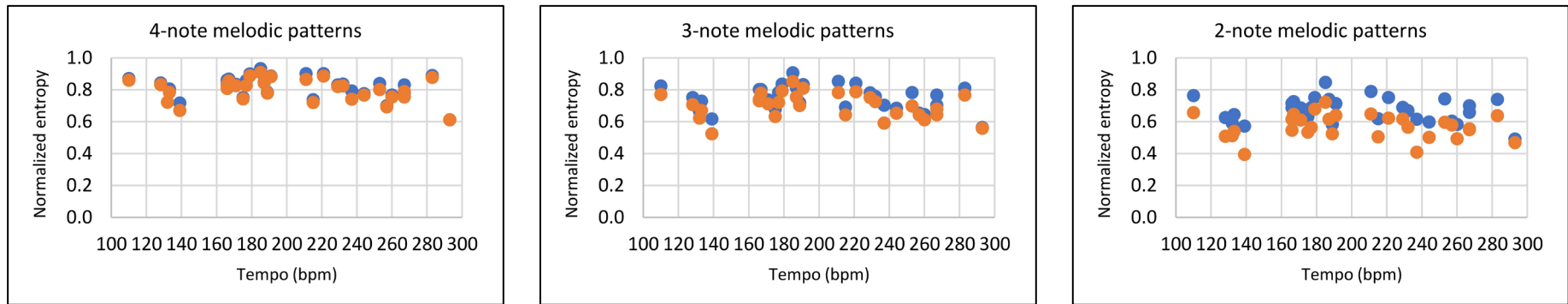


FIGURE 24 Effects of tempo on normalized entropy of chordal pitch class patterns and interval patterns with different pattern lengths (blue = chordal pitch class patterns; orange = interval patterns) (Paul Chambers's bass line reductions)

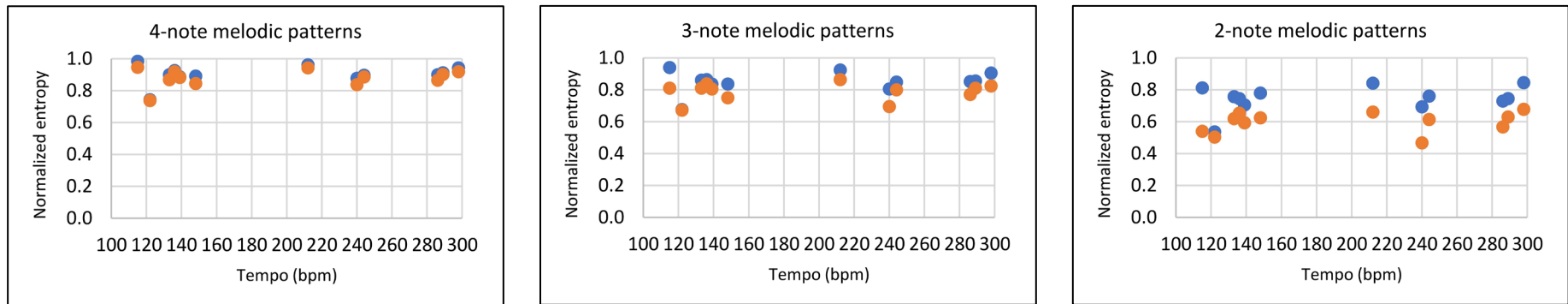


FIGURE 25 Effects of tempo on normalized entropy of chordal pitch class patterns and interval patterns with different pattern lengths (blue = chordal pitch class patterns; orange = interval patterns) (Ron Carter's bass line reductions)

### 6.1.2 Threshold level

As discussed in Chapter 5.3.1: Methodological problems related to segmentation, the more repeated and the longer the melodic pattern, the more plausible it is that the melodic pattern was retrieved as a single unit from memory during the performance. Previous studies have used a very low threshold level (at least two occurrences in a particular performance) to measure repetition in jazz improvisation (e.g., Norgaard, 2014). This threshold level is too low to exclude the possibility that the repeated melodic pattern was repeated by chance. As a rare exception, Norgaard et al. (2016) used two threshold levels to calculate the frequency of repeated melodic patterns: (1) at least two occurrences of the same melodic pattern and (2) at least four occurrences of the same melodic pattern. In the present study, I calculated the average number of different repeated chordal pitch class patterns that occurred at least twice (threshold level 1), at least three times (threshold level 2), at least four times (threshold level 3), and at least five times (threshold level 4) in a particular bass line reduction. In these analyses, pattern length was either 2 notes, 3 notes, or 4 notes. The abbreviation 'tl' refers to threshold level.

In Paul Chambers's bass line reductions, the average number of different repeated 4-note chordal pitch class patterns was 37.4 (tl 1), 20.6 (tl 2), 13.7 (tl 3), and 8.73 (tl 4). With 3-note chordal pitch class patterns, the average number was 36.6 (tl 1), 22.6 (tl 2), 15.5 (tl 3), and 11.2 (tl 4). Finally, the average number of different repeated 2-note chordal pitch class patterns was 33.2 (tl 1), 22.4 (tl 2), 16.8 (tl 3), and 12.9 (tl 4). In Ron Carter's bass line reductions, the average number of different repeated 4-note chordal pitch class patterns was 24.6 (tl 1), 11.1 (tl 2), 6.75 (tl 3), and 5.00 (tl 4), the average number of different repeated 3-note chordal pitch class patterns was 32.9 (tl 1), 15.9 (tl 2), 9.75 (tl 3), and 6.50 (tl 4), and the average number of different repeated 2-note chordal pitch class patterns was 35.7 (tl 1), 19.7 (tl 2), 13.6 (tl 3), and 10.6 (tl 4).

What is interesting in these results is how much tightening the threshold level decreased the average number of different repeated chordal pitch class patterns. For example, the average number of different repeated 4-note chordal pitch class patterns was 2.73 times larger in Paul Chambers's bass line reductions and 3.64 times larger in Ron Carter's bass line reductions when threshold level 1 was used instead of threshold level 3. As a result, using a low threshold level may lead to exaggerated estimations on the size of the vocabulary (i.e., storage of learned melodic patterns) of jazz musicians. For the absolute and relative frequency of recurring chordal pitch class patterns in each bass line reduction, see Table 21 in Appendix 2.

### 6.1.3 Removal of head sections

As discussed in Chapter 5.2.1: Selection of research material, some head sections were ignored due to a frequent use of half notes (e.g., *If I Were a Bell*). Head sections were also ignored if they were based on pre-composed material (e.g., *So What*). Note that ignoring head sections may lead to a significant loss of data. As

a result, head sections were removed only if necessary, based on the two criteria mentioned above.

The effect of removing head sections on the variability of melodic patterns was investigated by calculating the normalized entropy of chordal pitch class patterns and the relative frequency of non-recurring chordal pitch class patterns (using both calculation method 1 and 2) both when head sections were ignored and when they were considered. The average normalized entropy of 4-note chordal pitch class patterns was 0.013 units larger in Paul Chambers's bass line reductions when head sections were disregarded compared to when they were considered (0.033 units larger in Ron Carter's bass line reductions). The average relative frequency of non-recurring 4-note chordal pitch class patterns (calculation method 1) was 1.93 percentage points larger in Paul Chambers's bass line reductions when head sections were disregarded compared to when they were considered (3.68 percentage points larger in Ron Carter's bass line reductions). The average relative frequency of non-recurring 4-note chordal pitch class patterns (calculation method 2) was 3.75 percentage points larger in Paul Chambers's bass line reductions when head sections were disregarded compared to when they were considered (9.85 percentage points larger in Ron Carter's bass line reductions).

As expected, the results indicated that the normalized entropy of 4-note chordal pitch class patterns and the relative frequency of non-recurring 4-note chordal pitch class patterns (regardless of calculation method) were usually larger, when head sections were disregarded compared to when they were considered. See Table 22 in Appendix 2 for the normalized entropy of chordal pitch class patterns and the relative frequency of non-recurring chordal pitch patterns, when head sections were considered and when they were ignored.

#### **6.1.4 Identification of segment boundaries**

As discussed in Chapter 5.3.1: Methodological problems related to segmentation, identification of segment boundaries is a necessary stage to ensure that the analyzed melodic patterns correspond to plausible grouping structures of the music. However, segmentation of melodic patterns has been neglected in several previous studies (Weisberg et al., 2004; Norgaard, 2014; Norgaard et al., 2016; Norgaard & Römer, 2022). In two of these studies (Norgaard, 2014; Norgaard & Römer, 2022), the relative frequency of recurring melodic patterns was calculated as the proportion of notes that started a recurring melodic pattern with at least two occurrences in relation to the total number of notes<sup>110</sup>. To find out whether and how the decision to disregard the identification of segment boundaries affects the results, I investigated whether the relative frequency of notes that started a recurring 4-note interval pattern at any metrical location (where the identification of segment boundaries is disregarded) and the relative frequency of recurring 4-note interval patterns that started at the first beat of the bar (where

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<sup>110</sup> In Norgaard et al. (2016), the relative frequency of recurring melodic patterns was calculated as the average number of repeated melodic patterns per 100 notes.

the identification of segment boundaries is considered) gives similar results. Following Norgaard (2014), overlapping patterns that started at the same note were removed.

According to the results, the absolute number of notes that started a recurring 4-note interval pattern was considerably higher when segmentation of melodic patterns was neglected. This indicates that the decision to disregard the identification of segment boundaries in melodic patterns may overestimate the number of recurring melodic patterns in jazz improvisations. In addition, the relative frequency of recurring interval patterns was higher (but not always) when the identification of segment boundaries was neglected. The average difference between the relative frequency of notes that started a recurring 4-note interval pattern at any metrical location and the relative frequency of recurring 4-note interval patterns that started at the first beat of the bar was 8.95 percentage points in Paul Chambers's bass line reductions and 11.1 percentage points in Ron Carter's bass line reductions. The absolute difference between the relative frequency of notes that started a recurring 4-note interval pattern at any metrical location and the relative frequency of recurring 4-note interval patterns that started at the first beat of the bar was five percentage points or less in eight bass line reductions (six Paul Chambers's bass line reductions and two Ron Carter's bass line reductions). Note that the number of overlapping interval patterns that started at the same note was zero in all bass line reductions. However, this does not mean that the overall number of overlapping interval patterns is also zero. For instance, shorter repeated interval patterns may still occur as a part of longer interval patterns.

In order to determine the similarity of the results produced by these two measurement methods, a Kendall's tau correlation analysis with Bonferroni correction was performed to investigate the relationship between tempo and the relative frequency of notes that started a recurring 4-note interval pattern at any metrical location (measurement method A) and the relationship between tempo and the relative frequency of recurring 4-note interval patterns that started at the first beat of the bar (measurement method B). After Bonferroni correction, the alpha level for statistical significance was adjusted to .013 (.05/4). Note that correlation analysis was not used to compare the results obtained by these two measurement methods because there are several problems in the use of correlation to assess the agreement between two methods of measurement (Bland & Altman, 1986; Schober et al., 2018). For example, the results from one measurement may disagree with the other by being consistently higher or lower even in case of substantial correlation (Schober et al., 2018).

In Paul Chambers's bass line reductions, the results indicated a statistically non-significant and weak positive correlation between tempo and the relative frequency of notes that started a recurring 4-note interval pattern at any metrical location (measurement method A) ( $\tau\text{-}b = .27$ , 98.7% CI [-.08, .59],  $p = .04$ ), and between tempo and the relative frequency of recurring 4-note interval patterns that started at the first beat of the bar (measurement method B) ( $\tau\text{-}b = .22$ , 98.7% CI [-.15, .54],  $p = .09$ ). In Ron Carter's bass line reductions, the results indicated a

statistically non-significant and weak positive correlation between tempo and the relative frequency of notes that started a recurring 4-note interval pattern at any metrical location (measurement method A) ( $\tau\text{-}b = .21$ , 98.7% CI [-.40, .85],  $p = .38$ ), and between tempo and the relative frequency of recurring 4-note interval patterns that started at the first beat of the bar (measurement method B) ( $\tau\text{-}b = .12$ , 98.7% CI [-.57, .75],  $p = .64$ ).<sup>111</sup>

In summary, the results indicated a statistically non-significant and weak correlation between tempo and the relative frequency of recurring interval patterns regardless of the measurement method. The results also indicated that the use of measurement method B may lead to weaker correlations compared to measurement method A. For raw data used in these tests, see Table 23 in Appendix 2.

## 6.2 Temporal constraints and musical creativity

### 6.2.1 Tempo and variability of melodic patterns

Variability of melodic patterns was assessed by using the following methods of measurement: normalized entropy of chordal pitch class patterns, normalized entropy of interval patterns, relative frequency of non-recurring chordal pitch class patterns (with two different calculation methods), and relative frequency of non-recurring interval patterns (with two different calculation methods). These methods of measurement were used with melodic patterns of various length (2 notes, 3 notes, and 4 notes). In addition, relative frequency of notes that started a recurring 4-note interval pattern at any metrical location was calculated. In total, 19 measurements were used to determine the relationship between tempo and the variability of melodic patterns. The same methods of measurement were also used to determine the relationship between harmonic rhythm and the variability of melodic patterns.

See Table 3 for descriptive statistics of the data. Due to a large number of measurements, it was not possible to show visualizations of all distributions. Instead, scatter plots for the relationship between tempo and the normalized entropy of 4-note chordal pitch class patterns, and the relationship between tempo and the relative frequency of notes that started a recurring 4-note interval pattern at any metrical location are presented in Figures 26 and 27.<sup>112</sup> A visual examination of these scatter plots suggest that the variability of melodic patterns was higher, on average, in Ron Carter's bass line reductions compared to Paul Chambers's bass line reductions. Although not evident from these two scatter plots, it is also important to note that the variability of melodic patterns always increased with pattern length (which can be explained by an increasing number of possible

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111 As elsewhere in this study, all confidence intervals were bootstrapped.

112 Note that all figures in this study are based on descriptive statistics. As a result, effects of the length of analyzed bass line reductions were not considered in these figures.

combinations). Note that the relative frequency of notes that started a recurring interval pattern at any metrical location is a measure of redundancy. As a result, increased redundancy of bass line reductions indicates decreased variability of melodic patterns, and vice versa.

TABLE 3 Descriptive statistics

Method of measurement	<i>M</i> ( <i>SD</i> ) (Chambers)	Range (Chambers)	<i>M</i> ( <i>SD</i> ) (Carter)	Range (Carter)
Tempo (bpm)	202.1 (50.0)	110-293	196.8 (71.9)	115-298
Normalized entropy of 4-note chordal pitch class patterns	0.818 (0.072)	0.612-0.934	0.902 (0.060)	0.743-0.985
Normalized entropy of 4-note interval patterns	0.800 (0.071)	0.613-0.910	0.880 (0.057)	0.739-0.947
Normalized entropy of 3-note chordal pitch class patterns	0.752 (0.079)	0.564-0.907	0.851 (0.067)	0.677-0.940
Normalized entropy of 3-note interval patterns	0.702 (0.078)	0.525-0.853	0.788 (0.057)	0.672-0.864
Normalized entropy of 2-note chordal pitch class patterns	0.674 (0.078)	0.492-0.847	0.746 (0.082)	0.536-0.845
Normalized entropy of 2-note interval patterns	0.569 (0.076)	0.395-0.722	0.596 (0.065)	0.468-0.678
Relative frequency of non-recurring 4-note chordal pitch class patterns (I)	66.6% (10.0)	47.1%-85.9%	84.4% (6.52)	75.4%-96.0%
Relative frequency of non-recurring 4-note chordal pitch class patterns (II)	36.8% (14.4)	9.61%-70.5%	63.4% (14.5)	38.3%-91.4%

Method of measurement	<i>M (SD)</i> (Chambers)	Range (Chambers)	<i>M (SD)</i> (Carter)	Range (Carter)
Relative frequency of non-recurring 3-note chordal pitch class patterns (I)	57.1% (10.5)	37.5%-78.9%	73.8% (10.0)	53.3%-88.8%
Relative frequency of non-recurring 3-note chordal pitch class patterns (II)	25.1% (12.0)	6.01%-59.0%	46.6% (15.2)	18.6%-72.1%
Relative frequency of non-recurring 2-note chordal pitch class patterns (I)	44.9% (10.6)	16.7%-67.2%	57.6% (9.35)	43.1%-75.7%
Relative frequency of non-recurring 2-note chordal pitch class patterns (II)	14.6% (8.29)	1.50%-41.1%	25.2% (10.9)	8.33%-46.0%
Relative frequency of non-recurring 4-note interval patterns (I)	63.9% (9.49)	45.3%-81.9%	81.1% (6.81)	68.8%-91.0%
Relative frequency of non-recurring 4-note interval patterns (II)	32.9% (12.9)	9.61%-62.1%	56.7% (12.9)	38.2%-77.9%
Relative frequency of non-recurring 3-note interval patterns (I)	52.9% (9.64)	35.3%-70.8%	63.9% (6.97)	51.7%-77.6%
Relative frequency of non-recurring 3-note interval patterns (II)	19.3% (9.38)	6.01%-42.1%	31.9% (9.15)	17.4%-49.6%

Method of measurement	<i>M (SD)</i> (Chambers)	Range (Chambers)	<i>M (SD)</i> (Carter)	Range (Carter)
Relative frequency of non-recurring 2-note interval patterns (I)	25.5% (8.03)	9.38%-42.1%	30.1% (8.99)	13.6%-44.9%
Relative frequency of non-recurring 2-note interval patterns (II)	4.79% (3.28)	0.81%-14.7%	6.28% (2.90)	1.04%-10.2%
Relative frequency of notes that started a recurring 4-note interval pattern at any metrical location	76.0% (8.79)	58.3%-90.5%	54.4% (12.5)	29.1%-72.6%

*Note.*  $n = 30$  (Paul Chambers's bass line reductions).  $n = 12$  (Ron Carter's bass line reductions). I = calculation method 1; II = calculation method 2. For an explanation on the difference between these two calculation methods, see Chapter 5.3.3.2: Relative frequency of non-recurring melodic patterns.



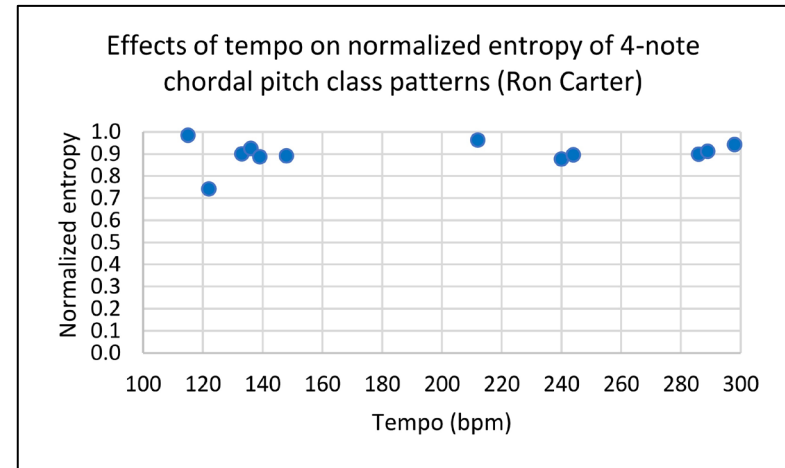
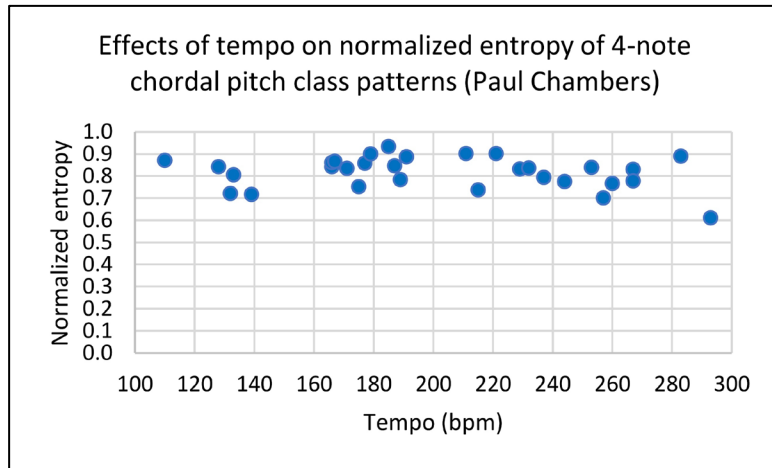


FIGURE 26 Effects of tempo on normalized entropy of 4-note chordal pitch class patterns

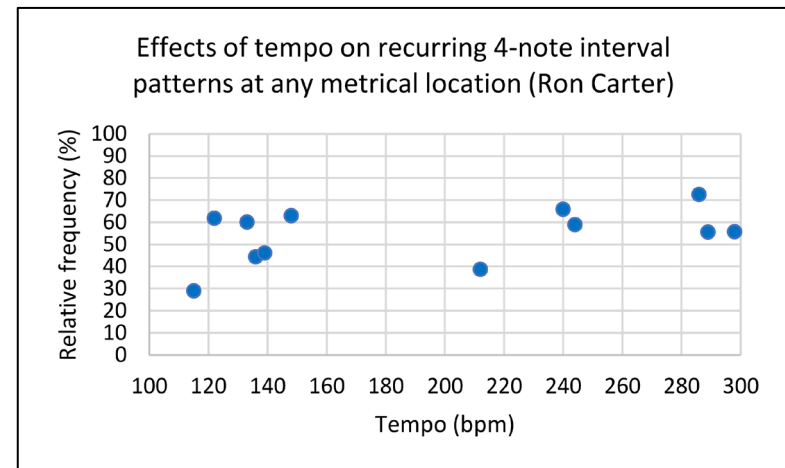
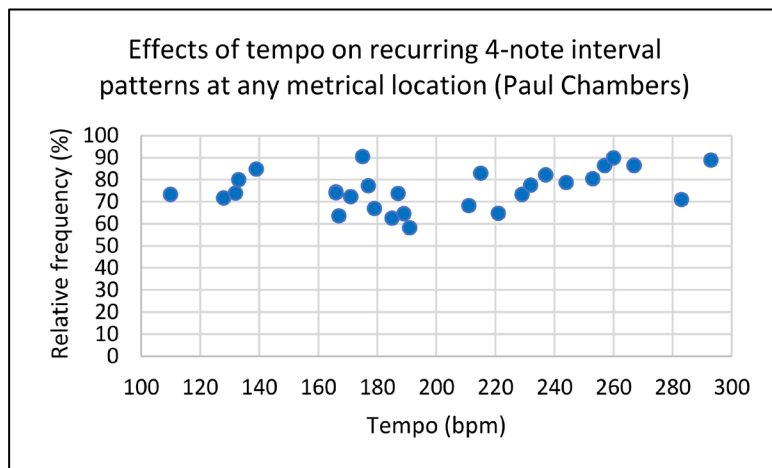


FIGURE 27 Effects of tempo on relative frequency of notes that started a recurring 4-note interval pattern at any metrical location

A Kendall's tau correlation analysis with Bonferroni correction was performed to determine the relationship between tempo and the variability of melodic patterns. After Bonferroni correction, the alpha level for statistical significance was adjusted to .003 (.05/19). The results are presented in Table 4. Note that all  $p$ -values in Table 4 (and elsewhere in this study) are original (uncorrected).

TABLE 4 Correlations between tempo and variability of melodic patterns

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.7% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.7% CI (bootstrapped) (Carter)
Normalized entropy of 4-note chordal pitch class patterns	$\tau_b = -.14$ $p = .27$ <b><math>\tau_b = -.11</math></b> <b><math>p = .40</math></b>	[-.48, .27]  <b>[-.49, .34]</b>	$\tau_b = .12$ $p = .64$ <b><math>\tau_b = .25</math></b> <b><math>p = .29</math></b>	[-.65, .90]  <b>[-.47, .86]</b>
Normalized entropy of 4-note interval patterns	$\tau_b = -.16$ $p = .21$ <b><math>\tau_b = -.13</math></b> <b><math>p = .32</math></b>	[-.53, .30]  <b>[-.51, .25]</b>	$\tau_b = .06$ $p = .84$ <b><math>\tau_b = .18</math></b> <b><math>p = .44</math></b>	[-.65, .85]  <b>[-.53, .86]</b>
Normalized entropy of 3-note chordal pitch class patterns	$\tau_b = -.14$ $p = .28$ <b><math>\tau_b = -.11</math></b> <b><math>p = .42</math></b>	[-.48, .29]  <b>[-.44, .28]</b>	$\tau_b = .09$ $p = .74$ <b><math>\tau_b = .23</math></b> <b><math>p = .33</math></b>	[-.67, .95]  <b>[-.37, .90]</b>
Normalized entropy of 3-note interval patterns	$\tau_b = -.15$ $p = .25$ <b><math>\tau_b = -.11</math></b> <b><math>p = .39</math></b>	[-.53, .21]  <b>[-.51, .28]</b>	$\tau_b = .05$ $p = .84$ <b><math>\tau_b = .15</math></b> <b><math>p = .53</math></b>	[-.67, .74]  <b>[-.56, .72]</b>
Normalized entropy of 2-note chordal pitch class patterns	$\tau_b = -.08$ $p = .53$ <b><math>\tau_b = -.04</math></b> <b><math>p = .74</math></b>	[-.48, .34]  <b>[-.42, .38]</b>	$\tau_b = .15$ $p = .55$ <b><math>\tau_b = .33</math></b> <b><math>p = .16</math></b>	[-.66, .80]  <b>[-.44, .81]</b>
Normalized entropy of 2-note interval patterns	$\tau_b = -.09$ $p = .51$ <b><math>\tau_b = -.04</math></b> <b><math>p = .78</math></b>	[-.47, .35]  <b>[-.37, .35]</b>	$\tau_b = .30$ $p = .20$ <b><math>\tau_b = .42</math></b> <b><math>p = .07</math></b>	[-.47, .86]  <b>[-.24, .93]</b>
Relative frequency of non-recurring 4-note chordal pitch class patterns (I)	$\tau_b = -.22$ $p = .08$ <b><math>\tau_b = -.20</math></b> <b><math>p = .14</math></b>	[-.62, .19]  <b>[-.61, .24]</b>	$\tau_b = 0$ $p = 1$ <b><math>\tau_b = .11</math></b> <b><math>p = .63</math></b>	[-.74, .85]  <b>[-.72, .84]</b>

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.7% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.7% CI (bootstrapped) (Carter)
Relative frequency of non-recurring 4-note chordal pitch class patterns (II)	$\tau_b = -.21$ $p = .11$ <b><math>\tau_b = -.17</math></b> <b><math>p = .19</math></b>	[-.60, .21]  <b>[-.57, .17]</b>	$\tau_b = 0$ $p = 1$ <b><math>\tau_b = .11</math></b> <b><math>p = .63</math></b>	[-.79, .77]  <b>[-.76, .81]</b>
Relative frequency of non-recurring 3-note chordal pitch class patterns (I)	$\tau_b = -.25$ $p = .05$ <b><math>\tau_b = -.23</math></b> <b><math>p = .08</math></b>	[-.63, .15]  <b>[-.62, .17]</b>	$\tau_b = -.03$ $p = .95$ <b><math>\tau_b = .07</math></b> <b><math>p = .77</math></b>	[-.75, .77]  <b>[-.80, .60]</b>
Relative frequency of non-recurring 3-note chordal pitch class patterns (II)	$\tau_b = -.24$ $p = .06$ <b><math>\tau_b = -.21</math></b> <b><math>p = .11</math></b>	[-.58, .19]  <b>[-.62, .13]</b>	$\tau_b = -.09$ $p = .74$ <b><math>\tau_b = .05</math></b> <b><math>p = .84</math></b>	[-.85, .71]  <b>[-.73, .72]</b>
Relative frequency of non-recurring 2-note chordal pitch class patterns (I)	$\tau_b = -.21$ $p = .10$ <b><math>\tau_b = -.18</math></b> <b><math>p = .17</math></b>	[-.59, .24]  <b>[-.52, .28]</b>	$\tau_b = -.02$ $p = .95$ <b><math>\tau_b = .16</math></b> <b><math>p = .50</math></b>	[-.76, .73]  <b>[-.55, .61]</b>
Relative frequency of non-recurring 2-note chordal pitch class patterns (II)	$\tau_b = -.18$ $p = .17$ <b><math>\tau_b = -.14</math></b> <b><math>p = .30</math></b>	[-.58, .20]  <b>[-.44, .23]</b>	$\tau_b = .03$ $p = .95$ <b><math>\tau_b = .25</math></b> <b><math>p = .28</math></b>	[-.64, .70]  <b>[-.37, .71]</b>
Relative frequency of non-recurring 4-note interval patterns (I)	$\tau_b = -.27$ $p = .04$ <b><math>\tau_b = -.24</math></b> <b><math>p = .06</math></b>	[-.61, .10]  <b>[-.62, .11]</b>	$\tau_b = -.18$ $p = .46$ <b><math>\tau_b = -.05</math></b> <b><math>p = .84</math></b>	[-.86, .63]  <b>[-.76, .73]</b>
Relative frequency of non-recurring 4-note interval patterns (II)	$\tau_b = -.22$ $p = .09$ <b><math>\tau_b = -.19</math></b> <b><math>p = .16</math></b>	[-.61, .24]  <b>[-.56, .23]</b>	$\tau_b = -.12$ $p = .64$ <b><math>\tau_b = .02</math></b> <b><math>p = .92</math></b>	[-.88, .64]  <b>[-.75, .66]</b>
Relative frequency of non-recurring 3-note interval patterns (I)	$\tau_b = -.30$ $p = .02$ <b><math>\tau_b = -.28</math></b> <b><math>p = .04</math></b>	[-.65, .15]  <b>[-.61, .15]</b>	$\tau_b = -.03$ $p = .95$ <b><math>\tau_b = .07</math></b> <b><math>p = .77</math></b>	[-.83, .91]  <b>[-.78, .71]</b>

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.7% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.7% CI (bootstrapped) (Carter)
Relative frequency of non-recurring 3-note interval patterns (II)	$\tau_b = -.28$ $p = .03$ <b><math>\tau_b = -.26</math></b> <b><math>p = .05</math></b>	$[-.68, .13]$  <b><math>[-.66, .20]</math></b>	$\tau_b = -.03$ $p = .95$ <b><math>\tau_b = .09</math></b> <b><math>p = .70</math></b>	$[-.83, .72]$  <b><math>[-.63, .80]</math></b>
Relative frequency of non-recurring 2-note interval patterns (I)	$\tau_b = -.35$ $p = .007$ <b><math>\tau_b = -.34</math></b> <b><math>p = .01</math></b>	$[-.59, .02]$  <b><math>[-.62, .03]</math></b>	$\tau_b = -.24$ $p = .31$ <b><math>\tau_b = -.18</math></b> <b><math>p = .45</math></b>	$[-.90, .56]$  <b><math>[-.85, .46]</math></b>
Relative frequency of non-recurring 2-note interval patterns (II)	$\tau_b = -.23$ $p = .07$ <b><math>\tau_b = -.20</math></b> <b><math>p = .12</math></b>	$[-.53, .18]$  <b><math>[-.47, .15]</math></b>	$\tau_b = -.15$ $p = .55$ <b><math>\tau_b &lt; .0001</math></b> <b><math>p = 1</math></b>	$[-.85, .65]$  <b><math>[-.81, .65]</math></b>
Relative frequency of notes that started a recurring 4-note interval pattern at any metrical location <sup>a</sup>	$\tau_b = -.27$ $p = .04$ <b><math>\tau_b = -.24</math></b> <b><math>p = .07</math></b>	$[-.62, .12]$  <b><math>[-.64, .17]</math></b>	$\tau_b = -.21$ $p = .38$ <b><math>\tau_b = -.11</math></b> <b><math>p = .63</math></b>	$[-.86, .64]$  <b><math>[-.73, .62]</math></b>

*Note.* Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval; I = calculation method 1; II = calculation method 2. For an explanation on the difference between these two calculation methods, see Chapter 5.3.3.2: Relative frequency of non-recurring melodic patterns. <sup>a</sup> The direction of the effect is corrected.

When controlling for the length of analyzed bass line reductions, all results were statistically non-significant after Bonferroni correction. In Paul Chambers's bass line reductions, 17 out of the 19 measurements indicated a statistically non-significant and negative correlation between tempo and the variability of melodic patterns and 2 out of the 19 measurements indicated a statistically non-significant and negligible correlation between the variables. The mean absolute tau-b was .18 (range: .04 to .34,  $SD = 0.08$ ). Based on this value and the high level of consistency of effect directions, the results indicated a statistically non-significant and weak negative correlation between tempo and the variability of melodic patterns. In Ron Carter's bass line reductions, 10 out of the 19 measurements indicated a statistically non-significant and positive correlation between the variables, 7 out of the 19 measurements indicated a statistically non-significant and negligible correlation between the variables, whereas two measurements indicated a statistically non-significant and negative correlation between the variables. The

mean absolute tau-b was .15 (range: 0 to .42,  $SD = 0.11$ ), which indicates a weak correlation between the variables. However, since only 10 out of the 19 measurements indicated the same effect direction, the results did not allow to make conclusions on the direction of the effect in Ron Carter's bass line reductions. For raw data used in these tests, see Tables 24 and 25 in Appendix 3.

I also investigated whether the data supports two predictions raised by Frieler et al. (2018). Based on 332 bass line transcriptions from 78 different bassists, Frieler et al. (2018) found that the use of consonant chordal pitch classes decreased with tempo and that note repetitions were used more often at fast tempos. Since the relative frequency of note repetitions differed between original bass lines and bass line reductions (as noted in Chapter 5.3.2: Basic conversion and segmentation of research material), I analyzed the relative frequency of note repetitions both with bass line reductions and the original bass lines.

The average relative frequency of consonant chordal pitch classes (defined here as the proportion of root notes, perfect and diminished fifths, and major and minor thirds combined) was 62.6% (range: 49.8% to 79.4%,  $SD = 7.07$ ) in Paul Chambers's bass line reductions and 63.7% (range: 49.0% to 87.3%,  $SD = 10.1$ ) in Ron Carter's bass line reductions. A Kendall's tau correlation analysis with Bonferroni correction was performed to determine the relationship between tempo and the relative frequency of consonant chordal pitch classes. After Bonferroni correction, the alpha level for statistical significance was adjusted to .025 (.05/2). When controlling for the length of analyzed bass line reductions, the results indicated a statistically non-significant and negligible correlation between tempo and the relative frequency of consonant chordal pitch classes in Paul Chambers's bass line reductions (tau-b = .07, 97.5% CI [-.25, .38],  $p = .59$ ) and a statistically non-significant and moderate negative correlation between the two variables in Ron Carter's bass line reductions (tau-b = -.30, 97.5% CI [-.86, .31],  $p = .20$ ).

These results did not support the hypothesis that jazz bassists use consonant chordal pitch classes more frequently at faster tempos compared to slower tempos (Frieler et al., 2018). When controlling for the length of analyzed bass line reductions, Kendall's tau correlation analysis indicated a statistically non-significant and negligible correlation between tempo and the relative frequency of consonant chordal pitch classes in Paul Chambers's bass line reductions and a statistically non-significant and moderate negative correlation between the two variables in Ron Carter's bass line reductions.

The average relative frequency of note repetitions was 1.49% in Paul Chambers's bass line reductions ( $n = 30$ , range: 0% to 3.78%,  $SD = 1.17$ ) and 7.99% in Ron Carter's bass line reductions ( $n = 12$ , range: 1.26% to 35.2%,  $SD = 9.72$ ). When the relative frequency of note repetitions was measured in the original bass lines instead of bass line reductions, the average relative frequency of note repetitions was 2.49% in Paul Chambers's bass lines ( $n = 30$ , range: 0% to 7.32%,  $SD = 1.94$ ) and 10.2% in Ron Carter's bass lines ( $n = 12$ , range: 1.34% to 23.4%,  $SD = 7.95$ ). A Kendall's tau correlation analysis with Bonferroni correction was performed to determine the relationship between tempo and note repetitions in bass line reductions and original bass lines. After Bonferroni correction, the alpha level for

statistical significance was adjusted to .013 (.05/4). When controlling for the length of analyzed bass lines/bass line reductions, the results indicated a statistically non-significant and negligible correlation between tempo and the relative frequency of note repetitions in Paul Chambers's bass line reductions ( $\tau\text{-}b = .08$ , 98.7% CI [-.26, .42],  $p = .52$ ), a statistically significant and moderate negative correlation between these two variables in Paul Chambers's original bass lines ( $\tau\text{-}b = -.37$ , 98.7% CI [-.65, -.004],  $p = .005$ ), a statistically non-significant and moderate negative correlation between the variables in Ron Carter's bass line reductions ( $\tau\text{-}b = -.30$ , 98.7% CI [-.83, .43],  $p = .19$ ), and a statistically non-significant and moderate negative correlation between the variables in Ron Carter's original bass lines ( $\tau\text{-}b = -.57$ , 98.7% CI [-.92, .15],  $p = .014$ ).

However, these results should be taken with caution. Since the reduction process removed simple note repetitions (which mainly consisted of dotted eighth notes followed by a sixteenth note with the same pitch class), a negative correlation between tempo and the relative frequency of note repetitions in original bass lines might only indicate that the bassist used less variable rhythms at fast tempos (and also fewer patterns where a dotted eighth note was followed by a sixteenth note with the same pitch class). In summary, the present results did not support the hypothesis that jazz bassists use note repetitions more frequently at fast tempos (Frieler et al., 2018). When controlling for the length of analyzed bass lines or bass line reductions, all correlations were negative except in Paul Chambers's bass line reductions (where it was not possible to make conclusions on the direction of the effect). These differences between the present results and those from Frieler et al. (2018) are probably caused by individual differences between even the most renowned jazz bassists. Some renowned jazz bassists may use consonant note choices and note repetitions more often at fast tempos, but this does not seem to apply to Paul Chambers and Ron Carter.

### 6.2.2 Harmonic rhythm and variability of melodic patterns

Descriptive statistics of the data regarding target variables were already shown in Table 3 and will not be repeated here. The mean average distance between chord changes was 1.47 (range: 0.61 to 10.67,  $SD = 1.86$ ) in Paul Chambers's bass line reductions ( $n = 30$ ). In Ron Carter's bass line reductions ( $n = 12$ ), the mean average distance between chord changes was 2.09 (range: 0.50 to 12.0,  $SD = 3.17$ ). As indicated by scatter plots below (see Figures 28 and 29), the range of harmonic rhythm values was very restricted as most of the values ranged from about 0.5 to about 2.0 notes between chord changes. Many of the harmonic rhythm values were also tied. Note that the value of 12.0 (in Ron Carter's bass line reductions) represents the situation where the musical work is based on one chord only (i.e., there was no chord changes). Since the average distance between chord changes was used to measure harmonic rhythm, it was necessary to use an artificial value to represent this situation.

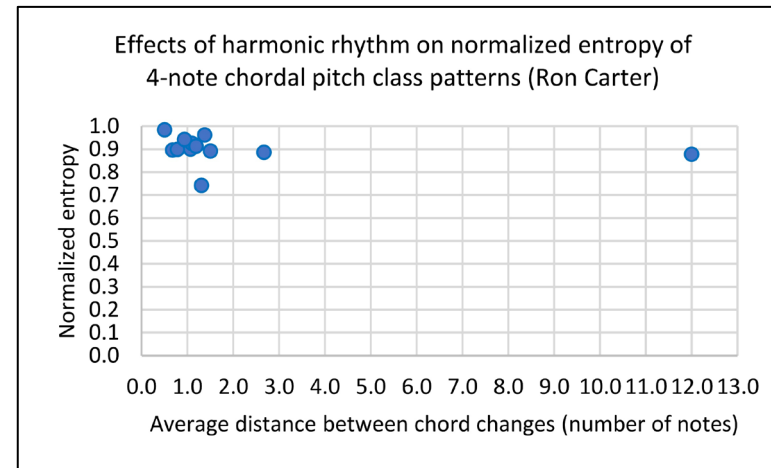
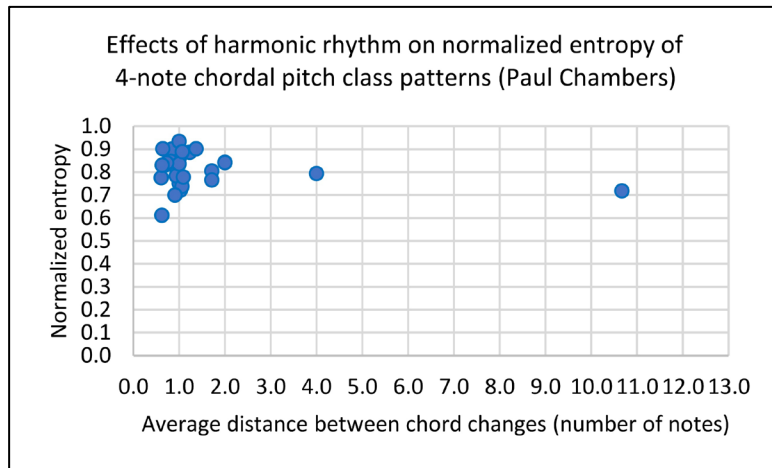


FIGURE 28 Effects of harmonic rhythm on normalized entropy of 4-note chordal pitch class patterns

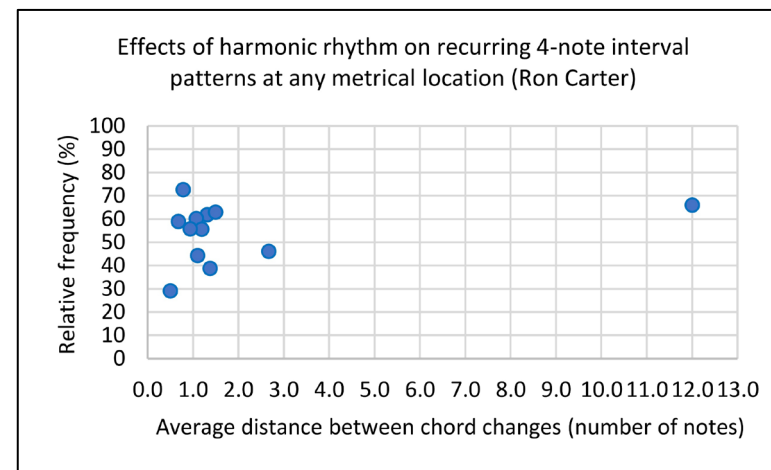
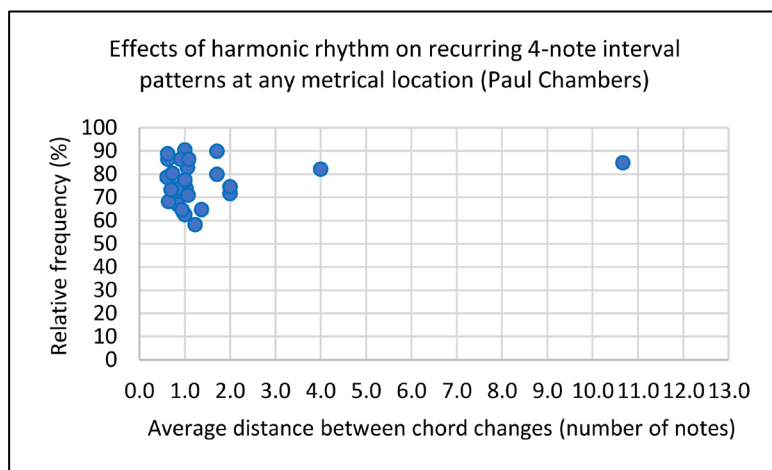


FIGURE 29 Effects of harmonic rhythm on relative frequency of notes that started a recurring 4-note interval pattern at any metrical location

A Kendall's tau correlation analysis with Bonferroni correction was performed to determine the relationship between harmonic rhythm and the variability of melodic patterns. After Bonferroni correction, the alpha level for statistical significance was adjusted to .003 (.05/19). The results are presented in Table 5.

TABLE 5 Correlations between harmonic rhythm and variability of melodic patterns

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.7% CI (bootstrap-ped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.7% CI (bootstrap-ped) (Carter)
Normalized entropy of 4-note chordal pitch class patterns	$\tau_b = .002$ $p = .99$ <b><math>\tau_b = -.01</math></b> <b><math>p = .95</math></b>	[-.44, .41]  [-.33, .37]	$\tau_b = -.36$ $p = .12$ <b><math>\tau_b = -.32</math></b> <b><math>p = .17</math></b>	[-.97, .64]  [-.92, .56]
Normalized entropy of 4-note interval patterns	$\tau_b = -.03$ $p = .82$ <b><math>\tau_b = -.04</math></b> <b><math>p = .75</math></b>	[-.42, .36]  [-.40, .33]	$\tau_b = -.30$ $p = .20$ <b><math>\tau_b = -.26</math></b> <b><math>p = .27</math></b>	[-.87, .53]  [-.81, .54]
Normalized entropy of 3-note chordal pitch class patterns	$\tau_b = -.08$ $p = .57$ <b><math>\tau_b = -.09</math></b> <b><math>p = .49</math></b>	[-.49, .29]  [-.45, .29]	$\tau_b = -.39$ $p = .09$ <b><math>\tau_b = -.35</math></b> <b><math>p = .13</math></b>	[-.98, .54]  [-.97, .63]
Normalized entropy of 3-note interval patterns	$\tau_b = -.11$ $p = .38$ <b><math>\tau_b = -.14</math></b> <b><math>p = .30</math></b>	[-.51, .34]  [-.55, .33]	$\tau_b = -.20$ $p = .37$ <b><math>\tau_b = -.15</math></b> <b><math>p = .52</math></b>	[-.80, .57]  [-.82, .67]
Normalized entropy of 2-note chordal pitch class patterns	$\tau_b = -.18$ $p = .17$ <b><math>\tau_b = -.20</math></b> <b><math>p = .13</math></b>	[-.58, .24]  [-.59, .22]	$\tau_b = -.33$ $p = .15$ <b><math>\tau_b = -.28</math></b> <b><math>p = .23</math></b>	[-.93, .38]  [-.84, .31]
Normalized entropy of 2-note interval patterns	$\tau_b = -.24$ $p = .07$ <b><math>\tau_b = -.28</math></b> <b><math>p = .03</math></b>	[-.64, .14]  [-.65, .08]	$\tau_b = -.06$ $p = .84$ <b><math>\tau_b = -.01</math></b> <b><math>p = .97</math></b>	[-.76, .69]  [-.77, .81]
Relative frequency of non-recurring 4-note pitch class patterns (I)	$\tau_b = .01$ $p = .94$ <b><math>\tau_b = -.001</math></b> <b><math>p = .996</math></b>	[-.42, .37]  [-.40, .39]	$\tau_b = -.18$ $p = .46$ <b><math>\tau_b = -.13</math></b> <b><math>p = .59</math></b>	[-.87, .75]  [-.88, .65]



Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.7% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.7% CI (bootstrapped) (Carter)
Relative frequency of non-recurring 4-note pitch class patterns (II)	$\tau_b = -.02$ $p = .86$ <b><math>\tau_b = -.04</math></b> <b><math>p = .78</math></b>	[-.45, .40] <b>[-.43, .31]</b>	$\tau_b = -.18$ $p = .46$ <b><math>\tau_b = -.13</math></b> <b><math>p = .59</math></b>	[-.81, .80] <b>[-.86, .67]</b>
Relative frequency of non-recurring 3-note pitch class patterns (I)	$\tau_b = -.07$ $p = .60$ <b><math>\tau_b = -.08</math></b> <b><math>p = .52</math></b>	[-.51, .33] <b>[-.44, .29]</b>	$\tau_b = -.15$ $p = .55$ <b><math>\tau_b = -.10</math></b> <b><math>p = .67</math></b>	[-.88, .61] <b>[-.92, .63]</b>
Relative frequency of non-recurring 3-note pitch class patterns (II)	$\tau_b = -.07$ $p = .59$ <b><math>\tau_b = -.09</math></b> <b><math>p = .48</math></b>	[-.53, .34] <b>[-.45, .23]</b>	$\tau_b = -.21$ $p = .38$ <b><math>\tau_b = -.14</math></b> <b><math>p = .54</math></b>	[-.86, .67] <b>[-.86, .59]</b>
Relative frequency of non-recurring 2-note pitch class patterns (I)	$\tau_b = -.07$ $p = .59$ <b><math>\tau_b = -.10</math></b> <b><math>p = .47</math></b>	[-.40, .32] <b>[-.42, .23]</b>	$\tau_b = -.08$ $p = .73$ <b><math>\tau_b = .02</math></b> <b><math>p = .93</math></b>	[-.75, .60] <b>[-.64, .54]</b>
Relative frequency of non-recurring 2-note pitch class patterns (II)	$\tau_b = -.10$ $p = .45$ <b><math>\tau_b = -.14</math></b> <b><math>p = .30</math></b>	[-.49, .33] <b>[-.48, .22]</b>	$\tau_b = -.21$ $p = .38$ <b><math>\tau_b = -.12</math></b> <b><math>p = .60</math></b>	[-.80, .51] <b>[-.78, .56]</b>
Relative frequency of non-recurring 4-note interval patterns (I)	$\tau_b = -.02$ $p = .87$ <b><math>\tau_b = -.03</math></b> <b><math>p = .80</math></b>	[-.40, .35] <b>[-.38, .36]</b>	$\tau_b = -.12$ $p = .64$ <b><math>\tau_b = -.04</math></b> <b><math>p = .88</math></b>	[-.77, .71] <b>[-.84, .69]</b>
Relative frequency of non-recurring 4-note interval patterns (II)	$\tau_b = -.05$ $p = .71$ <b><math>\tau_b = -.07</math></b> <b><math>p = .61</math></b>	[-.51, .38] <b>[-.41, .33]</b>	$\tau_b = -.18$ $p = .46$ <b><math>\tau_b = -.10</math></b> <b><math>p = .66</math></b>	[-.81, .71] <b>[-.78, .56]</b>
Relative frequency of non-recurring 3-note interval patterns (I)	$\tau_b = .10$ $p = .45$ <b><math>\tau_b = .09</math></b> <b><math>p = .47</math></b>	[-.27, .44] <b>[-.22, .39]</b>	$\tau_b = -.15$ $p = .55$ <b><math>\tau_b = -.10</math></b> <b><math>p = .67</math></b>	[-.75, .46] <b>[-.72, .61]</b>

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.7% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.7% CI (bootstrapped) (Carter)
Relative frequency of non-recurring 3-note interval patterns (II)	$r_b = .01$ $p = .94$ <b><math>r_b = -.003</math></b> <b><math>p = .98</math></b>	[-.34, .39]  <b>[-.37, .37]</b>	$r_b = -.15$ $p = .55$ <b><math>r_b = -.09</math></b> <b><math>p = .71</math></b>	[-.75, .55]  <b>[-.78, .66]</b>
Relative frequency of non-recurring 2-note interval patterns (I)	$r_b = .06$ $p = .67$ <b><math>r_b = .05</math></b> <b><math>p = .70</math></b>	[-.39, .46]  <b>[-.32, .43]</b>	$r_b = .06$ $p = .84$ <b><math>r_b = .12</math></b> <b><math>p = .61</math></b>	[-.82, .76]  <b>[-.81, .75]</b>
Relative frequency of non-recurring 2-note interval patterns (II)	$r_b = -.08$ $p = .52$ <b><math>r_b = -.12</math></b> <b><math>p = .37</math></b>	[-.47, .39]  <b>[-.46, .30]</b>	$r_b = .03$ $p = .95$ <b><math>r_b = .15</math></b> <b><math>p = .53</math></b>	[-.74, .92]  <b>[-.67, .72]</b>
Relative frequency of notes that started a recurring 4-note interval pattern at any metrical location <sup>a</sup>	$r_b = -.01$ $p = .94$ <b><math>r_b = -.03</math></b> <b><math>p = .84</math></b>	[-.40, .35]  <b>[-.39, .35]</b>	$r_b = -.15$ $p = .55$ <b><math>r_b = -.09</math></b> <b><math>p = .71</math></b>	[-.95, .57]  <b>[-.82, .67]</b>

*Note.* Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval; I = calculation method 1; II = calculation method 2. For an explanation on the difference between these two calculation methods, see Chapter 5.3.3.2: Relative frequency of non-recurring melodic patterns. <sup>a</sup> The direction of the effect is corrected.

When controlling for the length of analyzed bass line reductions, all results were statistically non-significant after Bonferroni correction. In Paul Chambers's bass line reductions, 14 out of the 19 measurements indicated a statistically non-significant and negligible correlation between harmonic rhythm and the variability of melodic patterns, whereas 5 out of the 19 measurements indicated a statistically non-significant and negative correlation between the variables. The mean absolute tau-b was .08 (range: .001 to .28,  $SD = 0.07$ ), which indicates a negligible correlation between the variables. Since most measurements indicated a negligible correlation, the results did not allow to make conclusions on the direction of the effect. In Ron Carter's bass line reductions, 10 out of the 19 measurements indicated a statistically non-significant and negative correlation between the variables, 7 out of the 19 measurements indicated a statistically non-significant and negligible correlation between the variables, whereas 2 out of the 19 measurements indicated a statistically non-significant and positive correlation between

the variables. The mean absolute tau-b was .14 (range: .01 to .35,  $SD = 0.10$ ), which indicates a weak correlation between the variables. Since only 10 out of the 19 measurements indicated the same effect direction, the results did not allow to make conclusions on the direction of the effect. For raw data used in these tests, see Tables 24 and 25 in Appendix 3.

The variability of melodic patterns (with chordal pitch class patterns only) was also measured separately in each harmonic rhythm category (instead of using the average distance of chord changes as a measure of harmonic rhythm). In Paul Chambers's bass line reductions ( $n = 30$ ), the average normalized entropy of 4-note chordal pitch class patterns in a four-beat harmonic rhythm was 0.789 (range: 0.489 to 1, AN = 102),<sup>113</sup> the average normalized entropy of 4-note chordal pitch class patterns in an eight-beat harmonic rhythm was 0.803 (range: 0.469 to 0.987, AN = 92), and the average normalized entropy of 4-note chordal pitch class patterns in a two-beat harmonic rhythm was 0.808 (range: 0.589 to 0.971, AN = 62). In Ron Carter's bass line reductions ( $n = 12$ ), the average normalized entropy of 4-note chordal pitch class patterns in a four-beat harmonic rhythm was 0.903 (range: 0.824 to 1, AN = 88), the average normalized entropy of 4-note chordal pitch class patterns in an eight-beat harmonic rhythm was 0.878 (range: 0.539 to 0.986, AN = 119), and the average normalized entropy of 4-note chordal pitch class patterns in a two-beat harmonic rhythm was 0.897 (range: 0.775 to 1, AN = 51).

Since the number of bars in a particular harmonic rhythm category was very small in some bass line reductions especially in a two-beat harmonic rhythm, I also calculated the average normalized entropy of chordal pitch class patterns in each harmonic rhythm category when all normalized entropy values based on less than 30 chordal pitch class patterns (which equals with the number of bars) were disregarded. In Paul Chambers's bass line reductions ( $n = 30$ ), the average normalized entropy of 4-note chordal pitch class patterns in a four-beat harmonic rhythm was 0.775 (range: 0.489 to 0.940, AN = 109), the average normalized entropy of 4-note chordal pitch class patterns in an eight-beat harmonic rhythm was 0.791 (range: 0.469 to 0.925, AN = 112), and the average normalized entropy of 4-note chordal pitch class patterns in a two-beat harmonic rhythm was 0.800 (range: 0.589 to 0.895, AN = 96). In Ron Carter's bass line reductions ( $n = 12$ ), the average normalized entropy of 4-note chordal pitch class patterns in a four-beat harmonic rhythm was 0.901 (range: 0.876 to 0.971, AN = 103), the average normalized entropy of 4-note chordal pitch class patterns in an eight-beat harmonic rhythm was 0.878 (range: 0.539 to 0.986, AN = 119), and the average normalized entropy of 4-note chordal pitch class patterns in a two-beat harmonic rhythm was 0.878 (range: 0.775 to 0.985, AN = 75).

When a threshold level of at least 30 chordal pitch class patterns in each harmonic rhythm category was used, the variability of chordal pitch class patterns was slightly higher in a two-beat harmonic rhythm compared to other harmonic rhythm categories in Paul Chambers's bass line reductions. However, differences in the average normalized entropy of chordal pitch class patterns

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113 AN refers to the average number of bars in a particular harmonic rhythm category.

between the harmonic rhythm categories were small (range: 0.775 to 0.800). In Ron Carter's bass line reductions, the variability of chordal pitch class patterns was highest in four-beat harmonic rhythm sections. As with Paul Chambers's bass line reductions, there were only slight differences in the average normalized entropy of chordal pitch class patterns between different harmonic rhythm categories (range: 0.878 to 0.901) in Ron Carter's bass line reductions. These findings indicate that harmonic rhythm had little effect on the variability of chordal pitch class patterns in both Paul Chambers's bass line reductions and Ron Carter's bass line reductions.

Note that the normalized entropy of 4-note chordal pitch class patterns and the normalized entropy of 4-note interval patterns in Paul Chambers's bass line reduction on *So What*, probably the most well-known modal jazz recording in the history of jazz, was more than one standard deviation below the average. Modal jazz compositions are usually thought to be less constraining because of their very slow harmonic rhythm. The lower variability of 4-note melodic patterns (compared to the average) in *So What* raises the question of whether a slow rate of chord changes merely caused problems to most musicians at that time, not vice versa. Compositions with only one or two chords were a new and challenging situation for many jazz musicians in the late 1950's (Szwed, 2003, pp. 175-176). As an example, Jimmy Heath (who replaced John Coltrane on a tour after the release of *Kind of Blue*) "had the same trouble with modes that most other musicians did in that period, trying to stay in one key as if it were a traditional tune, instead of reaching out and using a wider range of notes; or not knowing how to resolve the piece at the end with the usual harmonics" (Szwed, 2003, p. 179)<sup>114</sup>. However, it should be noted that the other two bass line reductions on modal compositions (*Milestones* with Paul Chambers on bass and *Passion Dance* with Ron Carter on bass) were close to the average normalized entropy of 4-note chordal pitch class patterns and the average normalized entropy of 4-note interval patterns. In addition, it is important to note that despite the high rate of recurring melodic patterns in Paul Chambers's bass line reduction on *So What*, this bass line introduced new chord substitutions. There were several occurrences of the use of upper structure substitutions in the Eb7 sections in this bass line, which were not used in any other Paul Chambers's bass line analyzed in the present study. Similarly, Paul Chambers's bass line on *Freddie Freeloader* is extraordinary in its frequent use of fifths as target notes which makes it different from any other bass line analyzed in this study.

### 6.2.3 Variability of target notes

In Paul Chambers's bass line reductions ( $n = 30$ ), the average normalized entropy of target notes was 0.262 (range: 0.141 to 0.367,  $SD = 0.047$ ). The average relative frequency of consonant target notes (root notes, major and minor thirds, and

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114 According to Jimmy Heath, "what was hard for me was the unfamiliar territory and that it ... stays in a mode and you don't resolve it at the end of a cadence like you do" (Porter, 1998, p. 162).

perfect fifths combined) was 86.4% (range: 63.7% to 97.3%,  $SD = 7.20$ ). The average relative frequency of root notes was 54.0% (range: 31.9% to 72.9%,  $SD = 9.60$ ). In Ron Carter's bass line reductions ( $n = 12$ ), the average normalized entropy of target notes was 0.302 (range: 0.094 to 0.450,  $SD = 0.090$ ). The average relative frequency of consonant target notes was 74.4% (range: 56.7% to 95.1%,  $SD = 11.2$ ). The average relative frequency of root notes was 52.6% (range: 29.8% to 89.8%,  $SD = 16.0$ ).

As noted in Chapter 5.2.3: Basic statistics of the data, root notes and perfect fifths were the most frequently used target notes (the term 'target note' refers to the first note in each bar) in both Paul Chambers's bass line reductions and Ron Carter's bass line reductions. In Paul Chambers's bass line reductions, root notes covered 53.6% of all notes that occurred in the first beat of the bar, whereas perfect fifths covered 21.4% of all notes that occurred in the first beat of the bar. In Ron Carter's bass line reductions, root notes covered 53.9% of all notes that occurred in the first beat of the bar, whereas perfect fifths covered 15.1% of all notes that occurred in the first beat of the bar. In both Paul Chambers's bass line reductions and Ron Carter's bass line reductions, other target notes were used much less frequently.

A Kendall's tau correlation analysis with Bonferroni correction was performed to determine the relationship between tempo and the variability of target notes and between harmonic rhythm and the variability of target notes. The variability of target notes was measured as the average normalized entropy of target notes, the relative frequency of consonant target notes, and the relative frequency of root notes. After Bonferroni correction, the alpha level for statistical significance was adjusted to .017 (.05/3). The results are presented in Table 6. Note that the lower the relative frequency of root notes/consonant target notes, the higher the variability of target notes. The direction of the effect is corrected in these results.

TABLE 6 Correlations between tempo/harmonic rhythm and variability of target notes

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	98.3% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	98.3% CI (bootstrapped) (Carter)
Correlations between tempo and variability of target notes				
Average normalized entropy of target notes	$\tau_b = .08$ $p = .56$ <b><math>\tau_b = .10</math></b> <b><math>p = .43</math></b>	$[-.31, .46]$ <b><math>[-.28, .42]</math></b>	$\tau_b = .06$ $p = .84$ <b><math>\tau_b = .21</math></b> <b><math>p = .38</math></b>	$[-.67, .70]$ <b><math>[-.48, .69]</math></b>
Relative frequency of consonant target notes <sup>a</sup>	$\tau_b = .002$ $p = .99$ <b><math>\tau_b = .003</math></b> <b><math>p = .98</math></b>	$[-.34, .33]$ <b><math>[-.34, .32]</math></b>	$\tau_b = .24$ $p = .31$ <b><math>\tau_b = .30</math></b> <b><math>p = .20</math></b>	$[-.41, .85]$ <b><math>[-.43, .83]</math></b>
Relative frequency of root notes <sup>a</sup>	$\tau_b = .02$ $p = .86$ <b><math>\tau_b = .01</math></b> <b><math>p = .92</math></b>	$[-.33, .42]$ <b><math>[-.34, .37]</math></b>	$\tau_b = .18$ $p = .46$ <b><math>\tau_b = .26</math></b> <b><math>p = .26</math></b>	$[-.52, .84]$ <b><math>[-.39, .84]</math></b>
Correlations between harmonic rhythm and variability of target notes				
Average normalized entropy of target notes	$\tau_b = .13$ $p = .32$ <b><math>\tau_b = .13</math></b> <b><math>p = .33</math></b>	$[-.20, .46]$ <b><math>[-.19, .44]</math></b>	$\tau_b = -.24$ $p = .31$ <b><math>\tau_b = -.18</math></b> <b><math>p = .44</math></b>	$[-.79, .26]$ <b><math>[-.76, .33]</math></b>
Relative frequency of consonant target notes <sup>a</sup>	$\tau_b = .09$ $p = .50$ <b><math>\tau_b = .09</math></b> <b><math>p = .50</math></b>	$[-.29, .47]$ <b><math>[-.28, .44]</math></b>	$\tau_b = -.18$ $p = .46$ <b><math>\tau_b = -.12</math></b> <b><math>p = .60</math></b>	$[-.73, .46]$ <b><math>[-.68, .45]</math></b>
Relative frequency of root notes <sup>a</sup>	$\tau_b = .30$ $p = .02$ <b><math>\tau_b = .31</math></b> <b><math>p = .02</math></b>	$[-.07, .61]$ <b><math>[-.07, .62]</math></b>	$\tau_b = -.18$ $p = .46$ <b><math>\tau_b = -.15</math></b> <b><math>p = .52</math></b>	$[-.75, .45]$ <b><math>[-.75, .45]</math></b>

Note. Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval.

<sup>a</sup> The direction of the effect is corrected.

When controlling for the length of analyzed bass line reductions, all results were statistically non-significant after Bonferroni correction. In Paul Chambers's bass line reductions, 2 out of the 3 measurements indicated a statistically non-

significant and negligible correlation between tempo and the variability of target notes, whereas one measurement indicated a statistically non-significant and weak positive correlation between the variables. The mean absolute tau-b was .04 (range: .003 to .10,  $SD = 0.05$ ). In addition, 2 out of the 3 measurements indicated a statistically non-significant and weak/moderate positive correlation between harmonic rhythm and the variability of target notes, whereas one measurement indicated a statistically non-significant and negligible correlation between the variables. The mean absolute tau-b was .18 (range: .09 to .31,  $SD = 0.12$ ). In Ron Carter's bass line reductions, all measurements indicated a statistically non-significant and weak to moderate positive correlation between tempo and the variability of target notes. The mean absolute tau-b was .26 (range: .21 to .30,  $SD = 0.05$ ). Also, all measurements indicated a statistically non-significant and weak negative correlation between harmonic rhythm and the variability of target notes. The mean absolute tau-b was .15 (range: .12 to .18,  $SD = 0.03$ ).

In summary, the results indicated that tempo and harmonic rhythm had different effects on the variability of target notes between these two bassists. Whereas most measurements indicated a statistically non-significant and weak positive correlation between tempo and the variability of target notes in Ron Carter's bass line reductions, most measurements indicated a statistically non-significant and negligible correlation between tempo and the variability of target notes in Paul Chambers's bass line reductions. Similarly, whereas most measurements indicated a statistically non-significant and positive correlation between harmonic rhythm and the variability of target notes in Paul Chambers's bass line reductions, all measurements indicated a statistically non-significant and negative correlation between harmonic rhythm and the variability of target notes in Ron Carter's bass line reductions. For raw data used in these tests, see Tables 26 and 27 in Appendix 4.

#### **6.2.4 Average length of recurring melodic patterns**

In Paul Chambers's bass line reductions ( $n = 30$ ), the average length of recurring melodic patterns (in intervals) was 6.52 (range: 3.68 to 11.4,  $SD = 2.35$ ). When the average length of recurring melodic patterns was converted to seconds based on the approximate tempo of the musical work, the average length of recurring melodic patterns (in seconds) was 2.00 (range: 1.06 to 3.93,  $SD = 0.74$ ). The average maximum length of recurring melodic patterns (in intervals) was 28.2 (range: 13 to 61,  $SD = 12.6$ ). The average maximum length of recurring melodic patterns (in seconds) was 8.58 (range: 3.16 to 15.8,  $SD = 3.56$ ). In Ron Carter's bass line reductions ( $n = 12$ ), the average length of recurring melodic patterns (in intervals) was 3.76 (range: 2.35 to 5.25,  $SD = 0.90$ ). The average length of recurring melodic patterns (in seconds) was 1.29 (range: 0.68 to 2.58,  $SD = 0.57$ ). The average maximum length of recurring melodic patterns (in intervals) was 24.5 (range: 7 to 63,  $SD = 19.1$ ). The average maximum length of recurring melodic patterns (in seconds) was 8.86 (range: 1.81 to 28.4,  $SD = 8.28$ ).

A Kendall's tau correlation analysis with Bonferroni correction was performed to assess the relationship between tempo and the average/maximum

length of recurring melodic patterns and between harmonic rhythm and the average/maximum length of recurring melodic patterns. After Bonferroni correction, the alpha level for statistical significance was adjusted to .013 (.05/4). The results are presented in Table 7.

TABLE 7 Correlations between tempo/harmonic rhythm and average or maximum length of recurring melodic patterns

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	98.7% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	98.7% CI (bootstrapped) (Carter)
Correlations between tempo and average/maximum length of recurring melodic patterns				
Average length of recurring melodic patterns (in intervals)	$\tau_b = .24$ $p = .06$ <b><math>\tau_b = .22</math></b> <b><math>p = .10</math></b>	[-.08, .60]  <b>[-.14, .53]</b>	$\tau_b = .09$ $p = .74$ <b><math>\tau_b &lt; .0001</math></b> <b><math>p = 1</math></b>	[-.66, .70]  <b>[-.58, .71]</b>
Average length of recurring melodic patterns (in seconds)	$\tau_b = -.26$ $p = .05$ <b><math>\tau_b = -.30</math></b> <b><math>p = .02</math></b>	[-.56, .09]  <b>[-.57, .03]</b>	$\tau_b = -.61^*$ $p = .005$ <b><math>\tau_b = -.57</math></b> <b><math>p = .01</math></b>	[-.98, -.03]  <b>[-.94, .14]</b>
Maximum length of recurring melodic patterns (in intervals)	$\tau_b = .24$ $p = .07$ <b><math>\tau_b = .21</math></b> <b><math>p = .11</math></b>	[-.11, .56]  <b>[-.18, .54]</b>	$\tau_b = -.09$ $p = .68$ <b><math>\tau_b = -.12</math></b> <b><math>p = .61</math></b>	[-.75, .62]  <b>[-.69, .57]</b>
Maximum length of recurring melodic patterns (in seconds)	$\tau_b = -.13$ $p = .31$ <b><math>\tau_b = -.18</math></b> <b><math>p = .18</math></b>	[-.47, .24]  <b>[-.50, .22]</b>	$\tau_b = -.39$ $p = .09$ <b><math>\tau_b = -.37</math></b> <b><math>p = .11</math></b>	[-.83, .15]  <b>[-.84, .34]</b>
Correlations between harmonic rhythm and average/maximum length of recurring melodic patterns				
Average length of recurring melodic patterns (in intervals)	$\tau_b = -.06$ $p = .63$ <b><math>\tau_b = -.06</math></b> <b><math>p = .66</math></b>	[-.38, .26]  <b>[-.35, .23]</b>	$\tau_b = .09$ $p = .74$ <b><math>\tau_b = .04</math></b> <b><math>p = .88</math></b>	[-.54, .66]  <b>[-.61, .60]</b>
Average length of recurring melodic patterns (in seconds)	$\tau_b = .13$ $p = .32$ <b><math>\tau_b = .14</math></b> <b><math>p = .28</math></b>	[-.18, .39]  <b>[-.16, .42]</b>	$\tau_b = .12$ $p = .64$ <b><math>\tau_b = .18</math></b> <b><math>p = .44</math></b>	[-.37, .50]  <b>[-.26, .60]</b>



Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	98.7% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	98.7% CI (bootstrapped) (Carter)
Maximum length of recurring melodic patterns (in intervals)	$\tau_b = -.04$ $p = .73$ <b><math>\tau_b = -.04</math></b> <b><math>p = .78</math></b>	$[-.33, .25]$ <b><math>[-.34, .25]</math></b>	$\tau_b = .06$ $p = .78$ <b><math>\tau_b = .05</math></b> <b><math>p = .83</math></b>	$[-.56, .83]$ <b><math>[-.54, .66]</math></b>
Maximum length of recurring melodic patterns (in seconds)	$\tau_b = .07$ $p = .57$ <b><math>\tau_b = .09</math></b> <b><math>p = .50</math></b>	$[-.19, .37]$ <b><math>[-.22, .37]</math></b>	$\tau_b = .03$ $p = .95$ <b><math>\tau_b = .06</math></b> <b><math>p = .78</math></b>	$[-.47, .53]$ <b><math>[-.44, .55]</math></b>

*Note.* Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval. \* Correlation is statistically significant at the Bonferroni adjusted alpha level (.013) (2-tailed).

When controlling for the length of analyzed bass line reductions, all results were statistically non-significant after Bonferroni correction. In both Paul Chambers's and Ron Carter's bass line reductions, the results indicated a statistically non-significant and negative correlation between tempo and the average length of recurring melodic patterns (in seconds), a statistically non-significant and negative correlation between tempo and the maximum length of recurring melodic patterns (in seconds), a statistically non-significant and weak positive correlation between harmonic rhythm and the average length of melodic patterns (in seconds), and statistically non-significant and negligible correlations between harmonic rhythm and the average length of recurring melodic patterns (in intervals) and between harmonic rhythm and the maximum length of recurring melodic patterns (both in intervals and in seconds). The results were mixed for the two bassists regarding the relationship between tempo and the average length of recurring melodic patterns (in intervals) and between tempo and the maximum length of recurring melodic patterns (in intervals). For raw data used in these analyses, see Table 28 in Appendix 4.

Note that the results indicated a statistically non-significant and negative correlation between tempo and the average or maximum length of melodic patterns (in seconds) in both Paul Chambers's and Ron Carter's bass line reductions, and a statistically non-significant and positive correlation between tempo and the average or maximum length of melodic patterns (in intervals) in Paul Chambers's bass line reductions (but not in Ron Carter's bass line reductions). For scatter plots on the relationship between tempo and the average length of recurring melodic patterns, see Figures 30 and 31.

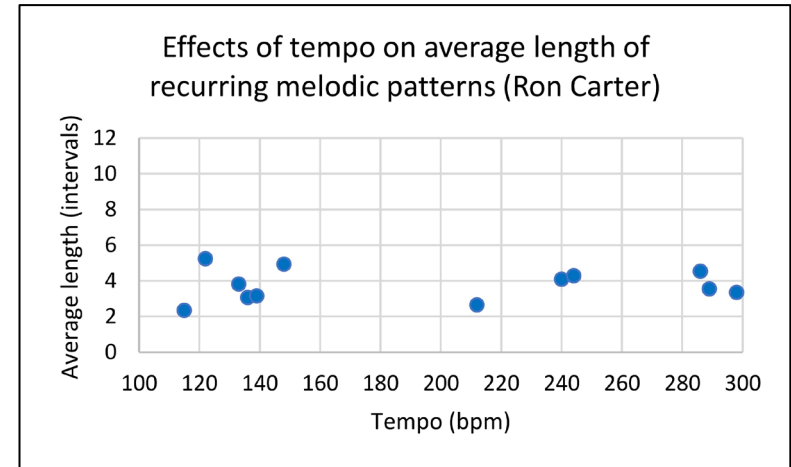
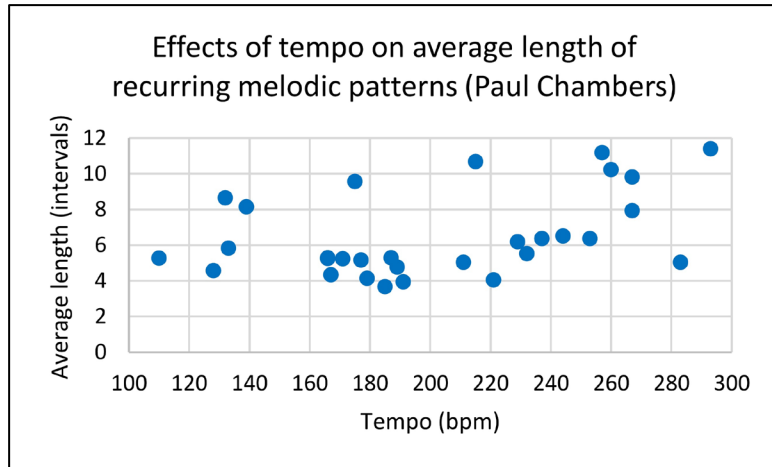


FIGURE 30 Effects of tempo on average length of recurring interval patterns (in intervals)

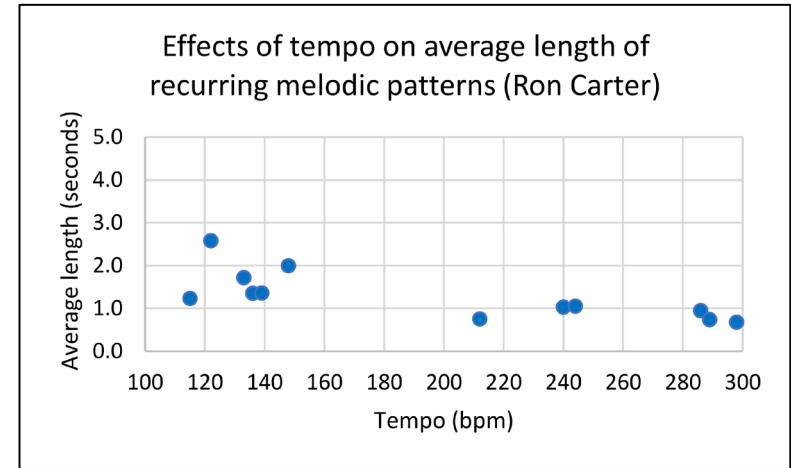
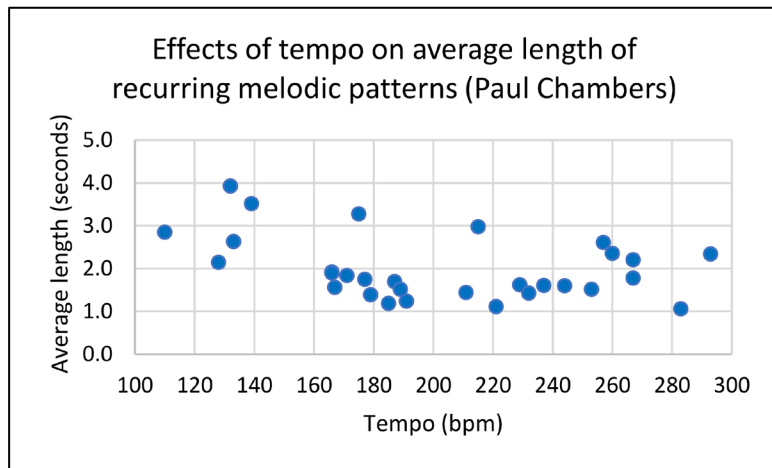


FIGURE 31 Effects of tempo on average length of recurring interval patterns (in seconds)

### 6.2.5 Melodic complexity

In the present study, the aim of investigating melodic complexity was to find out whether eminent jazz bassists' note choices are technically less demanding at fast tempos and fast harmonic rhythm compared to slow tempos and slow harmonic rhythm. In Paul Chambers's bass line reductions ( $n = 30$ ), the average interval size ranged from 2.17 to 3.71 semitones ( $M = 2.93$ ,  $SD = 0.34$ ), and the normalized entropy of interval size ranged from 0.282 to 0.415 ( $M = 0.338$ ,  $SD = 0.038$ ). An average interval size of two semitones refers to a major second, whereas an average interval size of four semitones refers to a major third. In Ron Carter's bass line reductions ( $n = 12$ ), the average interval size ranged from 2.89 to 5.14 semitones ( $M = 3.87$ ,  $SD = 0.69$ ), and the normalized entropy of interval size ranged from 0.328 to 0.488 ( $M = 0.393$ ,  $SD = 0.042$ ). An average interval size of three semitones refers to a minor third, whereas an average interval size of five semitones refers to a perfect fourth.

A Kendall's tau correlation analysis with Bonferroni correction was performed to determine the relationship between tempo and melodic complexity and between harmonic rhythm and melodic complexity. After Bonferroni correction, the alpha level for statistical significance was adjusted to .025 (.05/2). The results are presented in Tables 8 and 9.

TABLE 8 Correlations between tempo and melodic complexity

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	97.5% CI (bootstrap-ped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	97.5% CI (bootstrap-ped) (Carter)
Average interval size	$\tau_b = -.08$ $p = .52$ <b><math>\tau_b = -.08</math></b> <b><math>p = .57</math></b>	[-.40, .19]  <b>[-.34, .23]</b>	$\tau_b = -.32$ $p = .15$ <b><math>\tau_b = -.28</math></b> <b><math>p = .24</math></b>	[-.78, .25]  <b>[-.77, .31]</b>
Normalized entropy of interval size	$\tau_b = -.07$ $p = .59$ <b><math>\tau_b = -.01</math></b> <b><math>p = .94</math></b>	[-.36, .22]  <b>[-.28, .24]</b>	$\tau_b = -.38$ $p = .09$ <b><math>\tau_b = -.22</math></b> <b><math>p = .34</math></b>	[-.83, .15]  <b>[-.67, .26]</b>

Note. Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval.

TABLE 9 Correlations between harmonic rhythm and melodic complexity

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	97.5% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	97.5% CI (bootstrapped) (Carter)
Average interval size	$\tau_b = -.08$ $p = .52$	[-.56, .05]	$\tau_b = -.29$ $p = .19$	[-.76, .27]
	<b><math>\tau_b = -.28</math></b> <b><math>p = .03</math></b>	<b>[-.53, .02]</b>	<b><math>\tau_b = -.29</math></b> <b><math>p = .21</math></b>	<b>[-.71, .29]</b>
Normalized entropy of interval size	$\tau_b = -.17$ $p = .20$	[-.45, .14]	$\tau_b = -.17$ $p = .45$	[-.79, .50]
	<b><math>\tau_b = -.21</math></b> <b><math>p = .11</math></b>	<b>[-.46, .06]</b>	<b><math>\tau_b = -.03</math></b> <b><math>p = .89</math></b>	<b>[-.57, .42]</b>

Note. Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval.

When controlling for the length of analyzed bass line reductions, all results were statistically non-significant after Bonferroni correction. In Paul Chambers's bass line reductions, both measurements indicated a statistically non-significant and negligible correlation between tempo and melodic complexity. The mean absolute tau-b was .05 (range: .01 to .08,  $SD = 0.05$ ). Both measurements also indicated a statistically non-significant and weak negative correlation between harmonic rhythm and melodic complexity. In this case, the mean absolute tau-b was .25 (range: .21 to .28,  $SD = 0.05$ ). In Ron Carter's bass line reductions, both measurements indicated a statistically non-significant and weak negative correlation between tempo and melodic complexity. The mean absolute tau-b was .25 (range: .22 to .28,  $SD = 0.04$ ). However, whereas the other measurement indicated a statistically non-significant and weak negative correlation between harmonic rhythm and melodic complexity, the other measurement indicated a statistically non-significant and negligible correlation between the two variables. The mean absolute tau-b was .16 (range: .03 to .29,  $SD = 0.18$ ).

In summary, the results indicated a statistically non-significant and weak negative correlation between tempo and melodic complexity in Ron Carter's bass line reductions and a statistically non-significant and negligible correlation between tempo and melodic complexity in Paul Chambers's bass line reductions. Regarding the relationship between harmonic rhythm and melodic complexity, the results indicated a statistically non-significant and weak negative correlation between harmonic rhythm and melodic complexity in Paul Chambers's bass line reductions and a statistically non-significant and weak/negligible negative correlation between these two variables in Ron Carter's bass line reductions. For raw data used in these tests, see Table 29 in Appendix 4.

## 6.3 Temporal constraints and musical creativity

### 6.3.1 Transfer of melodic patterns

Transfer of melodic patterns was measured as the proportion of melodic pattern classes that occurred at least twice in two or more bass line reductions by the same musician in relation to the total number of melodic pattern classes that occurred at least twice in at least one bass line reduction by the same musician. In addition, I calculated the proportion of all instances of melodic patterns covered by melodic pattern classes that occurred at least twice in two or more bass line reductions by the same musician. Although all analyses were based on chordal pitch class patterns, I will use the terms ‘melodic pattern’ and ‘melodic pattern class’ in this chapter to avoid confusing use of words. The basic statistics and main results are presented in Table 10.

TABLE 10 Total number and proportion of melodic pattern classes that occurred at least twice in two or more bass line reductions

	4 notes <sup>a</sup>	3 notes <sup>a</sup>	2 notes <sup>a</sup>	4 notes <sup>b</sup>	3 notes <sup>b</sup>	2 notes <sup>b</sup>
A	188	186	157	33	71	83
B	1,122	1,099	996	294	392	428
C	2,778	4,332	5,616	347	860	1,633
D	6,746	6,746	6,746	2,589	2,589	2,589
E	16.8% (41.2%)	16.9% (64.1%)	15.8% (83.2%)	11.2% (13.4%)	18.1% (33.2%)	19.4% (63.1%)

*Note.* Number of notes refers to pattern length. A = total number of melodic pattern classes that occurred at least twice in two or more bass line reductions by the same musician; B = total number of melodic pattern classes that occurred at least twice in at least one bass line reduction by the same musician; C = total number of instances of melodic patterns that occurred at least twice in two or more bass line reductions by the same musician; D = total number of instances of melodic patterns in the bass line reductions of the same musician (the size of the sub-corpus); E = proportion of melodic pattern classes that occurred at least twice in two or more bass line reductions by the same musician (proportion of all instances of melodic patterns covered by melodic pattern classes that occurred at least twice in two or more bass line reductions by the same musician is presented in parentheses). <sup>a</sup> Paul Chambers’s bass line reductions. <sup>b</sup> Ron Carter’s bass line reductions.

According to the present results, 4-note melodic pattern classes that occurred at least twice in two or more bass line reductions covered 41.2% of all instances of 4-note melodic patterns in Paul Chambers’s bass line reductions (13.4% in Ron Carter’s bass line reductions). In contrast, 3-note melodic pattern classes that

occurred at least twice in two or more bass line reductions covered 64.1% of all instances of 3-note melodic patterns (33.2% in Ron Carter's bass line reductions) and 2-note melodic pattern classes that occurred at least twice in two or more bass line reductions covered 83.2% of all instances of 2-note melodic patterns in Paul Chambers's bass line reductions (63.1% in Ron Carter's bass line reductions). Although it is likely that larger sample sizes could have shown larger proportions of instances of melodic patterns covered by recurring melodic pattern classes, it is noteworthy that these proportions were still quite small when the length of analyzed melodic patterns was four notes.<sup>115</sup>

The results also showed that the proportion of recurring melodic pattern classes that occurred at least twice in two or more bass line reductions was quite small. In Paul Chambers's bass line reductions, 15.8% to 16.9% of all recurring melodic pattern classes occurred at least twice in at least two bass line reductions depending on pattern length. In Ron Carter's bass line reductions, 11.2% to 19.4% of all recurring melodic pattern classes occurred at least twice in at least two bass line reductions depending on pattern length. Note that the proportion of recurring 2-note melodic pattern classes that occurred at least twice in two or more bass line reductions was only 15.8% in Paul Chambers's bass line reductions, which means that 84.2% of all recurring 2-note melodic pattern classes occurred at least twice in only one bass line reduction. In Ron Carter's bass line reductions, the relative frequency of recurring 2-note melodic pattern classes that occurred at least twice in two or more bass line reductions was 19.4%. In other words, 80.6% of all recurring 2-note melodic patterns occurred at least twice only in one bass line reduction.

These findings indicate that even if recurring melodic pattern classes covered a large proportion of the sub-corpus at least when the length of analyzed melodic patterns was two notes, most recurring melodic pattern classes were not repeated across different bass line reductions. This indicates that both bassists used their repertoire of melodic patterns highly flexibly or they were able to invent new melodic patterns in their performances. As another interpretation of these results, it is possible that both musicians had a very large repertoire of learned melodic patterns and the huge size of the repertoire might explain why most of the recurring melodic pattern classes were not repeated across different bass line reductions (see Christensen et al., 2019). However, the first explanation is more plausible based on the high normalized entropy of melodic patterns and the high relative frequency of non-recurring melodic patterns values in many of the individual bass line reductions (see Tables 24 and 25 in Appendix 3). Nevertheless, there may be individual differences between jazz musicians with the same skill level in their dependence on inflexible repertoire of melodic patterns.

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115 Note that the research material contained roughly three times more bass line reductions from Paul Chambers compared to Ron Carter and that the proportion of instances of melodic patterns covered by melodic pattern classes that occurred at least twice in two or more bass line reductions was always higher in Paul Chambers's bass line reductions compared to Ron Carter's bass line reductions. In other words, the proportion of instances of melodic patterns covered by melodic pattern classes that occurred at least twice in two or more bass line reductions by the same musician scaled with sample size.

Note that the repetition of the same melodic pattern classes across different bass line reductions may also occur by chance, which means that the repetition of a melodic pattern class does not necessarily indicate that the repeated melodic pattern class was retrieved from memory during the performance. As a result, it is possible that using the very loose threshold level of at least two occurrences in two or more bass line reductions by the same musician may overestimate the number of learned melodic pattern classes that can be retrieved from memory during performance. To find out whether tighter threshold levels could substantially decrease the proportion of recurring melodic pattern classes that occurred across different bass line reductions, I analyzed the data by using two additional threshold levels: at least three occurrences in two or more bass line reductions (threshold level 2) and at least two occurrences in three or more bass line reductions (threshold level 3). The results are presented in Table 11.

TABLE 11 Proportion of melodic pattern classes that occurred at least three times in two or more bass line reductions or at least twice in at three or more bass line reductions

	4 notes <sup>a</sup>	3 notes <sup>a</sup>	2 notes <sup>a</sup>	4 notes <sup>b</sup>	3 notes <sup>b</sup>	2 notes <sup>b</sup>
Original	16.8% (41.2%)	16.9% (64.1%)	15.8% (83.2%)	11.2% (13.4%)	18.1% (33.2%)	19.4% (63.1%)
Threshold level 2	8.82% (29.8%)	10.5% (52.4%)	10.6% (72.6%)	5.78% (9.19%)	9.44% (21.6%)	10.5% (49.1%)
Threshold level 3	8.11% (30.6%)	10.5% (56.9%)	10.3% (77.5%)	2.72% (6.22%)	9.18% (23.4%)	11.2% (54.1%)

*Note.* Number of notes refers to pattern length. Original = proportion of melodic pattern classes that occurred at least twice in two or more bass line reductions. Threshold level 2 = proportion of melodic pattern classes that occurred at least three times in two or more bass line reductions. Threshold level 3 = proportion of melodic pattern classes that occurred at least twice in three or more bass line reductions. The proportion of recurring melodic pattern classes in relation to the size of the sub-corpus is shown in parentheses. <sup>a</sup> Paul Chambers's bass line reductions. <sup>b</sup> Ron Carter's bass line reductions.

Unsurprisingly, the use of tighter threshold level decreased the proportion of melodic pattern classes that occurred multiple times across different bass line reductions. Using a more restrictive threshold level (threshold level 2 or threshold level 3) could be useful to distinguish between learned melodic patterns and those that may have occurred by chance. In addition, it should be noted that harmonic context was considered in these analyses. It is possible that this decision may have led to a smaller number and proportion of melodic pattern classes that occurred repeatedly across different bass line reductions compared to when

harmonic context is disregarded. To investigate how harmonic context might affect the results, further research could analyze the same data both with chordal pitch class patterns and interval patterns.

### 6.3.2 Transfer of melodic contour patterns

In Paul Chambers's bass line reductions ( $n = 30$ ), the average normalized entropy of 4-note fuzzy interval patterns was 0.672 (range: 0.525 to 0.770,  $SD = 0.064$ ). The average normalized entropy of 4-note Parsons's code patterns was 0.379 (range: 0.312 to 0.447,  $SD = 0.031$ ). The average relative frequency of non-recurring 4-note fuzzy interval pattern classes was 51.9% (range: 35.4% to 69.4%,  $SD = 8.96$ ) and the average relative frequency of non-recurring 4-note fuzzy interval patterns was 17.4% (range: 6.31% to 35.8%,  $SD = 7.59$ ). The average relative frequency of non-recurring 4-note Parsons's code pattern classes was 13.2% (range: 0% to 26.7%,  $SD = 8.48$ ) and the average relative frequency of non-recurring 4-note Parsons's code patterns was 0.78% (range: 0% to 2.65%,  $SD = 0.63$ ).

In Ron Carter's bass lines ( $n = 12$ ), the average normalized entropy of 4-note fuzzy interval patterns was 0.791 (range: 0.687 to 0.908,  $SD = 0.056$ ). The average normalized entropy of 4-note Parsons's code patterns was 0.442 (range: 0.374 to 0.504,  $SD = 0.043$ ). The average relative frequency of non-recurring 4-note fuzzy interval pattern classes was 63.3% (range: 51.5% to 82.1%,  $SD = 8.96$ ) and the average relative frequency of non-recurring 4-note fuzzy interval patterns was 31.9% (range: 20.5% to 61.5%,  $SD = 11.5$ ). The average relative frequency of non-recurring 4-note Parsons's code pattern classes was 23.8% (range: 5.88% to 46.7%,  $SD = 11.7$ ) and the average relative frequency of non-recurring 4-note Parsons's code patterns was 2.00% (range: 0.45% to 3.36%,  $SD = 0.96$ ).

A Kendall's tau correlation analysis with Bonferroni correction was performed to determine the relationship between tempo and the variability of melodic contour patterns and between harmonic rhythm and the variability of melodic contour patterns. After Bonferroni correction, the alpha level for statistical significance was adjusted to .008 (.05/6). The results are presented in Tables 12 and 13.



TABLE 12 Correlations between tempo and variability of melodic contour patterns

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.2% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.2% CI (bootstrapped) (Carter)
Normalized entropy of 4-note fuzzy interval patterns	$\tau_b = -.13$ $p = .30$	[-.42, .18]	$\tau_b = -.12$ $p = .64$	[-.83, .61]
	<b><math>\tau_b = -.10</math></b> <b><math>p = .43</math></b>	<b>[-.41, .23]</b>	<b><math>\tau_b = -.02</math></b> <b><math>p = .92</math></b>	<b>[-.73, .62]</b>
Normalized entropy of 4-note Parsons's code patterns	$\tau_b = -.02$ $p = .87$	[-.43, .34]	$\tau_b = -.55$ $p = .01$	[-.89, -.07]
	<b><math>\tau_b = .04</math></b> <b><math>p = .75</math></b>	<b>[-.36, .34]</b>	<b><math>\tau_b = -.47</math></b> <b><math>p = .04</math></b>	<b>[-.85, .14]</b>
Relative frequency of non-recurring 4-note fuzzy interval pattern classes	$\tau_b = -.19$ $p = .14$	[-.55, .24]	$\tau_b = -.64^*$ $p = .003$	[-1, -.17]
	<b><math>\tau_b = -.16</math></b> <b><math>p = .23</math></b>	<b>[-.53, .17]</b>	<b><math>\tau_b = -.58</math></b> <b><math>p = .01</math></b>	<b>[-.92, .10]</b>
Relative frequency of non-recurring 4-note fuzzy interval patterns	$\tau_b = -.24$ $p = .07$	[-.58, .14]	$\tau_b = -.39$ $p = .09$	[-.89, .21]
	<b><math>\tau_b = -.21</math></b> <b><math>p = .11</math></b>	<b>[-.55, .19]</b>	<b><math>\tau_b = -.26</math></b> <b><math>p = .26</math></b>	<b>[-.80, .30]</b>
Relative frequency of non-recurring 4-note Parsons's code pattern classes	$\tau_b = -.002$ $p = .99$	[-.36, .38]	$\tau_b = .18$ $p = .46$	[-.41, .80]
	<b><math>\tau_b = -.001</math></b> <b><math>p = .99</math></b>	<b>[-.39, .37]</b>	<b><math>\tau_b = .17</math></b> <b><math>p = .46</math></b>	<b>[-.47, .83]</b>
Relative frequency of non-recurring 4-note Parsons's code patterns	$\tau_b = -.07$ $p = .62$	[-.41, .34]	$\tau_b = -.12$ $p = .64$	[-.67, .52]
	<b><math>\tau_b = -.03</math></b> <b><math>p = .80</math></b>	<b>[-.38, .32]</b>	<b><math>\tau_b = -.02</math></b> <b><math>p = .92</math></b>	<b>[-.61, .53]</b>

Note. Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval.  
 \* Correlation is statistically significant at the Bonferroni adjusted alpha level (.008) (2-tailed).

TABLE 13 Correlations between harmonic rhythm and variability of melodic contour patterns

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.2% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.2% CI (bootstrapped) (Carter)
Normalized entropy of 4-note fuzzy interval patterns	$\tau_b = -.01$ $p = .94$	[-.39, .36]	$\tau_b = -.30$ $p = .20$	[-.93, .41]
	<b><math>\tau_b = -.02</math></b> <b><math>p = .89</math></b>	<b>[-.41, .34]</b>	<b><math>\tau_b = -.26</math></b> <b><math>p = .27</math></b>	<b>[-.86, .39]</b>
Normalized entropy of 4-note Parsons's code patterns	$\tau_b = .03$ $p = .84$	[-.39, .42]	$\tau_b = 0$ $p = 1$	[-.71, .56]
	<b><math>\tau_b = .01</math></b> <b><math>p = .92</math></b>	<b>[-.35, .37]</b>	<b><math>\tau_b = .10</math></b> <b><math>p = .66</math></b>	<b>[-.41, .55]</b>
Relative frequency of non-recurring 4-note fuzzy interval pattern classes	$\tau_b = .07$ $p = .59$	[-.31, .40]	$\tau_b = -.03$ $p = .95$	[-.71, .70]
	<b><math>\tau_b = .06</math></b> <b><math>p = .62</math></b>	<b>[-.27, .39]</b>	<b><math>\tau_b = .09</math></b> <b><math>p = .69</math></b>	<b>[-.57, .68]</b>
Relative frequency of non-recurring 4-note fuzzy interval patterns	$\tau_b = .06$ $p = .67$	[-.28, .38]	$\tau_b = -.09$ $p = .74$	[-.75, .65]
	<b><math>\tau_b = .05</math></b> <b><math>p = .71</math></b>	<b>[-.27, .34]</b>	<b><math>\tau_b = .04</math></b> <b><math>p = .87</math></b>	<b>[-.62, .60]</b>
Relative frequency of non-recurring 4-note Parsons's code pattern classes	$\tau_b = -.04$ $p = .79$	[-.37, .28]	$\tau_b = -.12$ $p = .64$	[-.79, .56]
	<b><math>\tau_b = -.04</math></b> <b><math>p = .78</math></b>	<b>[-.34, .28]</b>	<b><math>\tau_b = -.14</math></b> <b><math>p = .56</math></b>	<b>[-.72, .47]</b>
Relative frequency of non-recurring 4-note Parsons's code patterns	$\tau_b = .02$ $p = .89$	[-.29, .35]	$\tau_b = -.18$ $p = .46$	[-.74, .42]
	<b><math>\tau_b = .01</math></b> <b><math>p = .93</math></b>	<b>[-.33, .28]</b>	<b><math>\tau_b = -.13</math></b> <b><math>p = .59</math></b>	<b>[-.72, .40]</b>

Note. Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval.

When controlling for the length of analyzed bass line reductions, all correlations between tempo and the variability of melodic contour patterns and between harmonic rhythm and the variability of melodic contour patterns were statistically

non-significant. In Paul Chambers's bass line reductions, 3 out of the 6 measurements indicated a statistically non-significant and weak negative correlation between tempo and the variability of melodic contour patterns, whereas the other measurements indicated a statistically non-significant and negligible correlation between the variables. The mean absolute tau-b was .09 (range: .001 to .21,  $SD = 0.08$ ), which indicates a negligible correlation between tempo and the variability of melodic contour patterns. Regarding the relationship between harmonic rhythm and the variability of melodic contour patterns, all measurements indicated a statistically non-significant and negligible correlation between the variables. The mean absolute tau-b was .03 (range: .01 to .06,  $SD = 0.02$ ).

In Ron Carter's bass line reductions, 3 out of the 6 measurements indicated a statistically non-significant and negative correlation between tempo and the variability of melodic contour patterns, 2 out of the 6 measurements indicated a statistically non-significant and negligible correlation between the variables, and 1 out of the 6 measurements indicated a statistically non-significant and weak positive correlation between the variables. The mean absolute tau-b was .25 (range: .02 to .58,  $SD = 0.23$ ), which indicates a weak correlation between the variables. However, since only 3 out of the 6 measurements indicated the same effect direction, the results did not allow to make conclusions on the direction of the effect. In regard to the relationship between harmonic rhythm and the variability of melodic contour patterns, 3 out of the 6 measurements indicated a statistically non-significant and weak negative correlation between the variables, 1 out of the 6 measurements indicated a statistically non-significant and weak positive correlation between the variables, and 2 out of the 6 measurements indicated a statistically non-significant and negligible correlation between the variables. The mean absolute tau-b was .13 (range: .04 to .26,  $SD = 0.07$ ), which indicates a weak correlation between the variables. However, the results did not allow to make conclusions on the direction of the effect since only half of the measurements indicated the same effect direction. For raw data used in these tests, see Table 30 in Appendix 5.

### 6.3.3 Average length of recurring melodic contour patterns

In Paul Chambers's bass line reductions ( $n = 30$ ), the average length of recurring fuzzy interval patterns (in intervals) was 6.84 (range: 3.79 to 19.2,  $SD = 3.29$ ). The average length of recurring fuzzy interval patterns (in seconds) was 2.08 (range: 1.06 to 4.48,  $SD = 0.91$ ). The average maximum length of recurring fuzzy interval patterns (in intervals) was 29.6 (range: 13 to 84,  $SD = 14.8$ ). The average maximum length of recurring fuzzy interval patterns (in seconds) was 9.02 (range: 4.03 to 19.6,  $SD = 4.00$ ). The average length of recurring Parsons's code patterns (in intervals) was 8.44 (range: 5.57 to 18.8,  $SD = 2.84$ ). The average length of recurring Parsons's code patterns (in seconds) was 2.60 (range: 1.32 to 4.85,  $SD = 0.89$ ). The average maximum length of recurring Parsons's code patterns (in intervals) was 34.7 (range: 15 to 85,  $SD = 15.2$ ). The average maximum length of recurring Parsons's code patterns (in seconds) was 10.6 (range: 4.86 to 19.8,  $SD = 4.31$ ).

In Ron Carter's bass line reductions ( $n = 12$ ), the average length of recurring fuzzy interval patterns (in intervals) was 5.44 (range: 2.36 to 11.0,  $SD = 3.08$ ). The average length of recurring fuzzy interval patterns (in seconds) was 1.94 (range: 0.62 to 4.94,  $SD = 1.38$ ). The average maximum length of recurring fuzzy interval patterns (in intervals) was 26.5 (range: 7 to 63,  $SD = 18.2$ ). The average maximum length of recurring fuzzy interval patterns (in seconds) was 9.57 (range: 2.01 to 28.4,  $SD = 8.07$ ). The average length of recurring Parsons's code patterns (in intervals) was 6.86 (range: 5.19 to 11.3,  $SD = 2.07$ ). The average length of recurring Parsons's code patterns (in seconds) was 2.38 (range: 1.07 to 5.10,  $SD = 1.17$ ). The average maximum length of recurring Parsons's code patterns (in intervals) was 31.3 (range: 15 to 71,  $SD = 17.5$ ). The average maximum length of recurring Parsons's code patterns (in seconds) was 11.1 (range: 3.02 to 32.0,  $SD = 8.10$ ).

A Kendall's tau correlation analysis with Bonferroni correction was performed to determine the relationship between tempo and the average or maximum length of recurring melodic contour patterns and between harmonic rhythm and the average or maximum length of recurring melodic contour patterns. After Bonferroni correction, the alpha level for statistical significance was adjusted to .006 (.05/8). The results are presented in Tables 14 and 15.

TABLE 14 Correlations between tempo and average/maximum length of recurring melodic contour patterns

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.4% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.4% CI (bootstrapped) (Carter)
Average length of recurring fuzzy interval patterns (in intervals)	$\tau_b = .22$ $p = .08$ <b><math>\tau_b = .20</math></b> <b><math>p = .13</math></b>	[-.14, .55]  <b>[-.14, .52]</b>	$\tau_b = -.12$ $p = .64$ <b><math>\tau_b = -.13</math></b> <b><math>p = .58</math></b>	[-.87, .64]  <b>[-.79, .68]</b>
Average length of recurring fuzzy interval patterns (in seconds)	$\tau_b = -.16$ $p = .22$ <b><math>\tau_b = -.20</math></b> <b><math>p = .14</math></b>	[-.56, .28]  <b>[-.52, .16]</b>	$\tau_b = -.52$ $p = .02$ <b><math>\tau_b = -.47</math></b> <b><math>p = .05</math></b>	[-1, .18]  <b>[-.93, .29]</b>
Maximum length of fuzzy interval patterns (in intervals)	$\tau_b = .22$ $p = .09$ <b><math>\tau_b = .19</math></b> <b><math>p = .15</math></b>	[-.14, .52]  <b>[-.16, .54]</b>	$\tau_b = -.18$ $p = .46$ <b><math>\tau_b = -.19</math></b> <b><math>p = .41</math></b>	[-.90, .61]  <b>[-.83, .55]</b>
Maximum length of fuzzy interval patterns (in seconds)	$\tau_b = -.16$ $p = .22$ <b><math>\tau_b = -.21</math></b> <b><math>p = .12</math></b>	[-.55, .23]  <b>[-.53, .18]</b>	$\tau_b = -.42$ $p = .06$ <b><math>\tau_b = -.39</math></b> <b><math>p = .09</math></b>	[-.96, .19]  <b>[-.92, .32]</b>

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.4% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.4% CI (bootstrapped) (Carter)
Average length of recurring Parsons's code patterns (in intervals)	$r_b = .22$ $p = .08$ <b><math>r_b = .20</math></b> <b><math>p = .13</math></b>	$[-.14, .58]$  <b><math>[-.16, .52]</math></b>	$r_b = -.09$ $p = .74$ <b><math>r_b = -.11</math></b> <b><math>p = .65</math></b>	$[-.67, .61]$  <b><math>[-.72, .60]</math></b>
Average length of recurring Parsons's code patterns (in seconds)	$r_b = -.33$ $p = .01$ <b><math>r_b = -.36^*</math></b> <b><math>p = .006</math></b>	$[-.69, .08]$  <b><math>[-.69, .05]</math></b>	$r_b = -.64^*$ $p = .003$ <b><math>r_b = -.58</math></b> <b><math>p = .01</math></b>	$[-1, -.04]$  <b><math>[-.96, .11]</math></b>
Maximum length of recurring Parsons's code patterns (in intervals)	$r_b = .22$ $p = .10$ <b><math>r_b = .19</math></b> <b><math>p = .15</math></b>	$[-.17, .54]$  <b><math>[-.17, .51]</math></b>	$r_b = -.15$ $p = .49$ <b><math>r_b = -.17</math></b> <b><math>p = .46</math></b>	$[-.83, .62]$  <b><math>[-.75, .46]</math></b>
Maximum length of recurring Parsons's code patterns (in seconds)	$r_b = -.16$ $p = .22$ <b><math>r_b = -.21</math></b> <b><math>p = .11</math></b>	$[-.50, .26]$  <b><math>[-.58, .19]</math></b>	$r_b = -.52$ $p = .02$ <b><math>r_b = -.47</math></b> <b><math>p = .05</math></b>	$[-.96, .11]$  <b><math>[-.93, .30]</math></b>

*Note.* Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval.  
\* Correlation is statistically significant at the Bonferroni adjusted alpha level (.006) (2-tailed).

TABLE 15 Correlations between harmonic rhythm and average/maximum length of recurring melodic contour patterns

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.4% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.4% CI (bootstrapped) (Carter)
Average length of recurring fuzzy interval patterns (in intervals)	$\tau_b = -.07$ $p = .57$ <b><math>\tau_b = -.07</math></b> <b><math>p = .60</math></b>	$[-.36, .21]$ <b><math>[-.37, .21]</math></b>	$\tau_b = 0$ $p = 1$ <b><math>\tau_b = 0</math></b> <b><math>p = 1</math></b>	$[-.63, .72]$ <b><math>[-.64, .58]</math></b>
Average length of recurring fuzzy interval patterns (in seconds)	$\tau_b = .05$ $p = .68$ <b><math>\tau_b = .06</math></b> <b><math>p = .63</math></b>	$[-.29, .39]$ <b><math>[-.24, .38]</math></b>	$\tau_b = .03$ $p = .95$ <b><math>\tau_b = .09</math></b> <b><math>p = .69</math></b>	$[-.48, .59]$ <b><math>[-.53, .54]</math></b>
Maximum length of fuzzy interval patterns (in intervals)	$\tau_b = -.01$ $p = .96$ <b><math>\tau_b = .004</math></b> <b><math>p = .98</math></b>	$[-.32, .27]$ <b><math>[-.29, .29]</math></b>	$\tau_b = 0$ $p = 1$ <b><math>\tau_b = 0</math></b> <b><math>p = 1</math></b>	$[-.70, .71]$ <b><math>[-.69, .68]</math></b>
Maximum length of fuzzy interval patterns (in seconds)	$\tau_b = .08$ $p = .54$ <b><math>\tau_b = .09</math></b> <b><math>p = .48</math></b>	$[-.24, .37]$ <b><math>[-.20, .37]</math></b>	$\tau_b = 0$ $p = 1$ <b><math>\tau_b = .04</math></b> <b><math>p = .86</math></b>	$[-.65, .67]$ <b><math>[-.57, .60]</math></b>
Average length of recurring Parsons's code patterns (in intervals)	$\tau_b = 0$ $p = 1$ <b><math>\tau_b = .01</math></b> <b><math>p = .94</math></b>	$[-.32, .30]$ <b><math>[-.29, .31]</math></b>	$\tau_b = -.03$ $p = .95$ <b><math>\tau_b = -.04</math></b> <b><math>p = .87</math></b>	$[-.60, .68]$ <b><math>[-.60, .59]</math></b>
Average length of recurring Parsons's code patterns (in seconds)	$\tau_b = .18$ $p = .16$ <b><math>\tau_b = .19</math></b> <b><math>p = .14</math></b>	$[-.16, .59]$ <b><math>[-.15, .53]</math></b>	$\tau_b = -.03$ $p = .95$ <b><math>\tau_b = .06</math></b> <b><math>p = .80</math></b>	$[-.66, .59]$ <b><math>[-.53, .58]</math></b>
Maximum length of recurring Parsons's code patterns (in intervals)	$\tau_b = 0$ $p = 1$ <b><math>\tau_b = .01</math></b> <b><math>p = .93</math></b>	$[-.34, .33]$ <b><math>[-.36, .32]</math></b>	$\tau_b = .03$ $p = .89$ <b><math>\tau_b = .02</math></b> <b><math>p = .92</math></b>	$[-.64, .59]$ <b><math>[-.62, .63]</math></b>

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.4% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.4% CI (bootstrapped) (Carter)
Maximum length of recurring Parsons's code patterns (in seconds)	$\tau_b = .12$ $p = .35$ <b><math>\tau_b = .14</math></b> <b><math>p = .29</math></b>	$[-.18, .44]$  <b><math>[-.20, .47]</math></b>	$\tau_b = -.03$ $p = .95$ <b><math>\tau_b = .03</math></b> <b><math>p = .90</math></b>	$[-.56, .55]$  <b><math>[-.51, .55]</math></b>

*Note.* Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval.

When controlling for the length of analyzed bass line reductions, all correlations were statistically non-significant after Bonferroni correction except for the correlation between tempo and the average length of recurring Parsons's code patterns (in seconds) in Paul Chambers's bass line reductions. In Paul Chambers's bass line reductions, all measurements indicated a statistically non-significant and weak positive correlation between tempo and the average/maximum length of recurring melodic contour patterns (in intervals) (mean absolute tau-b = .20, range: .19 to .20,  $SD = 0.01$ ), whereas 1 out of the 4 measurements indicated a statistically significant and moderate negative correlation between tempo and the average length of recurring melodic contour patterns (in seconds) and the other measurements indicated a statistically non-significant and weak negative correlation between tempo and the average length of recurring melodic contour patterns (in seconds) (mean absolute tau-b = .25, range: .20 to .36,  $SD = 0.08$ ). Moreover, 3 out of the 4 measurements indicated a statistically non-significant and negligible correlation between harmonic rhythm and the average/maximum length of recurring melodic contour patterns (in intervals) (mean absolute tau-b = .08, range: .01 to .19,  $SD = 0.08$ ) and between harmonic rhythm and the average/maximum length of recurring melodic contour patterns (in seconds) (mean absolute tau-b = .06, range: .004 to .14,  $SD = 0.07$ ). In Ron Carter's bass line reductions, all measurements indicated a statistically non-significant and weak negative correlation between tempo and the average/maximum length of recurring melodic contour patterns (in intervals) (mean absolute tau-b = .15, range: .11 to .19,  $SD = 0.04$ ) and a statistically non-significant and moderate to strong negative correlation between tempo and the average/maximum length of recurring melodic contour patterns (in seconds) (mean absolute tau-b = .48, range: .39 to .58,  $SD = 0.08$ ). All measurements indicated a statistically non-significant and negligible correlation between harmonic rhythm and the average/maximum length of recurring melodic contour patterns (in intervals) (mean absolute tau-b = .05, range: 0 to .09,  $SD = 0.04$ ) and between harmonic rhythm and the average/maximum length of recurring melodic contour patterns (in seconds) (mean absolute tau-b = .02, range: 0 to .04,  $SD = 0.02$ ).

In summary, all measurements indicated a statistically non-significant and negative correlation between tempo and the average or maximum length of recurring melodic contour patterns (in seconds). In addition, most measurements indicated a statistically non-significant and negligible correlation between harmonic rhythm and the average or maximum length of recurring melodic contour patterns (both in intervals and in seconds) in both Paul Chambers's and Ron Carter's bass line reductions. Regarding the relationship between tempo and the average or maximum length of recurring melodic contour patterns (in intervals), the results were mixed. In Paul Chambers's bass line reductions, all measurements indicated a statistically non-significant and weak positive correlation between tempo and the average/maximum length of melodic contour patterns (in intervals). In contrast, all measurements in Ron Carter's bass line reductions indicated a statistically non-significant and weak negative correlation between tempo and the average/maximum length of melodic contour patterns (in intervals). For raw data used in these tests, see Table 31 in Appendix 5.

#### 6.3.4 Transfer of approach-note patterns

In Paul Chambers's bass line reductions ( $n = 30$ ), the average normalized entropy of 2-note approach-note patterns was 0.343 (range: 0.207 to 0.445,  $SD = 0.055$ ), and the average normalized entropy of 3-note approach-note patterns was 0.622 (range: 0.503 to 0.749,  $SD = 0.061$ ). The average relative frequency of non-recurring 2-note approach-note pattern classes was 28.3% (range: 8.33% to 62.5%,  $SD = 11.0$ ), the average relative frequency of non-recurring 2-note approach-note patterns was 2.03% (range: 0.26% to 4.30%,  $SD = 1.19$ ), the average relative frequency of non-recurring 3-note approach-note pattern classes was 45.9% (range: 32.1% to 69.4%,  $SD = 9.05$ ), and the average relative frequency of non-recurring 3-note approach-note patterns was 12.3% (range: 3.96% to 26.9%,  $SD = 5.85$ ).

In Ron Carter's bass line reductions ( $n = 12$ ), the average normalized entropy of 2-note approach-note patterns was 0.457 (range: 0.352 to 0.561,  $SD = 0.058$ ), and the average normalized entropy of 3-note approach-note patterns was 0.744 (range: 0.599 to 0.860,  $SD = 0.072$ ). The average relative frequency of non-recurring 2-note approach-note pattern classes was 30.0% (range: 11.8% to 47.8%,  $SD = 10.3$ ), the average relative frequency of non-recurring 2-note approach-note patterns was 3.84% (range: 1.29% to 10.9%,  $SD = 2.64$ ), the average relative frequency of non-recurring 3-note approach-note pattern classes was 62.9% (range: 48.0% to 76.6%,  $SD = 8.29$ ), and the average relative frequency of non-recurring 3-note approach-note patterns was 28.5% (range: 12.2% to 48.5%,  $SD = 10.7$ ).

A Kendall's tau correlation analysis with Bonferroni correction was performed to determine the relationship between tempo and the variability of approach-note patterns and between harmonic rhythm and the variability of approach-note patterns. After Bonferroni correction, the alpha level for statistical significance was adjusted to .008 (.05/6). The results are presented in Tables 16 and 17.



TABLE 16 Correlations between tempo and variability of approach-note patterns

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.2% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.2% CI (bootstrapped) (Carter)
Normalized entropy of 2-note approach-note patterns	$\tau_b = -.10$	[-.43, .21]	$\tau_b = -.45$	[-.93, .15]
	$p = .44$		$p = .04$	
	<b><math>\tau_b = -.06</math></b> <b><math>p = .65</math></b>	<b>[-.37, .32]</b>	<b><math>\tau_b = -.39</math></b> <b><math>p = .10</math></b>	<b>[-.92, .29]</b>
Normalized entropy of 3-note approach-note patterns	$\tau_b = -.11$	[-.42, .23]	$\tau_b = -.14$	[-.82, .64]
	$p = .41$		$p = .54$	
	<b><math>\tau_b = -.06</math></b> <b><math>p = .65</math></b>	<b>[-.33, .23]</b>	<b><math>\tau_b = .01</math></b> <b><math>p = .96</math></b>	<b>[-.66, .51]</b>
Relative frequency of non-recurring 2-note approach-note pattern classes	$\tau_b = .01$	[-.36, .43]	$\tau_b = -.41$	[-.84, .20]
	$p = .93$		$p = .06$	
	<b><math>\tau_b = .03</math></b> <b><math>p = .83</math></b>	<b>[-.33, .44]</b>	<b><math>\tau_b = -.32</math></b> <b><math>p = .17</math></b>	<b>[-.87, .32]</b>
Relative frequency of non-recurring 2-note approach-note patterns	$\tau_b = -.13$	[-.45, .19]	$\tau_b = -.61^*$	[-.93, -.02]
	$p = .32$		$p = .005$	
	<b><math>\tau_b = -.08</math></b> <b><math>p = .52</math></b>	<b>[-.38, .22]</b>	<b><math>\tau_b = -.54</math></b> <b><math>p = .02</math></b>	<b>[-.92, .18]</b>
Relative frequency of non-recurring 3-note approach-note pattern classes	$\tau_b = -.30$	[-.61, .06]	$\tau_b = -.42$	[-.89, .24]
	$p = .02$		$p = .06$	
	<b><math>\tau_b = -.27</math></b> <b><math>p = .04</math></b>	<b>[-.56, .09]</b>	<b><math>\tau_b = -.33</math></b> <b><math>p = .16</math></b>	<b>[-.82, .35]</b>
Relative frequency of non-recurring 3-note approach-note patterns	$\tau_b = -.21$	[-.50, .13]	$\tau_b = -.27$	[-.79, .38]
	$p = .10$		$p = .25$	
	<b><math>\tau_b = -.18</math></b> <b><math>p = .17</math></b>	<b>[-.47, .18]</b>	<b><math>\tau_b = -.14</math></b> <b><math>p = .54</math></b>	<b>[-.65, .44]</b>

Note. Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval. \* Correlation is statistically significant at the Bonferroni adjusted alpha level (.008) (2-tailed).

TABLE 17 Correlations between harmonic rhythm and variability of approach-note patterns

Method of measurement	Kendall's tau-b (sig. 2-tailed) (Chambers)	99.2% CI (bootstrapped) (Chambers)	Kendall's tau-b (sig. 2-tailed) (Carter)	99.2% CI (bootstrapped) (Carter)
Normalized entropy of 2-note approach-note patterns	$\tau_b = .12$ $p = .37$ <b><math>\tau_b = .12</math></b> <b><math>p = .38</math></b>	[-.21, .41] <b>[-.22, .43]</b>	$\tau_b = -.03$ $p = .95$ <b><math>\tau_b = .04</math></b> <b><math>p = .85</math></b>	[-.74, .67] <b>[-.59, .70]</b>
Normalized entropy of 3-note approach-note patterns	$\tau_b = -.06$ $p = .65$ <b><math>\tau_b = -.08</math></b> <b><math>p = .54</math></b>	[-.35, .35] <b>[-.37, .24]</b>	$\tau_b = -.29$ $p = .19$ <b><math>\tau_b = -.22</math></b> <b><math>p = .34</math></b>	[-.97, .45] <b>[-.92, .48]</b>
Relative frequency of non-recurring 2-note approach-note pattern classes	$\tau_b = -.19$ $p = .16$ <b><math>\tau_b = -.19</math></b> <b><math>p = .14</math></b>	[-.51, .16] <b>[-.51, .16]</b>	$\tau_b = -.32$ $p = .15$ <b><math>\tau_b = -.26</math></b> <b><math>p = .26</math></b>	[-.91, .38] <b>[-.86, .40]</b>
Relative frequency of non-recurring 2-note approach-note patterns	$\tau_b = -.03$ $p = .82$ <b><math>\tau_b = -.05</math></b> <b><math>p = .71</math></b>	[-.36, .30] <b>[-.38, .27]</b>	$\tau_b = -.18$ $p = .46$ <b><math>\tau_b = -.07</math></b> <b><math>p = .77</math></b>	[-.76, .49] <b>[-.65, .48]</b>
Relative frequency of non-recurring 3-note approach-note pattern classes	$\tau_b = .05$ $p = .71$ <b><math>\tau_b = .04</math></b> <b><math>p = .75</math></b>	[-.29, .40] <b>[-.28, .34]</b>	$\tau_b = 0$ $p = 1$ <b><math>\tau_b = .10</math></b> <b><math>p = .66</math></b>	[-.69, .66] <b>[-.54, .68]</b>
Relative frequency of non-recurring 3-note approach-note patterns	$\tau_b = .06$ $p = .64$ <b><math>\tau_b = -.05</math></b> <b><math>p = .68</math></b>	[-.26, .37] <b>[-.26, .32]</b>	$\tau_b = -.09$ $p = .74$ <b><math>\tau_b = .01</math></b> <b><math>p = .98</math></b>	[-.74, .56] <b>[-.66, .66]</b>

Note. Correlation coefficients from which the influence of the length of analyzed bass line reductions was removed are in bold. CI = confidence interval.

When controlling for the length of analyzed bass line reductions, all correlations were statistically non-significant. In Paul Chambers's bass line reductions, 4 out of the 6 measurements indicated a statistically non-significant and negligible correlation between tempo and the variability of approach-note patterns, whereas 2 out of the 6 measurements indicated a statistically non-significant and weak negative correlation between the variables. The mean absolute tau-b was .11 (range: .03 to .27,  $SD = 0.09$ ). Based on that most measurements indicated a

negligible correlation between the variables, the results did not allow to make conclusions on the direction of the effect in Paul Chambers's bass line reductions. Moreover, 4 out of the 6 measurements indicated a statistically non-significant and negligible correlation between harmonic rhythm and the variability of approach-note patterns, whereas one measurement indicated a statistically non-significant and weak positive correlation between the two variables, and one measurement indicated a statistically non-significant and weak negative correlation between the variables. The mean absolute tau-b was .09 (range: .04 to .19,  $SD = 0.06$ ). Based on the mean absolute tau-b and the high proportion of negligible correlations between harmonic rhythm and the variability of approach-note patterns, the results did not allow to make conclusions on the direction of the effect in Paul Chambers's bass line reductions.

In Ron Carter's bass line reductions, 5 out of the 6 measurements indicated a statistically non-significant and negative correlation between tempo and the variability of approach-note patterns, whereas 1 out of the 6 measurements indicated a statistically non-significant and negligible correlation between the variables. The mean absolute tau-b was .29 (range: .01 to .54,  $SD = 0.19$ ). Based on the mean absolute tau-b and the high consistency of effect directions, the results indicate a statistically non-significant and weak negative correlation between tempo and the variability of approach-note patterns. In regard to the relationship between harmonic rhythm and the variability of approach-note patterns, 2 out of the 6 measurements indicated a statistically non-significant and weak negative correlation between the two variables, 1 out of the 6 measurements indicated a statistically non-significant and weak positive correlation between the variables, and 3 out of the 6 measurements indicated a statistically non-significant and negligible correlation between the variables. The mean absolute tau-b was .12 (range: .01 to .26,  $SD = 0.10$ ). Based on that half of the measurements indicated negligible correlations, the results did not allow to make conclusions on the direction of the effect in Ron Carter's bass line reductions.

In summary, the results did not allow to make conclusions on the direction of the effect between tempo and the variability of approach-note patterns in Paul Chambers's bass line reductions. In Ron Carter's bass line reductions, the results indicated a statistically non-significant and weak negative correlation between tempo and the variability of approach-note patterns. The results did not allow to make conclusions on the direction of the effect between harmonic rhythm and the variability of approach-note patterns in Paul Chambers's or Ron Carter's bass line reductions. For raw data used in these tests, see Table 32 in Appendix 5.

Note that the average relative frequency of recurring 2-note approach-note patterns was 98.0% (range: 95.7% to 99.7%,  $SD = 1.19$ ) (in Paul Chambers's bass line reductions) and 96.2% (range: 89.1% to 98.7%,  $SD = 2.64$ ) (in Ron Carter's bass line reductions). In comparison, the average relative frequency of recurring 2-note interval patterns was 95.2% (range: 85.3% to 99.2%,  $SD = 3.28$ ) (in Paul Chambers's bass line reductions) and 93.7% (range: 89.8% to 99.0%,  $SD = 2.90$ ) (in Ron Carter's bass line reductions). These findings indicate that both Paul Chambers and Ron Carter used very short well-learned approach-note patterns

and melodic patterns to a great extent. The use of short pre-learned patterns may decrease cognitive resources required to generate novel melodic patterns, since their use decreases the number of novel elements when larger melodic patterns are generated. This might partly explain why expert jazz bassists are able to produce novel melodic patterns effortlessly in real time at any tempo.

### 6.3.5 The role of context familiarity on musical creativity

The role of context familiarity on musical creativity was assessed by calculating the mean difference between the normalized entropy of 4-note chordal pitch class patterns in musical works with familiar chord progressions and the normalized entropy of 4-note chordal pitch class patterns in musical works with original chord progressions. A chord progression was considered familiar if the musical work was well-known, it was written or co-written by Paul Chambers or Ron Carter, or it was based on either the blues chord progression or the *Rhythm Changes* chord progression.

In Paul Chambers's bass line reductions, the average normalized entropy of 4-note chordal pitch class patterns was 0.826 in musical works with familiar chord progressions ( $n = 18$ , range: 0.701 to 0.902,  $SD = 0.060$ ) and 0.753 in musical works with original chord progressions ( $n = 6$ , range: 0.612 to 0.835,  $SD = 0.079$ ). In Ron Carter's bass line reductions, the average normalized entropy of 4-note chordal pitch class patterns was 0.908 in musical works with familiar chord progressions ( $n = 3$ , range: 0.897 to 0.926,  $SD = 0.016$ ) and 0.902 in musical works with original chord progressions ( $n = 8$ , range: 0.743 to 0.985,  $SD = 0.074$ ). These results indicate that both Paul Chambers's and Ron Carter's bass line reductions were at least slightly less repetitive in musical works with familiar chord progressions. This finding is consistent with Goldman (2013), according to which jazz improvisations are less predictable in familiar compared to unfamiliar contexts<sup>116</sup>. However, it should be noted that the difference between the two normalized entropy values was very small in Ron Carter's bass line reductions, which indicates that familiarity with the chord progression had practically no effect on the creativity of the bass line reductions.

Obviously, there are several major limitations to this analysis. First, the number of musical works with familiar chord progressions in relation to the number of musical works with original chord progressions was not sufficiently balanced. Whereas 75% of Paul Chambers's bass line reductions (18 out of 24) were based on a familiar chord progression, 73% of Ron Carter's bass line reductions (8 out of 11) were based on original chord progressions<sup>117</sup>. As another

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116 In contrast, Norgaard et al. (2016) found that repeated interval and pitch class patterns were played at least slightly more often in a familiar compared to an unfamiliar key. There was a statistically significant effect for key only with pitch class patterns and a single-task condition.

117 The following compositions were considered to be based on original chord progressions: *Apothegm*, *Dolphin Dance*, *E.S.P.*, *Giant Steps*, *Loose Bloose*, *Milestones*, *Mo' Joe*, *Moment's Notice*, *Passion Dance*, *Pinocchio*, *Seven Steps to Heaven*, *So What*, *Syeeda's Song Flute*, and *Witch Hunt*. The following compositions were based on either the blues chord progression or the *Rhythm Changes* chord progression, or they were thought to

limitation, it was difficult to assess musicians' subjective familiarity with chord progressions. I found previous recordings by Paul Chambers or Ron Carter only for 9 musical works in the research material<sup>118</sup>. Moreover, the lack of available live set lists from the bands investigated in the present study made it difficult to assess the familiarity of several musical works. Only in a few cases, it was possible to conclude that a particular musical work was played regularly on gigs. *All of You* and *Autumn Leaves* were regularly played by the 1960's Miles Davis Quintet (featuring Ron Carter) based on that they are featured on several live albums (e.g., *Miles Davis in Europe* recorded in 1963, *Live at the 1963 Monterey Jazz Festival*, and *My Funny Valentine* recorded in 1964). According to Porter (1998, p. 103), *Woody'n You* and *Oleo* were regularly played by the 1950's Miles Davis Quintet (featuring Paul Chambers).

Based on these considerable limitations, the present findings offer (at most) preliminary understanding on the role of context familiarity in jazz improvisation. In order to provide a more reliable assessment of the relationship between musical creativity and the familiarity with the chord progression, further research could use experimental conditions and ask expert musicians to improvise on completely novel chord progressions and familiar chord progressions based on either the blues or the *Rhythm Changes* chord changes with different preparation times and different types of ensembles (ensembles where musicians have been playing together for a long time and ensembles where musicians have not played together before). However, it is noteworthy that since both Paul Chambers and Ron Carter recorded hundreds of albums (including hundreds of individual musical works only some of which were also recorded later) and toured

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be familiar to the bassist otherwise: *A Foggy Day*, *All of You*, *All The Things You Are*, *Autumn Leaves*, *Blues by Five*, *Blue Train*, *Chamber Mates*, *Chasin' the Bird*, *C-Jam Blues*, *Cool Struttin'*, *Cotton Tail*, *Crazy Rhythm*, *Freddie Freeloader*, *Mr. P.C.*, *Oleo*, *Tenor Madness*, *The Theme*, *Woody'n You*, and *You'd Be So Nice to Come Home to*. The following compositions were disregarded since I was not able to assess their familiarity to the bassist: *I Can't Give You Anything but Love*, *It's a Blue World*, *If I Were a Bell*, *Excerpt* (based on the chord progression for *I'll Remember April*), and *I Could Write a Book*.

- 118 In addition to the version analyzed here, *A Foggy Day* was also recorded live in June 1956. *All The Things You Are* was also recorded for Ernie Henry's *Last Chorus* (recorded in 1957), Johnny Griffin's *A Blowin' Session* (recorded in 1957), and Sonny Red's *Out of the Blue* (1959) (rejected from the album) several years earlier compared to the version that was released in Jimmy Heath Quintet's album *On the Trail* (1964). *Autumn Leaves* was also recorded for Ernie Henry's *Last Chorus* (1957), and it was recorded live in September 1960, October 1960, and April 1961. *Crazy Rhythm* was also recorded for Red Garland Trio's earlier album *Dig It!* Paul Chambers recorded several takes of *Giant Steps* (non of which were released on John Coltrane's album *Giant Steps*) about a month before the two recording sessions that consisted of the takes that appeared on the album. However, based on the complexity of this composition, *Giant Steps* was not categorized as a familiar musical work. *Oleo* was also recorded live in June 1956. *The Theme* was also recorded for Miles Davis's *Miles* (recorded in November 1955) and *Workin' with the Miles Davis Quintet* (recorded in May 1956), and it was also recorded live in February 1956. *Woody'n You* was also recorded live in February 1956. *You'd Be So Nice to Come Home to* was also recorded for Cannonball Adderley's *Julian "Cannonball" Adderley* (1955) and Art Pepper's *Art Pepper Meets the Rhythm Section* (1957). The search for previous recordings of the musical works analyzed in this study (including live recordings) was mainly carried out by using Rob Palmer's discography of Paul Chambers's recordings (R. Palmer, 2012) and Peter Losin's Miles Ahead database (Losin, 2021).

extensively during this period, it seems plausible that they could not have been able to do this if they did not have the ability to learn new musical works and new chord progressions quickly.

I also tested the usefulness of the following two conditions to investigate subjective familiarity with a chord progression. According to the first condition, a chord progression is familiar if the musical work is well-known to the public. As a second condition, a musical work is familiar to the bassist if he/she worked as the band leader at the recording session.<sup>119</sup> Both of these conditions turned out to be problematic. There are a huge number of popular musical works written in the first part of the 20th century. As a result, it is difficult to know which popular musical works were familiar to jazz musicians without knowing whether they had recorded those musical works before and without knowing whether they had played those musical works regularly on gigs. Since both Paul Chambers and Ron Carter recorded hundreds of albums during the 1950's and 1960's and played probably thousands of gigs during that time, they were probably familiar with a large repertoire of musical works. In addition, note that even if Paul Chambers or Ron Carter led the recording session, this does not necessarily mean that the musical works for that recording session were chosen by them.

It is likely that only a small proportion of the musical works analyzed in this study were completely unfamiliar to the bassist before the recording session. For example, the musical works recorded for John Coltrane's *Blue Train* were rehearsed before the recording session (Ratliff, 2007/2011, p. 65; Porter, 1998, p. 127). As a result, even if John Coltrane's *Moment's Notice* (from *Blue Train*) was based on an original and relatively unfamiliar chord progression, the musical work was not completely unfamiliar to Paul Chambers since it was rehearsed at least to some extent before the recording session. Similarly, the first recording session for John Coltrane's *Giant Steps* took place in March 1959, but none of these takes were included on the album (Porter, 1998, p. 153). Instead, John Coltrane went back to the studio in May 1959 with a different line-up except for Paul Chambers who played in both recording sessions (Porter, 1998, p. 154). Note that *Giant Steps* is widely considered to be an especially challenging chord progression and it is typically played at an extremely fast tempo. Therefore, it is likely that Paul Chambers was deliberately trying to create a strong harmonic background for the soloists to help them keep up with the structure of the musical work with the expense of a relatively repetitive bass line.

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119 In addition to preparation time and the familiarity with the chord progression, the longevity of the ensemble and the amount of experience playing with the other members of the ensemble also play a role in context familiarity. Legendary ensembles like the 1950's Miles Davis Quintet (with Miles Davis, John Coltrane, Red Garland, Paul Chambers, and Philly Joe Jones) and the 1960's Miles Davis Quintet (with Miles Davis, Wayne Shorter, Herbie Hancock, Ron Carter, and Tony Williams) are well-known for their extraordinary level of ensemble playing and because both ensembles worked together for several years. As an example of how longevity of the ensemble influences the music, consider Miles Davis's comment on Philly Joe Jones (who had started to play with Davis already in 1953), "see he knew everything I was going to do, everything I was going to play; he anticipated me, felt what I was thinking" (Kahn, 2018, p. 47). However, the longevity of the ensembles and the amount of experience playing with each other were not considered in the present study.

Also note that paid rehearsals were a common policy in Blue Note Records (the company that released John Coltrane's *Blue Train*) (Ratliff, 2007/2011, p. 65). On the contrary, Prestige Records (the company that released many of the recordings analyzed in the present study) used a different policy with little preparation and rushed recording sessions (Ratliff, 2007/2011, p. 55). At Prestige Records, musicians were encouraged to record as many compositions as possible at each recording session, to avoid complicated compositions that would require preparation and several takes, and to use only one take for the sake of spontaneity (Porter, 1998, p. 101).<sup>120</sup> For example, Miles Davis's 1956 Prestige recordings (including *Workin' with the Miles Davis Quintet*, *Relaxin' with the Miles Davis Quintet*, *Steamin' with the Miles Davis Quintet*, and *Cookin' with the Miles Davis Quintet*) were all recorded in only two days with one take for each musical work (Carr, 1999, pp. 98-99). However, note that the band had played together extensively by that time and the musical works recorded in these sessions consisted of "their well-rehearsed live set list" (Kahn, 2018, p. 71)<sup>121</sup>. As another example, Miles Davis's *So What* is considered a musical work with an original chord progression based on that modal jazz was a novelty in 1959. Yet, as recalled by Jimmy Cobb (who played drums on *Kind of Blue*), *So What* was played "once or twice on gigs" before the recording session (Kahn, 2018, p. 129). As an exception, many of the musical works recorded by the mid-1960's Miles Davis Quintet were probably learned in the studio. Their live set lists consisted of mainly jazz standards with only a few original compositions from their albums (Waters, 2011, pp. 6-7).

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120 As an example of another completely different recording policy, Miles Davis's early recordings for Columbia Records combined parts from different takes to produce the best result (Porter, 1998, p. 102; Kahn, 2018, p. 71).

121 According to Ratliff (2007/2011), however, most of the musical works recorded for these 1956 Prestige recordings were not part of the band's regular repertoire. Based on an interview with Ira Gitler, Ratliff claimed that Miles Davis and Bob Weinstock (the director of Prestige Records) quickly collected standards and film music as additional material to these sessions. (Ratliff, 2007/2011, p. 45.)

## 7 DISCUSSION

### 7.1 General discussion of main results

#### 7.1.1 Temporal constraints and musical creativity

Expert-level improvisation is characterized by risk-taking, an ability to surprise, and lack of redundancy (Wopereis et al., 2013). In fact, improvisation requires that each performance is different and is in contrast to the mere reproduction of existing performances (Sparti, 2016). This indicates that measuring creativity as the lack of repetition is consistent with common artistic goals of jazz musicians. However, the aim to avoid redundancy is not the only artistic goal among jazz musicians and the musical quality of jazz improvisations also depends, of course, on other qualities than just lack of repetition. Drawing attention solely to the lack of repetition disregards other types of musical creativity such as novel chord substitutions in Paul Chambers's bass line for *So What*, for example.

Only a few previous studies have investigated the relationship between temporal constraints and musical creativity in expert-level jazz improvisation. According to Lehmann and Goldhahn (2016), melodic patterns that occurred after longer pauses (0.5 seconds) were 1.35 times more likely to be non-redundant compared to melodic patterns which did not appear after a rest. In another study, Dean (2014) found that the use of well-learned finger patterns increased in fast passages. Both studies investigated jazz musicians of the same level as the current research, but these studies were based on very small sample sizes. Lehmann and Goldhahn studied eight solos by John Coltrane over the same chord progression (*Giant Steps*), whereas Dean studied four solos of Pat Metheny. In addition to these studies, Frieler (2014) investigated 204 solos by sixty jazz musicians and found that pattern use increased at fast tempos. Frieler also found that repeated patterns usually occurred in the same solo and not across different solos. In another study, pattern use was not found to increase with tempo (Frieler et al., 2018).



Although the latter two studies were based on large sample sizes, it is unclear whether and how inter-individual differences between the musicians influenced the results.

One of my main aims in this study was to investigate how tempo and harmonic rhythm are related to creativity in pattern use (as operationalized by the variability of melodic patterns) by using multiple measurements: normalized entropy of chordal pitch class patterns, normalized entropy of interval patterns, relative frequency of non-recurring chordal pitch class patterns (using two different calculation methods), relative frequency of non-recurring interval patterns (using two different calculation methods), and relative frequency of notes that started a recurring melodic pattern at any metrical location. All these measurements (except for the relative frequency of notes that started a recurring melodic pattern at any metrical location) were used with three different pattern lengths (2 notes, 3 notes, and 4 notes).

The present research was unable to find statistically significant correlations between tempo and the variability of melodic patterns in Paul Chambers's and Ron Carter's bass line reductions. In Paul Chambers's bass line reductions, 17 out of the 19 measurements indicated a statistically non-significant and weak negative correlation between tempo and the variability of melodic patterns. The mean absolute tau-b was .18, which indicates a weak correlation between the two variables. In Ron Carter's bass line reductions, only 10 out of the 19 measurements indicated the same effect direction. Therefore, the results did not allow to make conclusions on the direction of the effect. The mean absolute tau-b was .15, which indicates a weak correlation between tempo and the variability of melodic patterns. Although the present results were inconclusive, they provide preliminary evidence that tempo may have a small or negligible effect on creativity in pattern use in Paul Chambers's and Ron Carter's bass line reductions. In addition, the results from the analysis of Paul Chambers's bass line reductions provided preliminary support to previous research, according to which creativity in pattern use decreases with tempo (Lehmann & Goldhahn, 2016; Dean, 2014; Frieler, 2014; for contrasting results, see Frieler et al., 2018). However, the results from the analysis of Ron Carter's bass line reductions did not support these findings.

The research was also unable to find statistically significant correlations between harmonic rhythm and the variability of melodic patterns in both Paul Chambers's and Ron Carter's bass line reductions. In Paul Chambers's bass line reductions, most measurements (14 out of 19) indicated a statistically non-significant and negligible correlation between harmonic rhythm and the variability of melodic patterns. The mean absolute tau-b was .08, which also indicates a negligible correlation between the two variables. In Ron Carter's bass line reductions, only 10 out of the 19 measurements indicated the same effect direction, because of why the results did not allow to make conclusions on the direction of the effect. The mean absolute tau-b was .14, which indicates a weak correlation between the variables. Although the results were inconclusive, they provide preliminary evidence that harmonic rhythm may have a small or negligible effect on creativity in pattern use in Paul Chambers's and Ron Carter's bass line reductions. Also

note that when the average normalized entropy of 4-note chordal pitch class patterns was calculated separately in each harmonic rhythm category using a threshold level of at least thirty bars in a particular harmonic rhythm category, differences in the variability of melodic patterns were small between the harmonic rhythm categories.

Creativity in pattern use was generally lower in Paul Chambers's bass line reductions compared to Ron Carter's bass line reductions. One explanation for this could be Ron Carter's preference for upper structure chord notes (e.g., b9, #9, and #11) in some of his bass lines (Nurmi, 2018). Upper structure chord notes offer to take full advantage of the possibilities of the harmonic context and their use allows a much wider range of note choices compared to using mainly root notes, thirds, and fifths. Based on the present results, however, the differences between these two bassists in their use of upper structure chord notes and roots, thirds, and fifths were small. As an alternative explanation, it is possible that the higher proportion of familiar chord progressions in Paul Chambers's bass line reductions and the higher proportion of novel chord progressions in Ron Carter's bass line reductions contributes to the lower creativity scores in Paul Chambers's compared to Ron Carter's bass line reductions. In addition, it is possible that Ron Carter considered the lack of repetition as a more important goal compared to Paul Chambers.

Based on that the average level of creativity (at the level of pattern use) was higher in Ron Carter's bass line reductions compared to Paul Chambers's bass line reductions, Ron Carter relied on pre-learned melodic patterns to a lesser extent compared to Paul Chambers. Yet it should be noted that the present results indicated a statistically non-significant and positive correlation between tempo and the average length of melodic patterns (in intervals) in Paul Chambers's bass line reductions (a similar effect was not found in Ron Carter's bass line reductions). This finding indicates that Paul Chambers may have been able to circumvent challenges caused by increasing tempo by playing longer pre-learned melodic patterns at faster tempos.

Note that creativity was measured at the global level, that is, at the level of the entire bass line reduction. Such an approach disregards all differences that occur only in a particular harmonic rhythm, for instance. As an example, Paul Chambers's bass line reduction on *Freddie Freeloader* is exceptional in that fifths are used extensively as target notes, but only when harmonic rhythm is one chord change per bar. In this bass line reduction, the proportion of fifths that appeared as target notes in a one chord change per bar harmonic rhythm was 85.4%, which indicates a new way of building bass lines. In addition, the occurrence of root notes was exceptionally low in this bass line reduction (specifically in harmonic rhythm of one chord change per bar). In this harmonic rhythm, root notes accounted for only 2.08% of all target notes.

Interestingly, the relatively low level of creativity in Paul Chambers's bass line reduction on *So What* (probably the most famous example of bass lines in a modal jazz context) does not correspond with the common understanding that modal jazz is less constraining because of the slow harmonic rhythm. On the

contrary, based on the relatively low level of creativity in pattern use in this bass line reduction, the slow rate of chord changes seems to be an obstacle to the generation of novel ideas, not vice versa. However, based on that creativity in pattern use was close to average in the two other bass line reductions based on a modal song form (Paul Chambers's bass line reduction on *Milestones* and Ron Carter's bass line reduction on *Passion Dance*), and based on the small differences in the creativity of the bass line reductions at the level of pattern use between different harmonic rhythm categories in regard to both Paul Chambers's and Ron Carter's bass line reductions, the overall results do not support the claim that slow harmonic rhythm is related to decreased level of creativity in pattern use, at least in regard to Paul Chambers's and Ron Carter's bass line reductions.

### 7.1.2 Transfer of learning in jazz improvisation

The present study also investigated transfer of learning among eminent jazz musicians. Transfer of learning refers to the ability to use acquired knowledge in different situations and when learning new skills and knowledge (Haskell, 2001, p. xiii). For instance, when a novel task is carried out with ease, it can be assumed that there is positive transfer of knowledge between the two tasks (C. Palmer, 2012).

Several studies have paid attention to the fact that jazz musicians tend to reuse the same melodic patterns in their solos at least to some extent (Owens, 1974; Berliner, 1994; Weisberg et al., 2004; Norgaard, 2014; Norgaard & Römer, 2022). For instance, Weisberg et al. (2004) found 3,395 interval patterns that occurred at least twice in six solos by Charlie Parker. Moreover, the average proportion of notes captured by recurring 4-interval melodic patterns was 90% in these six solos. Norgaard (2014) found that 99.3% of notes in a sample of 48 solos by Charlie Parker were part of some recurring interval pattern with at least three intervals. In contrast to these studies, Owens (1974) (in his extensive study of about 250 Charlie Parker solos) found only 97 recurring melodic patterns (or motives, as he called them) that formed 64 pattern categories. Approximately one quarter (17/64) of these pattern categories accounted for most of all recurring patterns.

According to the present results, a relatively small proportion of recurring melodic pattern classes were repeated two or more times in at least two bass line reductions. For example, 16.8% of all recurring 4-note melodic pattern classes occurred at least twice in two or more bass line reductions by Paul Chambers and 11.2% of all recurring 4-note melodic pattern classes occurred at least twice in two or more bass line reductions by Ron Carter. The proportion of recurring melodic pattern classes that occurred at least twice in at least two bass line reductions by the same musician was small even when the length of analyzed melodic patterns was only two notes. In Paul Chambers's bass line reductions, 15.8% of all recurring 2-note melodic pattern classes occurred at least twice in two or more bass line reductions. In Ron Carter's bass line reductions, 19.4% of all recurring 2-note melodic pattern classes occurred at least twice in two or more bass line reductions. In other words, 84.2% of all recurring 2-note melodic pattern classes

occurred at least twice in only one bass line reduction (although it is possible that some of these melodic pattern classes occurred once in these other bass line reductions). Similarly, 80.6% of all recurring 2-note melodic pattern classes were not repeated across different bass line reductions by Ron Carter.

The present finding that only a small proportion of recurring melodic pattern classes were repeated two or more times in two or more bass line reductions by the same musician suggests that learning a large storage of melodic patterns does not play a central role in Paul Chambers's and Ron Carter's bass line reductions. In line with this result, Frieler (2014) found that repeated patterns usually occurred in the same solo and not across different solos. The present result is also consistent with Johnson-Laird (2002), who de-emphasized the importance of acquiring a large storage of well-learned melodic patterns in jazz improvisation. In another paper, Johnson-Laird also argued that only a complete beginner, if anyone, uses well-learned melodic patterns all the time and continued that "it is easier [...] to make up new melodies than to remember a vast array of motifs and to modify them to fit the chord sequence" (Johnson-Laird, 1988, p. 211). For this part, the present findings contradict with Pressing (1988, 1998), Weisberg et al. (2004), and Norgaard (2014), who emphasized the role of well-learned melodic patterns in jazz improvisation or improvised music in general. Even if pre-learned melodic patterns may contribute to increased creativity in jazz improvisation, their use seems to explain only a part of the creativity of expert-level jazz musicians.

Also note that the number of pre-learned melodic patterns among eminent jazz bassists might not be even close to estimated vocabulary sizes of average native speakers. For instance, Brysbaert et al. (2016) estimated that native speakers of American English know about 42,000 lemmas (uninflected words) on average or about 11,100 word families on average at the age of 20. In addition, these authors estimated that average native speakers have acquired a vocabulary of about 48,200 lemmas or about 13,400 word families by the age of 60.<sup>122</sup> In comparison, the total number of melodic pattern classes that occurred at least twice in one or more bass line reductions ranged from 996 to 1,122 (depending on pattern length) in Paul Chambers's bass line reductions and from 294 to 428 (depending on pattern length) in Ron Carter's bass line reductions. Using a tighter threshold level for the number of pre-learned melodic patterns, the total number of melodic pattern classes that occurred at least twice in two or more bass line reductions ranged from 157 to 188 (depending on pattern length) in Paul Chambers's bass line reductions and from 33 to 83 (depending on pattern length) in Ron Carter's bass line reductions. The large differences between the estimated vocabulary size in language use and the total number of melodic pattern classes that occurred at least twice in one or more bass line reductions (or at least twice in two or more bass line reductions) indicate that there may be little or no

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122 Brysbaert et al. (2016) estimated vocabulary size based on how many words people understood (receptive knowledge) instead of how many words they used themselves (productive knowledge). According to these authors, productive knowledge of words is less than half of the receptive knowledge of words. In addition, note that the number of word families indicates the number of building blocks from which lemmas come from (Brysbaert et al., 2016, p. 8).

similarities between language and jazz improvisation in terms of vocabulary use even if the number of pre-learned melodic patterns in Paul Chambers's or Ron Carter's bass line reductions is probably underestimated because of small sample sizes.

Based on previous research, there seems to be considerable differences in the use of pre-learned melodic patterns among expert jazz musicians. According to Norgaard and Römer (2022, p. 19), for example, the relative frequency of notes that started a recurring 4-interval interval pattern at any metrical location was 62.0% (in Michael Brecker's solos), 41.6% (in Steve Coleman's solos), 63.4% (in John Coltrane's solos), 60.3% (in Miles Davis's solos), 51.2% (in David Liebman's solos), 55.8% (in Charlie Parker's solos), 48.8% (in Sonny Rollins's solos), and 46.4% (in Wayne Shorter's solos). In comparison, the average relative frequency of notes that started a recurring 4-note interval pattern at any metrical location was 76.0% in Paul Chambers's bass line reductions and 54.4% in Ron Carter's bass line reductions. However, it should be noted that Norgaard and Römer (2022) did not exclude very small differences between interval patterns. In addition, Norgaard and Römer calculated the relative frequency of notes that started a recurring 4-interval pattern at any metrical location in a corpus, whereas I calculated the relative frequency of notes that started a recurring 4-note (i.e., 3-interval) pattern at any metrical location separately for each musical work and reported the average of these relative frequency values. As a result, the results are not fully comparable.

### 7.1.3 Methodological findings

Recent studies on the rate of repetition in jazz improvisation have disregarded harmonic context and have solely focused on interval patterns. However, it has been unclear how this decision may have influenced the results. Based on the present results, the normalized entropy of melodic patterns and the relative frequency of non-recurring melodic patterns (regardless of which one of the two calculation methods was used) were almost always lower when individual notes were encoded in relation to the current chord compared to when harmonic context was disregarded. However, differences between these values were very small with 4-note melodic patterns. For example, the maximum difference between the normalized entropy of 4-note chordal pitch class patterns (where harmonic context is taken into account) and the normalized entropy of 4-note interval patterns (where harmonic context is disregarded) was 0.053 ( $M = 0.018$ ,  $SD = 0.014$ ) (in Paul Chambers's bass line reductions) and 0.046 ( $M = 0.022$ ,  $SD = 0.015$ ) (in Ron Carter's bass line reductions). Based on these very small differences, further studies could benefit from ignoring harmonic context to avoid problems with the identification of the chord progression as long as the length of analyzed melodic patterns is at least 4 notes. The correct identification of harmonic context is often not a simple task, and it is also unclear whether harmonic context should be identified based on the combined note choices of all musicians or only based on the chords played by the pianist or the guitar player. In addition, photographs of lead sheets are rarely available from recording sessions. As a result, it is often

difficult to know the exact chord progressions to which musicians were improvising in recording sessions.

'Melodic chunk' (which refers to information that is composed of smaller subsets and retrieved from memory as a single unit) is an important concept in the study of repetition of melodic patterns. In the present study, I assumed that the more frequently repeated and the longer the melodic pattern in question, the more plausible it is that the melodic pattern was retrieved from memory as a single unit (i.e., as a melodic chunk) during a performance of music. However, previous studies have paid little attention to this issue. In the case of low threshold levels (e.g., two occurrences in a particular musical work), it is always possible that at least some melodic patterns were repeated by chance instead of being retrieved from memory as a melodic chunk. Except for Norgaard (2014), previous studies have also paid little attention to overlapping melodic patterns. However, the present results indicated that the average length of recurring melodic patterns, when all 42 bass line reductions were combined, was only 0.31 intervals (0.12 seconds) smaller after the third step of the overlapping melodic patterns removal process compared to the average length of recurring melodic patterns after the first step of the removal process.

Finally, the present study used walking bass lines to circumvent methodological difficulties related to segmentation. Walking bass lines provide ideal research data regarding segmentation since they (in contrast to solos) usually do not afford conflicting grouping structures. An analysis of grouping structure was presumed to be an important, if not a necessary requirement of accurate measurement of how much jazz musicians repeat the same melodic patterns in their improvisations. According to the present results, the absolute number of notes that started a recurring interval pattern was always higher when the identification of segment boundaries was neglected. This finding indicates that the decision to neglect the segmentation process may overestimate the absolute number of recurring melodic patterns in jazz improvisation. In addition, the relative frequency of notes that started a recurring interval pattern at any metrical location was usually higher compared to the relative frequency of recurring interval patterns when all patterns were required to have a specific starting and ending point. For example, whereas the relative frequency of notes that started a recurring 4-note interval pattern at any metrical location was 62.6% in the reduced version of Paul Chambers's bass line on *I Can't Give You Anything but Love*, the relative frequency of recurring interval patterns that started at the first beat of the bar was 37.9% in the reduced version of this bass line. However, it is noteworthy that the rank orders of the observation pairs were quite similar when the same data was analyzed by the relative frequency of notes that started a recurring interval pattern at any metrical location (in which case the identification of segment boundaries was neglected) or the relative frequency of interval patterns that started at the first beat of the bar (in which case segment boundaries were identified). This finding indicates that even if calculating the relative frequency of notes that started a recurring interval pattern at any metrical location may produce

inaccurate results in terms of the absolute frequency of recurring interval patterns, the results may still be fairly accurate in terms of the rank orders.

## 7.2 Implications of the study

### 7.2.1 Chunking in motor sequence production

The emergence of motor chunks (action sequences that are encoded and recalled as single units) is often used to explain improvements in performance in various tasks. As an example, classic chunking theory predicts that the number and size of chunks increase with skill level (Chase & Simon, 1973). In the present study, I investigated whether expert jazz bassists rely heavily on pre-learned chunks as indicated by the relative frequency of recurring melodic patterns (which were assumed to be pre-learned) and whether the size of chunks increases with tempo as indicated by a positive correlation between tempo and the average length of melodic patterns (in intervals) and between tempo and the maximum length of recurring melodic patterns (in intervals).

According to the present results, the average relative frequency of recurring 4-note chordal pitch class patterns was 33.4% (range: 14.1% to 52.9%,  $SD = 10.0$ ) and they covered, on average, 17.9% (range: 10.8% to 61.0%,  $SD = 8.54$ ) of all occurrences of chordal pitch class patterns in Paul Chambers's bass line reductions. In Ron Carter's bass line reductions, the average relative frequency of recurring 4-note chordal pitch class patterns was 15.6% (range: 4.04% to 24.6%,  $SD = 6.52$ ) and they covered, on average, 11.4% (range: 7.59% to 15.3%,  $SD = 2.84$ ) of all occurrences of chordal pitch class patterns. In comparison, the average relative frequency of recurring 4-note interval patterns was 36.1% (range: 18.1% to 54.7%,  $SD = 9.49$ ) and they covered, on average, 67.1% (range: 37.9% to 90.4%,  $SD = 12.9$ ) of all occurrences of interval patterns in Paul Chambers's bass line reductions. In Ron Carter's bass line reductions, the average relative frequency of recurring 4-note interval patterns was 18.9% (range: 8.99% to 31.3%,  $SD = 6.81$ ) and they covered, on average, 43.3% (range: 22.1% to 61.8%,  $SD = 12.9$ ) of all occurrences of interval patterns.

In contrast to the above-mentioned predictions, neither bassist relied heavily on pre-learned melodic patterns as indicated by the relative frequency of recurring melodic patterns (at least when the relative frequency of chordal pitch class patterns was calculated instead of the relative frequency of interval patterns). However, the present findings do not contradict with the assumption that probably all expert jazz musicians rely on pre-learned melodic patterns at least to some extent. Whenever pre-learned melodic patterns are used, musicians must be able to quickly search for melodic patterns that are appropriate in the present context. Most likely, this search process occurs automatically.

When controlling for the length of analyzed bass line reductions, the results indicated a statistically non-significant and weak positive correlation between tempo and the average length of recurring melodic patterns (in intervals) and

between tempo and the maximum length of recurring melodic patterns (in intervals) in Paul Chambers's bass line reductions. In contrast, the results indicated a statistically non-significant and negligible correlation between tempo and the average length of recurring melodic patterns (in intervals) and a statistically non-significant and weak negative correlation between tempo and the maximum length of recurring melodic patterns (in intervals) in Ron Carter's bass line reductions. According to these findings, Paul Chambers may have relied on larger chunks at faster tempos to compensate increasing time pressures. However, as indicated by contrasting results in Ron Carter's bass line reductions, this might not be a necessary strategy to cope with fast tempos.<sup>123</sup>

Further research could investigate whether expert jazz musicians are able to update their action plans at very short timescales. If execution of actions can be rapidly interrupted and replaced by new action goals, this could (at least partly) explain why expert jazz musicians do not need to rely heavily on pre-learned melodic patterns in order to improvise fluently. According to Goldman (2019), improvising musicians are constantly guided by feedback of their own playing and their co-performers' playing and this continuous feedback allows them "to change course fluently [...] in response to a new idea of their own or that of a fellow performer" (Goldman, 2019, p. 284). Further research is needed to clarify the relationship between sensory feedback and decision-making in jazz improvisation. However, it is likely that it is not only continuous feedback which allows improvising musicians to make quick changes to their actions plans, but also their ability to make quick responses to feedback may contribute<sup>124</sup>.

To acquire more knowledge about whether and how expert jazz musicians can make quick changes to their action plans, further research could also investigate whether expert jazz musicians' superior motor dexterity is related to a capacity to switch rapidly to new action goals at fast tempos. Increased motor dexterity among expert jazz musicians might not only allow them to play effortlessly at extreme tempos, but it might also help jazz musicians to make fluent changes to their action goals even at a very fast tempo.

## 7.2.2 Action planning in expert jazz improvisation

According to Pachet (2012), expert jazz musicians' ability to perform effortlessly even at virtuoso tempos can be explained by that they delegate the choice of

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123 It is possible that an increased length of repeated melodic patterns at fast tempos is related to mental slowing. The following statement by saxophonist David Liebman is interesting in this regard: "while one may feel the second and fourth beat in each bar at a normal tempo, it helps to place four bars together as a unit with only one downbeat when the bars are moving quickly. Large groupings of units give the player a wider space to think in. This mental slowing down of the pace can help the musical flow." (Liebman, 1996, pp. 39-40.)

124 According to a recent study, musicians have shorter simple reaction times for auditory and tactile stimuli compared to non-musicians (Landry & Champoux, 2017), which indicates that musicians may be able to use feedback to guide their choices more fluently compared to non-musicians. In addition, it is likely that expert jazz improvisers' ability to use feedback of their own playing and their co-performers' playing is better compared to novice jazz improvisers.



individual notes to subconscious levels of processing and allocate their attention to higher-level properties of music (e.g., melodic contour, chromaticity, tonality). Based on this claim, I investigated whether the generation of novel melodic patterns at any tempo might be facilitated using well-learned approach-note patterns and melodic contour patterns.

The results showed that the average relative frequency of recurring 2-note approach-note patterns (i.e., melodic patterns that consist of the last note of the bar and the first note of the next bar) was very high (98.0% in Paul Chambers's bass line reductions and 96.2% in Ron Carter's bass line reductions). Thus, recurring approach-note patterns covered a very large proportion of all 2-note approach-note patterns in these bass line reductions. In comparison, the average relative frequency of recurring 3-note approach-note patterns was substantially lower (87.7% in Paul Chambers's bass line reductions and 71.5% in Ron Carter's bass line reductions). This finding may partly explain why expert jazz bassists are able to produce novel melodic patterns effortlessly in real time and regardless of tempo. An extensive use of pre-learned approach-note patterns may decrease cognitive resources required in the generation of novel melodic patterns by decreasing the number of elements to be selected. In addition, the use of pre-learned approach-note patterns may give additional time to prepare upcoming note choices.

According to previous research, expert musicians allocate their attention to higher levels of music and allow automatic processes to operate at the note-to-note level (Pressing, 1988; Ramalho et al., 1999; Chaffin et al., 2006; Berkowitz, 2010). This claim is consistent with Fidlon (2011) and Norgaard (2011), according to which action planning among experienced jazz musicians is directed to abstract sketches and architectural features of music (e.g., note density, register) in contrast to the surface level of music. In other words, the cognitive control of note choices may be (at least at very fast tempos) limited to higher-level musical parameters (like melodic contour), whereas lower-level decisions like individual note choices may be subject to automatic processing in expert jazz improvisation. In addition, higher-level action planning (e.g., planning at the level of melodic contour) may also function as a constraint for automatic generation of melodic patterns. According to the present results, the relative frequency of non-recurring melodic contour patterns was low in terms of both fuzzy interval patterns and Parsons's code patterns. In Paul Chambers's bass line reductions, the relative frequency of non-recurring fuzzy interval patterns was 17.4% (range: 6.31% to 35.8%,  $SD = 7.59$ ) and the relative frequency of non-recurring Parsons's code patterns was 0.78% (range: 0% to 2.65%,  $SD = 0.63$ ). In Ron Carter's bass line reductions, the relative frequency of non-recurring fuzzy interval patterns was 31.9% (range: 20.5% to 61.5%,  $SD = 11.5$ ) and the relative frequency of non-recurring Parsons's code patterns was 2.00% (range: 0.45% to 3.36%,  $SD = 0.96$ ). Based on the low proportion of non-recurring melodic contour patterns, these findings indicate that expert jazz bassists' note choices may be based on a limited set of melodic contour patterns. However, it should be noted that the present results only show that if expert jazz bassists' cognitive control of note choices were directed to

melodic contour instead of individual notes, their decisions would be based on a limited set of melodic contour patterns.

Interestingly, the average length of melodic patterns was within the usual average integration interval (or usual estimated duration of the psychological present) in Paul Chambers's bass line reductions, but not in Ron Carter's bass line reductions. According to earlier studies, an automatic integration process (which binds successive events into units) may play a role in both perception and action (Pöppel, 1997; Wittmann & Pöppel, 1999). Based on these studies, the maximum duration of integrated units is about three seconds (Szeląg et al., 1996; Pöppel, 1997) or five seconds (Fraisse, 1984), whereas the minimum duration of integrated units is about one second (Szeląg et al., 1996). In the present study, the duration of integrated units was measured as the average length of recurring melodic patterns in seconds. In Paul Chambers's bass line reductions, the average length of recurring melodic patterns was 2.00 seconds (range: 1.06 to 3.93,  $SD = 0.74$ ), whereas the average length of recurring melodic patterns in Ron Carter's bass line reductions was 1.29 seconds (range: 0.68 to 2.58,  $SD = 0.57$ ). However, the average length of melodic patterns was at least two seconds in only 11 out of the 30 bass line reductions by Paul Chambers and only 2 out of the 12 bass line reductions by Ron Carter. The average length of melodic patterns was more than three seconds in three Paul Chambers's bass line reductions, whereas the average length of melodic patterns was always less than 3 seconds in Ron Carter's bass line reductions. The highest average length of recurring melodic patterns was 3.93 seconds (in Paul Chambers's bass line reduction on *Autumn Leaves*). Even if the average length of recurring melodic patterns was often smaller than the usual 2–3 seconds, the average length of these recurring melodic patterns was still within the temporal limits of chunk perception (Godøy et al., 2010; Godøy, 2014).

According to Szeląg et al. (1996), the duration of integrated units decreased as the metronome frequency (the number of events per second) increased. In comparison, previous research on sight-reading indicates that the distance (in seconds) between the fixated note on a musical score and the currently played note is reduced at fast tempos (Furneaux & Land, 1999). Although the present results were statistically non-significant, it is noteworthy that they indicated a negative correlation between tempo and the average length of melodic patterns (in seconds) in both Paul Chambers's bass line reductions and Ron Carter's bass line reductions, and a positive correlation between tempo and the average length of melodic patterns (in intervals) in Paul Chambers's bass line reductions (but not in Ron Carter's bass line reductions).

Compared to the average length of melodic patterns, the average length of fuzzy interval patterns and Parsons's code patterns in both Paul Chambers's bass line reductions and Ron Carter's bass line reductions were more similar to the previous findings on the average duration of integrated units, although the highest average length of fuzzy interval patterns and Parsons's code patterns exceeded the usual upper limit of integrated units (about 3 seconds). According to the present results, the average length of fuzzy interval patterns was 2.08 seconds (range: 1.06 to 4.48,  $SD = 0.91$ ) in Paul Chambers's bass line reductions and 1.94

seconds (range: 0.62 to 4.94,  $SD = 1.38$ ) in Ron Carter's bass line reductions. The average length of Parsons's code patterns was 2.60 seconds (range: 1.32 to 4.85,  $SD = 0.89$ ) in Paul Chambers's bass line reductions and 2.38 seconds (range: 1.07 to 5.10,  $SD = 1.17$ ) in Ron Carter's bass line reductions. In Paul Chambers's bass line reductions, the average length of fuzzy interval patterns was at least two seconds in 12 out of the 30 bass line reductions. The average length of Parsons's code patterns was at least two seconds in 21 out of the 30 bass line reductions. In Ron Carter's bass line reductions, the average length of fuzzy interval patterns was at least two seconds in 5 out of the 12 bass line reductions. The average length of Parsons's code patterns was at least two seconds in 7 out of the 12 bass line reductions. The average length of fuzzy interval patterns was more than three seconds in five Paul Chambers's bass line reductions and three Ron Carter's bass line reductions. The average length of Parsons's code patterns was more than three seconds in seven Paul Chambers's bass line reductions and three Ron Carter's bass line reductions.

Previous research on the range of planning has been based on identifying anticipatory and perseveratory errors to indicate the scope of simultaneously activated events in music performance (Palmer & van de Sande, 1995; Palmer & Pfordresher, 2003; Pfordresher et al., 2007). In case of improvised music, the identification of errors, however, is not an option since improvisations do not allow to verify whether the sounds played by musicians were intentional (i.e., not accidental) by comparing these sounds with those intended by the composer. To circumvent this problem, I assumed that the average length of recurring melodic patterns (i.e., the average length of recurring melodic chunks) could at least provide a rough estimate of the range of planning in improvised music. This assumption is based on that a melodic chunk is retrieved from memory as a single unit (however, it is not plausible that all notes of longer repeated melodic patterns would be simultaneously activated). Note that non-recurring melodic patterns were excluded from this analysis. The reason for this decision was that it is impossible to estimate the length of melodic patterns if they are not repeated.

The range model of planning (Palmer & Pfordresher, 2003; Pfordresher et al., 2007) predicts that the range of planning (in number of notes) decreases with tempo. The present results, however, indicated a statistically non-significant and weak positive correlation between tempo and the average length of recurring melodic patterns (in intervals) in Paul Chambers's bass line reductions and a statistically non-significant and negligible correlation between tempo and the average length of recurring melodic patterns (in intervals) in Ron Carter's bass line reductions. Interestingly, the present results also suggested that the range of planning might be larger in jazz improvisation compared to non-improvised music (or to be more precise, music that is less improvised). Whereas Pfordresher et al. (2007, p. 81) found a median range of planning of 2.95 notes, the average length of recurring melodic patterns was 6.52 intervals ( $Mdn$ : 5.42 intervals) in Paul Chambers's bass line reductions and 3.76 intervals ( $Mdn$ : 3.69 intervals) in Ron Carter's bass line reductions. In comparison, Norgaard (2014, p. 278) found that

the average length of melodic patterns was 7.3 intervals in a corpus of 48 solos by Charlie Parker.

### 7.2.3 Towards new theories and models of expert jazz improvisation

In contrast to underlying mechanisms common to all forms of creativity, recent progress in creativity research has identified partly different neural correlates between artistic and scientific creativity (Shi et al., 2017) and between musical and literary/artistic creativity (Chen et al., 2020). Therefore, there seems to be several ways of how humans can generate creative products, none of which can explain human creativity in all occurrences.

Previous research has proposed a number of sources of creativity, or more generally, sources of variability in behavior. These include, for example, random fluctuations at neural level (Faisal et al., 2008; Renart & Machens, 2014), motor variability (Dhawale et al., 2017; Orth et al., 2017), constraints (Torrents et al., 2020), emergence caused by interaction between collaborating musicians (Bishop, 2018; Sawyer & DeZutter, 2009), novel combinations of pre-existing knowledge (Mednick, 1962; Schubert, 2011, 2021), blind variation and selective retention (Campbell, 1960; Simonton, 2003), cognitive flexibility and cognitive persistence (Nijstad et al., 2010), and mind wandering (Palhares et al., 2022). In this chapter, several mechanisms underlying musical creativity in jazz improvisation are reviewed and their relation to the present results is discussed. The aim is to integrate isolated findings and contribute to cumulative knowledge on basic mechanisms of musical creativity, which could be used to develop new theories and models of expert jazz improvisation.

In his highly influential theory of jazz improvisation, Pressing (1988, 1998) emphasized the role of pre-learned musical materials in fluent improvisation. In contrast to this view, Johnson-Laird (2002) argued that decision-making in jazz improvisation is primarily based on rules rather than retrieving pre-learned patterns from memory. Johnson-Laird did not deny that jazz improvisers use pre-learned musical materials in their playing, but he claimed that only a complete beginner, if anyone, uses pre-learned patterns all the time (Johnson-Laird, 1988, p. 211). According to the present results, pre-learned melodic patterns and the acquisition of an extensive “vocabulary” of melodic patterns may have lesser significance on expert-level jazz improvisation compared to Pressing (1988, 1998), based on that creativity in pattern use (which indicates the rate of online creation of novel melodic patterns in contrast to retrieval of pre-learned melodic patterns from memory) was quite high in Paul Chambers’s bass line reductions and especially Ron Carter’s bass line reductions and that the proportion of melodic pattern classes that occurred at least twice in two or more bass line reductions was small in both Paul Chambers’s and Ron Carter’s bass line reductions. Consistent with Norgaard (2011), the present results suggest that both pre-learned patterns and abstract harmonic, rhythmic, and melodic knowledge play a role in expert-level jazz improvisation. Also note that repetition of melodic patterns occurred in all bass line reductions, which suggests that even eminent experts cannot

completely avoid repeating their well-learned melodic patterns<sup>125</sup>. Moreover, the present results suggest that expert jazz improvisers might be able to make quick changes to their action plans based on that the normalized entropy of melodic patterns increased and the proportion of recurring melodic patterns decreased with pattern length. As an alternative explanation, the variability of melodic patterns may increase with pattern length simply because increased pattern length allows a larger number of possible combinations.

Pressing (1988) claimed that improvisations are series of non-overlapping event clusters, which highlights the importance of event groups in jazz improvisers' action control. Making decisions at the level of event groups in contrast to choosing each note separately provides several advantages for improvising musicians. For instance, note-to-note level planning of upcoming movements is impossible at fast tempos and thus decision-making at the level of event groups allows to improvise fluently at fast tempos (Palmer & van de Sande, 1995; Pachet, 2012). In addition, decision-making at the level of event groups allows more time to make decisions compared to the note-to-note level. For example, when planning occurs at the level of two quarter notes at a time instead of one quarter note at a time at the tempo of 300 bpm, the inter-onset interval between the subsequent groups of two notes (compared to the inter-onset interval between subsequent notes) increases from 200 to 400 milliseconds. In case of 4-note groups, the inter-onset interval between the subsequent groups of quarter notes is 800 milliseconds at this tempo.<sup>126</sup> Despite of this advantage at fast tempos, it is important to note that decision-making at the note-to-note level may still be useful at very slow tempos. For instance, when improvising half notes at the tempo of 60 bpm, the inter-onset interval between the subsequent notes is two seconds. At such a slow tempo, it is difficult to see how musicians could benefit from planning larger units in advance or relying solely on higher-level decision-making.

Although decision-making at the level of event clusters (to use Pressing's terminology) is an important aspect in jazz improvisation, it is also important to consider the role of continuous decision-making. Goldman (2019) recently suggested that improvising musicians continuously evaluate their own decisions and those of their co-performers, in which process "feedback is continuously guiding movements, and thus they are in some sense constantly deciding what to do next" (Goldman, 2019, p. 284). In another study, Norgaard et al. (2023) suggested that "both motor patterns and continuous processes" are involved in musical improvisation. In their view, "a player may start a line by inserting a pre-learned pitch pattern of a specific length. But as this specific pattern is played, music expectancy principles may shape continuations of the pattern that are then

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125 On the other hand, repeated melodic patterns may sometimes operate as cues for other musicians and highlight important transitions between the sections of a composition.

126 In the present data, the quickest tempos were around 300 bpm. At this tempo, both Paul Chambers and Ron Carter merely played quarter notes. Playing quarter notes at the tempo of 300 bpm corresponds to playing five notes per second. In other words, the maximum inter-onset interval between subsequent quarter notes at this tempo is about 200 milliseconds which corresponds to simple reaction times for auditory stimulus among musicians (Landry & Champoux, 2017).

played in a continuous dynamical process.” (Norgaard et al., 2023, p. 11.) As suggested by these authors, continuous decision-making in jazz improvisation may be based on sensory feedback (Goldman, 2019) or melodic expectations (Norgaard et al., 2023). As a background for this discussion, note that researchers have long debated on whether consciousness is characterized by discrete or continuous perceptions (e.g., Herzog et al., 2020). Similarly, the question of whether decision-making is continuous (i.e., operates at the note-to-note level) or discrete (i.e., operates at the level of note groups), or both, is a fundamental problem in the psychological research of jazz improvisation.

It is a common view that novel outcomes in jazz improvisation and other forms of creativity are never developed *ex nihilo* (out of nothing) (e.g., Johnson-Laird, 2002; Canonne & Aucouturier, 2016; Daikoku et al., 2021) and that the generation of novel products requires formation of new links between pre-existing units of knowledge (e.g., Mednick, 1962; Schubert, 2011, 2021). For example, Hodgson (2006) proposed that jazz improvisation might involve a process of combining pre-learned 2-note structures into larger phrases. With the assumption that all pre-learned 2-note structures are invariant, the relative frequency of non-recurring 2-note melodic patterns (using calculation method 1) should be zero, at least if a very large amount of data including all performances by a particular musician was available.

According to the present results, the relative frequency of non-recurring 2-note chordal pitch class patterns (using calculation method 1) was relatively high (44.9% on average in Paul Chambers’s bass line reductions and 57.6% on average in Ron Carter’s bass line reductions), although it should be noted that the relative frequency of non-recurring 2-note interval patterns (using calculation method 1) was considerably smaller (25.5% in Paul Chambers’s bass line reductions and 30.1% in Ron Carter’s bass line reductions). It is also noteworthy that the proportion of recurring 2-note melodic pattern classes that occurred at least twice in two or more bass line reductions was 15.8% in Paul Chambers’s bass line reductions. This means that 84.2% of all recurring 2-note melodic pattern classes occurred at least twice in only one bass line reduction. In Ron Carter’s bass line reductions, the proportion of recurring 2-note melodic pattern classes that occurred at least twice in two or more bass line reductions was 19.4%, which means that 80.6% of all recurring 2-note melodic pattern classes occurred at least twice in only one of Ron Carter’s bass line reductions. In summary, these findings indicate that even if the proportion of non-recurring 2-note melodic patterns was quite high at least with chordal pitch class patterns, a large proportion of all recurring 2-note melodic pattern classes occurred at least twice in only one bass line reduction in both Paul Chambers’s and Ron Carter’s bass line reductions, which indicates that many of the melodic patterns may have been “invented” during performance and that other kinds of knowledge (e.g., harmonic knowledge of what notes fit to a particular context) and skills (e.g., the ability to make variations of melodic patterns) may play a more important role in expert jazz bass playing compared to the use of well-learned melodic patterns or

combining parts of such melodic patterns, at least in regard to Paul Chambers and Ron Carter.

However, it is important to note that saying something is “invented” during performance does not mean that it was created without the use of long-term memory. The basic idea of my criticism was not to deny that the generation of novel ideas and products is based on acquired knowledge in long-term memory. Instead, my criticism was only concerned with the more specific argument that the combination of pre-learned melodic patterns with little or no variation plays a central role in the creativity of expert-level jazz improvisers. The present results do not support the view that expert-level jazz improvisations consist of pre-learned melodic patterns that are simply combined in a row to create a melody. Further research is needed to clarify what kind of knowledge (from long-term memory) is used in expert-level jazz improvisation and what types of variation expert-level jazz improvisers might use to produce a variety of outputs based on a limited knowledge base.

Inhibition plays an important role in motor control of complex movements (Gerloff & Hummel, 2012). Similarly, inhibition of stereotypical actions (Norgaard et al., 2019) and risk-taking (Wopereis et al., 2013) are both associated with expertise in jazz improvisation. However, several studies suggest that creativity in music and other domains is associated with the lack of inhibitory control and not the other way around (Carson et al., 2003; Kleinmintz et al., 2014; Ivancovsky et al., 2018). As a result, it is possible that both inhibition of habitual melodic patterns and attenuated cognitive control play a role in expert jazz improvisation. The latter of these processes, attenuated cognitive control associated with loose evaluation of ideas, is important since the generation of novel melodic patterns may require a highly flexible web of associations that is facilitated by attenuated evaluation of generated responses. Even if these processes seem contradictory, they are not necessarily conflicting at all because inhibition of stereotyped actions and evaluation of ideas may be two different processes.

Several previous studies have proposed that lower-level processes in jazz improvisation are, at least largely, automatic. According to Berkowitz (2010), even expert jazz musicians are unaware of many processes that occur during improvisation and much of what occurs in improvisation is only witnessed by the improviser. In his view, expert improvisation is characterized by a state of “letting go,” where automated processes operate at the note-to-note level and attentional resources are directed to higher-level processes. Ramalho et al. (1999) proposed that intentions at higher levels of abstraction (e.g., pitch contour, density, general plan) may trigger the retrieval of appropriate melodic patterns from memory. Similarly, Chaffin et al. (2006) argued that musicians benefit from guiding their attention to higher levels of abstraction in music performance. In addition, several studies suggest that expert jazz musicians rely more on Type 1 processing compared to Type 2 processing (Limb & Braun, 2008; Liu et al., 2012; Adhikari et al., 2016; Lopata et al., 2017; Rosen et al., 2016, 2017, 2020), which indicates that the generation of novel melodic patterns may become automatic, at least partly, with extended practice. In support to this claim, several studies have

also shown that the activation of brain regions involved in volitional control of actions and action planning is decreased during musical improvisation (Limb & Braun, 2008; McPherson et al., 2016; Tachibana et al., 2019).

According to the present results, Paul Chambers's and Ron Carter's bass line reductions were highly variable at the level of melodic patterns, but there was much more repetition at higher levels of musical structure as indicated by that the same melodic contour patterns were repeated to a great extent in the bass line reductions of both bassists. In Paul Chambers's bass line reductions, the average relative frequency of non-recurring 4-note fuzzy interval patterns was 17.4% and the average relative frequency of non-recurring 4-note Parsons's code patterns was 0.78%. In Ron Carter's bass line reductions, the average relative frequency of non-recurring 4-note fuzzy interval patterns was 31.9% and the average relative frequency of non-recurring 4-note Parsons's code patterns was 2.00%. Based on earlier research (Berkowitz, 2010; Ramalho et al., 1999; Chaffin et al., 2006), higher-level planning at the level of melodic contour may constrain automatically generated note choices in jazz improvisation. In addition to melodic contour, note choices may be also limited by many other constraints, including harmonic context, harmonic knowledge (e.g., knowledge of what notes are appropriate in a given harmonic context), improvisation strategies (e.g., the use of target note technique), other higher-level features of music (e.g., timbre, density, tonality), and the larger musical context (i.e., what note choices are appropriate based on the notes played by other musicians). In addition, it is possible that the source of idea generation may also affect the content of automatically generated note choices.

The present results indicate that expert jazz bassists may rely on a limited number of melodic contour patterns in their improvisations. In comparison, Pachet (2012) argued that expert-level musicians' ability to perform effortlessly at a virtuoso tempo can be explained by that they delegate the choice of individual notes to subconscious levels of processing and allocate their attention to higher-level properties of music. The present results also indicate that both Paul Chambers and Ron Carter often repeated the same 2-note approach-note patterns in their bass line reductions. It is possible that the use of pre-learned approach-note patterns may decrease cognitive resources required in the generation of novel melodic patterns, since the use of such pre-learned structures decreases the number of elements to be selected. This could provide a partial explanation of why expert jazz bassists are able to produce novel melodic patterns effortlessly in real time at any tempo.

It is noteworthy that the present results generally did not support Love's (2017) ecological model on jazz improvisation. Love (2017, p. 42) predicted that the frequency of repeated melodic patterns should be higher compared to what has been suggested in previous research, that the frequency of repeated melodic patterns should be high regardless of tempo, and that improvisations on unfamiliar musical works should be highly repetitive. According to the present results, the repetition of melodic patterns was not high. In Paul Chambers's bass line reductions, the average relative frequency of recurring 4-note chordal pitch



class patterns was 33.4% and the average relative frequency of recurring 4-note interval patterns was 36.1% (using calculation method 1). In Ron Carter's bass line reductions, the average relative frequency of recurring 4-note chordal pitch class patterns was 15.6% and the average relative frequency of recurring 4-note interval patterns was 18.9%. On the other hand, the present results indicated that the bass line reductions were at least slightly more predictable with musical works based on original chord progressions compared to familiar chord progressions at least in Paul Chambers's bass line reductions. Finally, the present results provided preliminary evidence that tempo may have a small or negligible effect on the variability of melodic patterns.

The present results did not support the hypothesis that jazz bassists use consonant chordal pitch classes more often at fast tempos, which suggests that, in contrast to Frieler et al. (2018), neither Paul Chambers nor Ron Carter relaxed the harmonic constraints of note choices to circumvent challenges caused by increasing tempo. When controlling for the length of analyzed bass line reductions, the results indicated a statistically non-significant and negligible correlation between tempo and the relative frequency of chordal pitch classes in Paul Chambers's bass line reductions and a statistically non-significant and moderate negative correlation between these two variables in Ron Carter's bass line reductions. Similarly, the present results did not support the hypothesis that jazz bassists use note repetitions more often at fast tempos (which also allows to circumvent challenges caused by increasing tempo) (Frieler et al., 2018). When controlling for the length of analyzed bass line reductions, the results indicated a statistically non-significant and negligible correlation between tempo and the relative frequency of note repetitions in Paul Chambers's bass line reductions and a statistically non-significant and moderate negative correlation between the two variables in Ron Carter's bass line reductions. When original bass lines were analyzed instead of bass line reductions, the results indicated a statistically significant and moderate negative correlation between the two variables in Paul Chambers's original bass lines and a statistically non-significant and moderate negative correlation between the two variables in Ron Carter's original bass lines. Despite the statistical significance, however, the importance of these results is not clear as these results might only indicate that Paul Chambers and Ron Carter used more variable rhythms at slower tempos compared to faster tempos. It is possible that these differences between the present results and those of Frieler et al. (2018) are caused by individual differences between jazz bassists. Whereas some jazz bassists may use relaxed harmonic constraints at fast tempos or more note repetitions at fast tempos to circumvent challenges caused by increasing tempo, this does not seem to apply with Paul Chambers and Ron Carter.

Note that Ron Carter's bass line reductions relied less on pre-learned melodic patterns compared to Paul Chambers's bass line reductions. There are at least three possible explanations for this difference between the two bassists. First, jazz musicians' repertoire of pre-learned melodic patterns may change from time to time (see Weisberg et al., 2004, Projection of formulas over time section), because of why the same melodic patterns are not extensively repeated between

bass lines if the bass lines are separated by a long time span (which means that some bass lines were recorded much earlier compared to the other bass lines). As another possibility, Ron Carter may have simply relied on motor-generated ideas to a lesser extent compared to Paul Chambers and concentrated more on other sources of idea generation. Third, Ron Carter may have valued the element of surprise and unpredictability to a greater extent compared to Paul Chambers, which means that the novelty of musical ideas may have been more important to Ron Carter compared to Paul Chambers.

## 8 LIMITATIONS

Although the overall amount of research material in terms of individual notes (37,340 notes in total) and melodic patterns (9,335 melodic patterns in total) was quite high, the number of bass line reductions was small. The research material included only 30 bass line reductions by Paul Chambers and 12 bass line reductions by Ron Carter. This problem could have been easily avoided by using short samples from each bass line reduction instead of using full-length bass line reductions. The explanation for using full-length bass line reductions (if possible) was that the accuracy of measurement increases with the length of analyzed musical works. Compared to solos, I assumed that walking bass lines allow a more accurate measurement of musical creativity, because solos are often relatively short whereas bassists play all the time from the beginning to the end of the musical work. Considering the exploratory nature of the present study and the advantage of using more data from each improvisation compared to previous studies, the accuracy of measurement (which improves the quality of data) was a more important aim than the possibility to use a larger sample size. However, it is important to note that a large variation in the length of analyzed bass line reductions can lead to biased results. To avoid this problem, the length of analyzed bass line reductions was used as a third variable in Kendall's tau partial correlation analyses. As another solution, further research could aim to minimize differences in the length of analyzed bass line reductions.

As another problem, many of the individual confidence intervals were quite wide, which indicates a low precision of effect size estimates. The average width of confidence intervals was 0.69 (range: 0.51 to 0.88,  $SD = 0.08$ ) in Paul Chambers's bass line reductions and 1.26 (range: 0.86 to 1.60,  $SD = 0.17$ ) in Ron Carter's bass line reductions. Most confidence intervals also included the null effect, which indicates considerable uncertainty in effect direction. The statistical power of the results was usually below the generally accepted level of 0.80, which indicates that the probability of Type II errors (i.e., probability of false negative findings) was rarely 20% or less. Assuming that May and Looney's (2020) calculations for Spearman's rho and Kendall's coefficient of concordance are approximately true for Kendall's tau, the sample size per each bassist should have been about

90 bass line reductions to achieve a statistical power of 0.80 given an effect size of  $\tau = .30$  ( $\alpha = 0.05$ , two-tailed) (May & Looney, 2020). Given an effect size of  $\tau = .20$  ( $\alpha = 0.05$ , two-tailed), a sample size of about 200 bass line reductions per each bassist would have been needed to achieve a statistical power of 0.80 (May & Looney, 2020). Thus, the present sample sizes were much smaller than what would have been required to achieve a generally accepted level of statistical power. Sample sizes could have been easily increased by splitting all bass line reductions (see Frieler, 2020). As another possibility, all data could have been put together (instead of analyzing the bass line reductions from the two musicians separately) and analyzed with methods proposed by Bland and Altman (1994, 1995a, 1995b). In addition, sample sizes could have been increased by using shorter transcriptions. However, these possibilities to increase the sample size of the study were not utilized. As a defence to this decision, it should be noted that the basic intention of my study was merely to provide hypotheses for further research, avoid using untested assumptions, and investigate methodological issues that could have unwanted consequences in large-scale studies.

The present results were mostly statistically non-significant and, therefore, inconclusive. As another limitation, the research material included bass line reductions from only two musicians (because of why the results cannot be generalized to other musicians with a similar level of expertise regardless of the statistical significance of the results) and included only a small fraction of the total output of these two musicians. As a result, it is possible that the selection of performances may have accidentally influenced the results. However, it is likely that the performance level of expert musicians differs little from day to day if their skills have not suffered from physical traumas or a sustained decrease in overall playing time. Yet, as evident in exceptionally low creativity scores in some bass line reductions (e.g., *Giant Steps*), mediating effects like the complexity of the chord progression, the familiarity with the chord progression, or the decision to focus on underlining the chord changes as clearly as possible may influence the results.

The present study investigated walking bass lines and therefore the results cannot be directly compared with previous studies that have investigated solos. Also, it should be noted that the analyzed bass line reductions were recorded over a relatively long time. In studies of transfer of learning in jazz improvisation, it could be helpful to focus on recordings from a much shorter time span (e.g., by analyzing complete albums recorded during one or a few days instead of analyzing performances recorded over several years) since expert jazz musicians' repertoire of melodic patterns may change over the years. As another limitation, all note durations that differed from quarter notes were converted to quarter notes or removed. Accordingly, the present study focused exclusively on melody at the expense of losing all information related to rhythm. Finally, it should be noted that the present research provides a very limited perspective on creativity. However, it is fair to say that it is practically impossible to investigate all aspects of creativity in a single study.

## 9 RECOMMENDATIONS FOR FURTHER RESEARCH

It was necessary to exclude several interesting research questions from this study. For instance, the present study focused on chunks and questions regarding the effect of statistical learning (e.g., the probability of playing a specific note or notes given the notes played earlier) on musical creativity were not investigated. Further research could also investigate whether the selection of motor commands to achieve a desired action is more difficult at fast tempos compared to slow tempos and whether the scarcity of time to select motor commands functions as a source of unintentional actions in jazz improvisation regardless of the level of expertise.

To my knowledge, there are no previous studies that have investigated the number of events per second at which a transition from the note-to-note level processing to processing at the level of larger and more abstract entities could occur. According to previous research, it is impossible (even for virtuoso musicians) to plan upcoming actions at the note-to-note level at fast tempos (Palmer & van de Sande, 1995; Pachet, 2012). At the tempo of 300 bpm, for example, the distance between the onsets of two beats is 200 milliseconds. At this timescale, musicians can merely react to auditory and tactile stimuli in a pre-defined way (e.g., press a mouse button when they hear a stimulus) (Landry & Champoux, 2017).

It is an open question whether the role of sensory feedback is similar or different in improvised music compared to playing well-learned music from memory. There is also a lack of knowledge regarding the role of audiation-generated ideas in improvised music and the relationship between room acoustics and the ability to produce audiated musical ideas correctly. Moreover, the question of what underlying processes are involved in creativity among expert-level jazz musicians has barely been touched. Further research could also benefit from finding new and more reliable ways to measure creativity in improvised jazz solos.

There is still little knowledge of how expert jazz improvisers differ from expert classical musicians in terms of their skills. Such knowledge could provide new insights for understanding how expert jazz musicians can generate novel musical ideas at any tempo. Anticipation and its relation to context familiarity is

another little understood aspect of fluent jazz improvisation. It is likely that anticipation of upcoming chord changes and awareness of the present position in a song form have a crucial role in fluent improvisation. Unfamiliarity with the chord progression is likely to disrupt the anticipation of upcoming chord changes and may therefore cause negative effects on performance quality. However, there are no studies that have investigated these issues.

Conservative forms of the 4E cognition and dynamic systems research could provide new insights to creative processes in jazz improvisation as suggested by recent research that has investigated how environmental factors and bodily experiences can facilitate the production of creative responses in divergent thinking tasks. From the 4E cognition framework, it could be useful to investigate how familiarity with the instrument and performing in different kinds of venues influence musical creativity. Case studies of how physical and bodily traumas affect the role of the body as a mediator between the external world and the mind could also have an important impact on our knowledge about creativity among both expert and amateur musicians. Moreover, further research on emergence could help to explain novelty in jazz improvisation without using simplistic explanations based on stringing together pre-learned melodic patterns. Moreover, further research could explore the application of methods borrowed from dynamic systems research (e.g., cross-recurrence quantification analysis), the relationship between audition-generated ideas and sensory-motor associations, and the question of whether and to what extent audition-generated ideas are constrained by existing knowledge.

Carefully conducted interviews with expert musicians could be highly beneficial and provide novel and valuable insights on the psychology of music performance. These qualitative studies could be complemented with empirical research to ensure the reliability and generalization of the evidence. In addition, investigations of practicing habits of musicians could be useful to gain more understanding of underlying processes in improvisation as it is likely that improvised performances are, at least to some extent, based on strategies, knowledge, and skills that are practiced offline. Such investigations could focus on musicians at all levels of expertise because experts are unlikely to be required to practice the same things as novices.

As an alternative to solos, further research could pay more attention to walking bass lines and other less explored forms of musical creativity. The quantity of available walking bass line transcriptions has increased rapidly in recent years. As a result, researchers may soon have the opportunity to use relatively large databases of walking bass line transcriptions in their work.

## SUMMARY IN FINNISH

Tutkimukseni ensisijaisena tavoitteena oli selvittää, miten päätöksentekoon ja toiminnan suunnitteluun liittyvät ajalliset rajoitteet sekä sävelkuvioita koskevan tietovaraston koko ovat yhteydessä huipputason jazzbasistien luovuuteen. Ajalliset rajoitteet ovat improvisoinnin kannalta keskeisessä roolissa, koska improvisoitaessa musiikin tekeminen tapahtuu samanaikaisesti sen esittämisen kanssa. Näin ollen mitä nopeampi tempo musiikissa on ja mitä tiheämmin esitettävän teoksen soinnut vaihtuvat, sitä vähemmän muusikoilla on aikaa tehdä esitettävää musiikkia koskevia päätöksiä senhetkisessä musiikillisessa kontekstissa. Myös sävelkuvioita koskevan tietovaraston koolla on katsottu olevan merkittävä rooli jazzimprovisoinnin kannalta, jopa siinä määrin että laajan sävelkuviovaraston oppimisen on ajateltu olevan välttämätön edellytys jazzimprovisointitaitojen kehittymiselle. Tutkimuksen aineisto koostui 42:sta Paul Chambersin (1935–1969) ja Ron Carterin (s. 1937) vuosien 1956–1968 välillä levyttämän bassolinjan nuotinnoksesta, joissa neljäsosanuoteista poikkeavat sävelkestot on poistettu tai muutettu neljäsosanuoteiksi. Tutkittavat henkilöt ovat jazzmusiikin historian kannalta erittäin merkittäviä muusikoita.

Ajallisten rajoitteiden ja huipputason jazzmuusikoiden luovuuden välistä yhteyttä tutkittiin Kendallin osittaisjärjestyskorrelaatiota käyttäen selvittämällä, miten esitettävän musiikin tempo ja harmoninen rytmi ovat yhteydessä sävelkuvioiden vaihtelevuuteen, kun bassolinjareduktioiden pituuden vaikutus tuloksiin on poistettu. Tutkimuksessa ei löydetty tilastollisesti merkitseviä yhteyksiä tempon tai harmonisen rytmin sekä sävelkuvioiden vaihtelevuuden välillä. Paul Chambersin bassolinjareduktioissa ( $n = 30$ ) havaittiin tilastollisesti ei-merkitsevä ja heikko negatiivinen korrelaatio tempon ja sävelkuvioiden vaihtelevuuden välillä (keskimääräinen absoluuttinen tau-b = .18) ja tilastollisesti ei-merkitsevä ja käytännössä olematon korrelaatio harmonisen rytmin ja sävelkuvioiden vaihtelevuuden välillä (keskimääräinen absoluuttinen tau-b = .08). Ron Carterin bassolinjareduktioissa ( $n = 12$ ) havaittiin tilastollisesti ei-merkitsevä ja heikko korrelaatio tempon ja sävelkuvioiden vaihtelevuuden välillä (keskimääräinen absoluuttinen tau-b = .15) sekä harmonisen rytmin ja sävelkuvioiden vaihtelevuuden välillä (keskimääräinen absoluuttinen tau-b = .14). Vaikka tulokset olivat tilastollisesti ei-merkitseviä, ne antavat alustavaa näyttöä siitä, että tempolla ja harmonisella rytmillä saattaa olla vähäinen tai käytännössä olematon vaikutus sävelkuvioiden vaihtelevuuteen huipputason jazzmuusikoiden bassolinjoissa. Tulokset eivät mahdollistaneet efektin suuntaa koskevia päätelmiä lukuun ottamatta Paul Chambersin bassolinjareduktioita tempon ja sävelkuvioiden vaihtelevuuden välisen yhteyden osalta.

Neljän sävelen mittaisten sävelkuvioiden keskimääräinen normalisoitu entropia oli 0,818 Paul Chambersin bassolinjareduktioissa ja 0,902 Ron Carterin bassolinjareduktioissa, kun sävelten suhde vallitsevaan sointuun otettiin huomioon. Tulos viittaa siihen, että bassolinjareduktioiden yllätyksellisyys oli keskimäärin varsin lähellä maksimitasoa. Vastaavasti neljän sävelen mittaisten ei-toistuvien sävelkuvioiluokkien keskimääräinen osuus kaikista samassa

bassolinjareduktiossa esiintyneistä sävelkuvioluokista oli Paul Chambersin bassolinjareduktioissa 66,6 prosenttia ja Ron Carterin bassolinjareduktioissa 84,4 prosenttia, kun sävelten suhde vallitsevaan sointuun otettiin huomioon. Tämä tarkoittaa sitä, että pääosa sävelkuvioluokista esiintyi vain kerran jossakin tietyssä bassolinjareduktiossa. Samojen sävelkuvioluokkien toistuminen eri bassolinjareduktioiden välillä oli varsin vähäistä. Vähintään kahdessa eri bassolinjareduktiossa ja vähintään kahdesti toistuvien sävelkuvioluokkien osuus kaikista toistuvista sävelkuvioluokista oli 15,8–16,9 prosenttia Paul Chambersin bassolinjareduktioissa (kattaen 41,2–83,2 prosenttia kaikista sävelkuvioista) ja 11,2–19,4 prosenttia Ron Carterin bassolinjareduktioissa (kattaen 13,4–63,1 prosenttia kaikista sävelkuvioista) tarkasteltujen sävelkuvioiden pituudesta riippuen. Tulos viittaa siihen, että sävelkuvioita koskevalla tietovaraston koolla vaikuttaisi olevan yllättävän vähäinen merkitys näiden kahden huipputason jazzbasistin luovuudelle.

Kun esimerkiksi Norgaardin ja Römerin (2022) mukaan Michael Breckerin, Steve Colemanin, John Coltranen, Miles Davisin, David Liebmanin, Charlie Parkerin, Sonny Rollinsin ja Wayne Shorterin soloissa 42–63 prosenttia sävelistä aloitti jonkun toistuvan neljän intervallin mittaisen sävelkuvion miltä tahansa iskulta, Paul Chambersin bassolinjareduktioissa keskimäärin 76,0 prosenttia sävelistä aloitti jonkun toistuvan neljän sävelen mittaisen sävelkuvion miltä tahansa iskulta ja vastaavasti Ron Carterin bassolinjareduktioissa keskimäärin 54,4 prosenttia sävelistä aloitti jonkun toistuvan neljän sävelen mittaisen sävelkuvion miltä tahansa iskulta. Samalla on kuitenkin huomioitava, että tulokset eivät ole täysin vertailukelpoisia. Toisin kuin Norgaardin ja Römerin tutkimuksessa, omassa tutkimuksessani kaikki neljäsosanuoteista poikkeavat sävelkestot joko poistettiin tai muutettiin neljäsosanuoteiksi. Tämän lisäksi Norgaardin ja Römerin tutkimuksessa tarkasteltujen sävelkuvioiden pituus oli neljä intervallia (eli viisi säveltä), kun taas omassa tutkimuksessani tarkasteltujen sävelkuvioiden pituus oli kolme intervallia (eli neljä säveltä). Lisäksi siinä missä Norgaardin ja Römerin tutkimuksessa jonkun toistuvan sävelkuvion aloittavien sävelten suhteellinen frekvenssi laskettiin koko korpuksen eli kaikkien saman esittäjän improvisaatioiden tasolla, omassa tutkimuksessani jonkun toistuvan sävelkuvion aloittavien sävelten suhteellinen frekvenssi laskettiin jokaisen bassolinjareduktion osalta erikseen ja ilmoitettiin keskiarvon muodossa.

Tutkimuksessa havaittiin tilastollisesti ei-merkittävä ja positiivinen korrelaatio tempon ja toistuvien sävelkuvioiden keskimääräisen pituuden välillä (intervallien lukumääränä mitattuna) Paul Chambersin bassolinjareduktioissa sekä tilastollisesti ei-merkittävä ja negatiivinen korrelaatio tempon ja toistuvien sävelkuvioiden keskimääräisen keston välillä (sekunteina mitattuna) niin Paul Chambersin kuin myös Ron Carterin bassolinjareduktioissa. Tutkimuksessa havaittiin Paul Chambersin bassolinjareduktioiden osalta myös tilastollisesti ei-merkittävä ja heikko negatiivinen korrelaatio tempon ja sävelkuvioiden vaihtelevuuden välillä. Tulokset viittaavat siihen, että ainakin Paul Chambers saattoi kompensoida päätöksentekoon ja toiminnan suunnitteluun liittyvien ajallisten rajoitteiden tiukentumista käyttämällä nopeissa tempoissa enemmän opittuja sävelkuvioita ja



elementtien lukumäärän osalta myös pidempiä opittuja sävelkuvioita verrattuna hitaisiin tempoihin.

Jazzmusiikin tutkimuksen kannalta on merkitsevää, että harmonisen kontekstin huomiotta jättäminen ei juurikaan vaikuttanut tuloksiin, kun analysoitavien sävelkuvioiden pituus oli neljä säveltä. Harmonisen kontekstin huomioiminen on ongelmallista tilanteissa, joissa esiintyy epätyypillisiä tai monitulkintaisia sointukorvauksia tai joissa melodian suhde sointuun on muuten epäselvä. Koska harmonisen kontekstin huomiotta jättäminen ei näyttänyt juurikaan vaikuttavan mittaustuloksiin olettaen, että sävelkuvioiden pituus on riittävä, tutkimusten luotettavuuden kannalta on suositeltavaa jättää harmoninen konteksti huomiotta, kun tarkasteltavien sävelkuvioiden pituus on vähintään neljä säveltä.

Tutkimukseni poikkesi useimmista aiemmista jazzmusiikin tutkimuksista siinä, että tutkimuksen aineisto koostui soolojen sijaan bassolinjoista. Soolojen käyttöä tutkimusaineistona puoltaa se, että niiden nuotinnoksia on runsaasti tarjolla. Soolot ovat kuitenkin kestoiltaan usein melko lyhyitä, millä saattaa olla vaikutusta tutkimusten luotettavuuteen. Esimerkiksi hyvin laajassa Weimar Jazz Database -tietokannassa olevien jazzsoolojen ( $N = 456$ ) mediaanikesto on 87 sekuntia eli yksi minuutti ja 27 sekuntia (Pfleiderer, 2017, s. 30), kun tutkimukseni aineistona käyttämäni bassolinjojen keskimääräinen kesto oli 280 sekuntia eli neljä minuuttia ja 40 sekuntia (mediaanikesto: 251 sekuntia).

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## APPENDICES

### Appendix 1: Supplementary tables for Chapters 5.2.1 and 5.3.2

TABLE 18 Average tempo in each bass line

Musical work (Paul Chambers)	Tempo 1	Tempo 2	Tempo 3	Tempo 4	<i>M</i>	Range
A Foggy Day	212	216	218 **	215 **	215	212-218
All of You	166	167	166	165	166	165-167
All the Things You Are	230	231	232	235	232	230-235
Apothegm	171	171	170	170	171	170-171
Autumn Leaves	136	129	136 **	127 **	132	127-136
Blues by Five	178	178	176	177	177	176-178
Blue Train	134	135	133	130	133	130-135
Chamber Mates	270	269	259	271 **	267	259-271
Chasin' the Bird	179 **	179 **	177 **	182 **	179	177-182
C-Jam Blues	165	165	173 **	162 **	166	162-173
Cool Struttin'	111	110	109	110	110	109-111
Cotton Tail	252	249	252	258 **	253	249-258
Crazy Rhythm	285	285	283 **	278 **	283	278-285
Excerpt	220	223	220 **	222 **	221	220-223
Freddie Freeloader	128	128	128	129	128	128-129
Giant Steps	286	291	302	291 **	293	286-302
I Can't Give You Anything but Love	179 **	188 **	188 **	185 **	185	179-188
I Could Write a Book	228	230	226	232	229	226-232
If I Were a Bell	190	189	188	182	187	182-190
It's a Blue World	189	190	195 **	191 **	191	189-195
Milestones	238	240	235	233	237	233-240

Musical work (Paul Chambers)	Tempo 1	Tempo 2	Tempo 3	Tempo 4	M	Range
Moment's Notice	236	246	245	247	244	236-247
Mr. P.C.	252	258	268	262	260	252-268
Oleo	268	270	266	265	267	265-270
So What	140	136	139	139	139	136-140
Syeeda's Song Flute	187	189	189	191 **	189	187-191
Tenor Madness	174	175	177	175	175	174-177
The Theme	209 **	214 **	210	211 **	211	209-214
Woody'n You	255	258	250	263 **	257	250-263
You'd Be So Nice to Come Home to	169 **	168 **	162 **	168 **	167	162-169

Musical work (Ron Carter)	Tempo 1	Tempo 2	Tempo 3	Tempo 4	M	Range
Autumn Leaves (1961)	135	138	136 **	136 **	136	135-138
Autumn Leaves (1964)	135	132	133	132	133	132-135
Dolphin Dance	120	120	124	124	122	120-124
E.S.P.	285	286	295	291	289	285-295
Israel	146	147	147	152	148	146-152
Loose Bloose	115	117	114	115	115	114-117
Mo' Joe	298	300	294	300	298	294-300
Oleo	245	245	245	240 **	244	240-245
Passion Dance	244	240	238	236 **	240	236-244
Pinocchio	207	209	215	215	212	207-215
Seven Steps to Heaven	284	286	288	287	286	284-288
Witch Hunt	138	139	139	138	139	138-139

*Note.* Tempo 1 and tempo 2 were both measured at the end of the first solo. Tempo 3 was measured at the end of the second solo. Tempo 4 was measured at the end of the third solo. Exceptions (\*\*): *A Foggy Day* (tempo 3 was measured at the beginning of the first solo, tempo 4 at the end of Red Garland's second solo). *Autumn Leaves* (Paul Chambers), *Autumn Leaves* (1961) (Ron Carter), *Crazy Rhythm*, and *It's a Blue World* (tempo 3 was measured at the beginning of the first solo, tempo 4 at the beginning of the final head

section). *Chamber Mates* (tempo 4 was measured at the beginning of the final head section). *Chasin' the Bird* (tempo 1 and tempo 2 were measured at the end of Hank Jones's solo, tempo 3 at the end of Kenny Burrell's solo, tempo 4 at the beginning of Hank Jones's solo). *C-Jam Blues* (tempo 3 was measured at the beginning of the first solo, tempo 4 at the beginning of Red Garland's second solo). *Oleo* (Ron Carter) (tempo 4 was measured at the beginning of the final head section). *Passion Dance* (tempo 4 was measured at the beginning of the second solo). *Cotton Tail* (tempo 4 was measured at the end of the trade-off section before the final head section). *Excerpt* (tempo 3 was measured at the end of the musical work, tempo 4 at the middle of the musical work). *Giant Steps* and *Syeeda's Song Flute* (tempo 4 was measured at the beginning of the first solo). *I Can't Give You Anything but Love* (tempo 1 and tempo 2 were measured at the end of Red Garland's solo, tempo 3 at the beginning of Red Garland's solo, tempo 4 at the beginning of the musical work). *The Theme* (tempo 1 and tempo 2 were measured at the end of the second solo, tempo 4 at the beginning of the second solo). *Woody'n You* (tempo 4 was measured at the beginning of the first solo). *You'd Be So Nice to Come Home to* (tempo 1 and tempo 2 were at the end of the second solo, tempo 3 at the end of the third solo, tempo 4 at the beginning of the second solo).

TABLE 19 Proportion of bars with at least one reduced note

Musical work (Paul Chambers)	Number of reduced bars	Proportion of reduced bars	Tempo
A Foggy Day	8 (155)	5.16%	215
All of You	4 (155)	2.58%	166
All the Things You Are	12 (275)	4.36%	232
Apothegm	24 (221)	10.9%	171
Autumn Leaves	28 (96)	29.2%	132
Blues by Five	20 (328)	6.10%	177
Blue Train	95 (288)	33.0%	133
Chamber Mates	0 (142)	0%	267
Chasin' the Bird	35 (128)	27.3%	179
C-Jam Blues	88 (274)	32.1%	166
Cool Struttin'	64 (154)	41.6%	110
Cotton Tail	4 (261)	1.53%	253
Crazy Rhythm	2 (113)	1.77%	283
Excerpt	0 (192)	0%	221
Freddie Freeloader	122 (288)	42.4%	128
Giant Steps	17 (333)	5.11%	293
I Can't Give You Anything but Love	11 (95)	11.6%	185
I Could Write a Book	4 (197)	2.03%	229
If I Were a Bell	19 (270)	7.04%	187
It's a Blue World	35 (154)	22.7%	191
Milestones	0 (204)	0%	237
Moment's Notice	2 (369)	0.54%	244
Mr. P.C.	0 (392)	0%	260
Oleo	0 (343)	0%	267
So What	64 (227)	28.2%	139
Syedda's Song Flute	28 (128)	21.9%	189

Musical work (Paul Chambers)	Number of reduced bars	Proportion of reduced bars	Tempo
Tenor Madness	33 (465)	7.10%	175
The Theme	11 (126)	8.73%	211
Woody'n You	3 (245)	1.22%	257
You'd Be So Nice to Come Home to	36 (128)	28.1%	167
Musical work (Ron Carter)	Number of reduced bars	Proportion of reduced bars	Tempo
Autumn Leaves (1961)	87 (160)	54.4%	136
Autumn Leaves (1964)	131 (189)	69.3%	133
Dolphin Dance	236 (264)	89.4%	122
E.S.P.	12 (310)	3.87%	289
Israel	96 (119)	80.7%	148
Loose Bloose	69 (104)	66.4%	115
Mo' Joe	0 (166)	0%	298
Oleo	63 (216)	29.2%	244
Passion Dance	79 (288)	27.4%	240
Pinocchio	99 (224)	44.2%	212
Seven Steps to Heaven	10 (297)	3.37%	286
Witch Hunt	203 (252)	80.6%	139

*Note.* The number of reduced bars refers to the number of bars that included at least one reduced note. Similarly, the proportion of reduced bars refers to the proportion of bars that included at least one reduced note. The total number of bars in each bass line reduction is shown in parentheses.



## Appendix 2: Supplementary tables for Chapters 6.1.1 to 6.1.4

TABLE 20 The role of harmonic context in measurement of musical creativity

Musical work (Paul Chambers)	2-note patterns	3-note patterns	4-note patterns	No. of bars
A Foggy Day	-0.114 (-21/-8)	-0.048 (+4/0)	-0.017 (+3/+1)	155
All of You	-0.100 (-29/-18)	-0.063 (-11/-14)	-0.030 (-8/-9)	155
All the Things You Are	-0.104 (-25/-8)	-0.032 (-4/-5)	-0.012 (-2/-2)	275
Apothegm	-0.076 (-22/-10)	-0.024 (-6/-5)	-0.009 (-1/-3)	221
Autumn Leaves	-0.079 (-17/-9)	-0.041 (-11/-7)	0 (0/0)	96
Blues by Five	-0.125 (-19/-8)	-0.063 (-3/-6)	-0.031 (-3/-6)	328
Blue Train	-0.106 (-6/-5)	-0.058 (-2/-5)	-0.021 (-1/-2)	288
Chamber Mates	-0.108 (-15/-6)	-0.060 (-6/-5)	-0.024 (-3/-4)	142
Chasin' the Bird	-0.073 (-10/-9.5)	-0.043 (-3.5/-7)	-0.013 (-5/-7)	128
C-Jam Blues	-0.142 (-19/-9)	-0.071 (-5/-8)	-0.033 (-8/-9)	274
Cool Struttin'	-0.106 (-20/-11)	-0.052 (-4/-6)	-0.010 (-4/-4)	154
Cotton Tail	-0.147 (-31/-15)	-0.085 (-8.5/-10)	-0.038 (-3/-5)	261
Crazy Rhythm	-0.102 (-36/-21)	-0.043 (-2/-5)	-0.012 (-6/-6)	113
Excerpt	-0.129 (-27/-16)	-0.054 (-1/-6)	-0.016 (-9/-10)	192
Freddie Freeloader	-0.118 (-21/-8)	-0.044 (0/-3)	-0.009 (0/-2)	288
Giant Steps	-0.022 (0/-1)	-0.005 (+1/0)	+0.001 (-1/0)	333
I Can't Give You Anything but Love	-0.125 (-27/-26)	-0.054 (-11/-17)	-0.024 (-4/-9)	95
I Could Write a Book	-0.072 (-10/-7)	-0.029 (-6/-6)	-0.011 (-2/-3)	197
If I Were a Bell	-0.125 (-23/-12)	-0.060 (-12/-12)	-0.003 (-2/-4)	270
It's a Blue World	-0.075 (-17/-11)	-0.023 (-2.5/-5)	-0.004 (-1/-2)	154
Milestones	-0.206 (-10/-5)	-0.112 (-1/-5)	-0.053 (-3/-5)	204
Moment's Notice	-0.096 (-32/-7)	-0.031 (-3/-4)	-0.009 (-3/-2)	369
Mr. P.C.	-0.090 (-11/-2)	-0.033 (-2.5/-2)	-0.012 (-3/-2)	392

Musical work (Paul Chambers)	2-note patterns	3-note patterns	4-note patterns	No. of bars
Oleo	-0.145 (-14/-8)	-0.088 (-1/-5)	-0.041 (0/-4)	343
So What	-0.177 (-16/-6)	-0.092 (+2/-4)	-0.047 (-6/-6)	227
Syeeda's Song Flute	-0.058 (-16/-5)	-0.018 (-7/-5)	-0.005 (-1/0)	128
Tenor Madness	-0.096 (-13/-5)	-0.047 (-4/-3)	-0.010 (-4/-3)	465
The Theme	-0.142 (-28/-19)	-0.071 (-10/-14)	-0.036 (-3.5/-8)	126
Woody'n You	-0.023 (-18/-5)	-0.010 (-5/-2)	-0.007 (-2/-2)	245
You'd Be So Nice to Come Home to	-0.079 (-28/-15)	-0.022 (+2/-1)	-0.013 (+2/+1)	128
Musical work (Ron Carter)	2-note patterns	3-note patterns	4-note patterns	No. of bars
Autumn Leaves (1961)	-0.091 (-28/-18.5)	-0.026 (-10/-12)	-0.006 (-2/-3)	160
Autumn Leaves (1964)	-0.138 (-22/-17)	-0.051 (-9/-13)	-0.032 (-2/-7)	189
Dolphin Dance	-0.032 (-9/-3)	-0.005 (-1/-2)	-0.004 (+1/+1)	264
E.S.P.	-0.117 (-35/-18)	-0.045 (-13/-16)	-0.010 (-4/-6)	310
Israel	-0.155 (-27/-21)	-0.087 (-14/-17)	-0.046 (-1/-5)	119
Loose Bloose	-0.272 (-31/-28)	-0.129 (-18/-34)	-0.038 (-5/-13)	104
Mo' Joe	-0.167 (-33/-31)	-0.081 (-10/-19)	-0.024 (-5/-9)	166
Oleo	-0.147 (-27/-16)	-0.047 (-2/-6)	-0.011 (-2/-3)	216
Passion Dance	-0.226 (-35/-14)	-0.110 (-6/-12)	-0.040 (-8/-12)	288
Pinocchio	-0.181 (-45/-38)	-0.060 (-11/-21)	-0.019 (-3/-8)	224
Seven Steps to Heaven	-0.161 (-28/-13)	-0.080 (-13/-17)	-0.034 (-7/-11)	297
Witch Hunt	-0.111 (-10/-10)	-0.031 (-10/-10)	-0.004 (0/-1)	252

*Note.* This table shows the difference between the normalized entropy of chordal pitch class patterns (where harmonic context is considered) and the normalized entropy of interval patterns (where harmonic context is disregarded) in each bass. The differences (in percentage points) between the relative frequency of chordal pitch class patterns and the relative frequency of interval patterns are also shown in parentheses. For example, -0.030 indicates that the average normalized entropy of melodic patterns was 0.030 (3.0 percentage points) lower when harmonic context was disregarded.

TABLE 21 Influence of threshold level

Musical work (Paul Chambers)	At least 2 occurrences	At least 3 occurrences	At least 4 occurrences	At least 5 occurrences
A Foggy Day (2 notes)	22 (54%/88%)	15 (37%/79%)	13 (32%/75%)	8 (20%/62%)
A Foggy Day (3 notes)	26 (52%/85%)	18 (36%/74%)	16 (32%/70%)	12 (24%/60%)
A Foggy Day (4 notes)	28 (45%/78%)	18 (29%/65%)	14 (23%/57%)	9 (15%/45%)
All of You (2 notes)	25 (40%/75%)	14 (22%/61%)	7 (11%/48%)	6 (10%/45%)
All of You (3 notes)	22 (26%/59%)	14 (16%/49%)	6 (7%/34%)	6 (7%/34%)
All of You (4 notes)	19 (18%/46%)	11 (11%/35%)	3 (3%/20%)	3 (3%/20%)
All the Things You Are (2 notes)	43 (58%/89%)	31 (42%/80%)	23 (31%/71%)	17 (23%/63%)
All the Things You Are (3 notes)	52 (48%/79%)	31 (28%/64%)	22 (20%/54%)	13 (12%/41%)
All the Things You Are (4 notes)	52 (34%/64%)	23 (15%/43%)	14 (9%/33%)	9 (6%/26%)
Apothegm (2 notes)	35 (53%/86%)	23 (35%/75%)	17 (26%/67%)	15 (23%/63%)
Apothegm (3 notes)	35 (41%/77%)	22 (26%/65%)	16 (19%/57%)	12 (14%/50%)
Apothegm (4 notes)	39 (32%/62%)	19 (16%/44%)	15 (12%/39%)	8 (7%/26%)
Autumn Leaves (2 notes)	13 (46%/84%)	8 (29%/74%)	7 (25%/71%)	5 (18%/63%)
Autumn Leaves (3 notes)	16 (80%/79%)	9 (45%/65%)	7 (35%/58%)	3 (15%/42%)
Autumn Leaves (4 notes)	14 (33%/71%)	9 (21%/60%)	8 (19%/57%)	4 (10%/41%)
Blues by Five (2 notes)	54 (59%/89%)	35 (38%/77%)	25 (27%/68%)	20 (22%/62%)
Blues by Five (3 notes)	65 (46%/77%)	34 (24%/58%)	22 (16%/47%)	14 (10%/38%)
Blues by Five (4 notes)	56 (29%/58%)	26 (13%/40%)	18 (9%/33%)	10 (5%/23%)
Blue Train (2 notes)	37 (55%/90%)	26 (39%/82%)	21 (31%/77%)	19 (28%/74%)
Blue Train (3 notes)	38 (37%/77%)	27 (26%/70%)	23 (22%/66%)	21 (20%/63%)
Blue Train (4 notes)	44 (31%/66%)	26 (18%/53%)	20 (14%/47%)	13 (9%/37.5%)
Chamber Mates (2 notes)	24 (65%/91%)	17 (46%/81%)	14 (38%/75%)	14 (38%/75%)
Chamber Mates (3 notes)	26 (57%/86%)	19 (41%/76%)	14 (30%/65%)	12 (26%/60%)
Chamber Mates (4 notes)	29 (45%/75%)	17 (27%/58%)	10 (16%/44%)	8 (12.5%/38%)
Chasin' the Bird (2 notes)	26 (48%/78%)	16 (30%/62.5%)	9 (17%/46%)	6 (11%/37%)
Chasin' the Bird (3 notes)	27 (37.5%/65%)	15 (21%/46%)	7 (10%/27%)	3 (4%/15%)

Musical work (Paul Chambers)	At least 2 occurrences	At least 3 occurrences	At least 4 occurrences	At least 5 occurrences
Chasin' the Bird (4 notes)	24 (27%/48%)	10 (11%/27%)	4 (4%/12.5%)	0 (0%/0%)
C-Jam Blues (2 notes)	44 (56%/88%)	28 (36%/76%)	22 (28%/69%)	6 (8%/64%)
C-Jam Blues (3 notes)	48 (37%/70%)	27 (21%/55%)	19 (15%/46%)	15 (12%/41%)
C-Jam Blues (4 notes)	44 (28%/59%)	22 (14%/43%)	15 (10%/35%)	8 (5%/25%)
Cool Struttin' (2 notes)	36 (60%/84%)	21 (35%/65%)	15 (25%/53%)	10 (17%/40%)
Cool Struttin' (3 notes)	37 (47%/73%)	16 (20%/45%)	10 (13%/34%)	5 (6%/21%)
Cool Struttin' (4 notes)	35 (37%/61%)	13 (14%/32%)	6 (6%/19%)	3 (3%/11%)
Cotton Tail (2 notes)	48 (50%/82%)	31 (32%/69%)	19 (20%/55%)	15 (16%/49%)
Cotton Tail (3 notes)	51 (44%/75%)	26 (22%/56%)	16 (14%/44%)	11 (9%/37%)
Cotton Tail (4 notes)	51 (36%/66%)	24 (17%/45%)	17 (12%/37%)	9 (6%/25%)
Crazy Rhythm (2 notes)	20 (40%/73%)	14 (28%/63%)	9 (18%/50%)	5 (10%/35%)
Crazy Rhythm (3 notes)	20 (33%/65%)	15 (25%/56%)	8 (13%/37%)	5 (8%/27%)
Crazy Rhythm (4 notes)	19 (24%/48%)	11 (14%/34%)	4 (5%/15%)	1 (1%/4%)
Excerpt (2 notes)	37 (48%/79%)	22 (29%/64%)	15 (19%/53%)	9 (12%/40%)
Excerpt (3 notes)	38 (36%/64%)	20 (19%/45%)	10 (9%/30%)	7 (7%/23%)
Excerpt (4 notes)	30 (22%/45%)	13 (10%/27%)	5 (4%/15%)	3 (2%/10%)
Freddie Freeloader (2 notes)	36 (47%/89%)	28 (41%/83%)	19 (28%/74%)	16 (24%/70%)
Freddie Freeloader (3 notes)	46 (39%/75%)	32 (27%/65%)	19 (16%/52%)	11 (9%/41%)
Freddie Freeloader (4 notes)	48 (29%/58%)	23 (14%/41%)	13 (8%/31%)	7 (4%/22%)
Giant Steps (2 notes)	25 (83%/98%)	21 (70%/96%)	19 (63%/94%)	17 (57%/92%)
Giant Steps (3 notes)	32 (62%/94%)	27 (52%/91%)	20 (38%/85%)	16 (31%/80%)
Giant Steps (4 notes)	36 (53%/90%)	28 (41%/86%)	22 (32%/80%)	19 (28%/77%)
I Can't Give You... (2 notes)	19 (33%/59%)	8 (14%/36%)	4 (7%/23%)	4 (7%/23%)
I Can't Give You... (3 notes)	15 (21%/41%)	5 (7%/20%)	2 (3%/11%)	1 (1%/6%)
I Can't Give You... (4 notes)	11 (14%/29%)	3 (4%/13%)	1 (1%/6%)	1 (1%/6%)
I Could Write a Book (2 notes)	34 (52%/84%)	17 (26%/66%)	14 (21%/62%)	9 (14%/52%)
I Could Write a Book (3 notes)	32 (34%/69%)	18 (19%/55%)	12 (13%/46%)	9 (10%/40%)
I Could Write a Book (4 notes)	30 (27%/58%)	16 (14%/44%)	11 (10%/36%)	6 (5%/26%)

Musical work (Paul Chambers)	At least 2 occurrences	At least 3 occurrences	At least 4 occurrences	At least 5 occurrences
If I Were a Bell (2 notes)	51 (55%/84%)	35 (38%/73%)	23 (25%/59%)	16 (17%/49%)
If I Were a Bell (3 notes)	48 (35%/67%)	28 (20%/52%)	16 (12%/39%)	12 (9%/33%)
If I Were a Bell (4 notes)	48 (30%/58%)	21 (13%/38%)	14 (9%/30%)	9 (6%/23%)
It's a Blue World (2 notes)	28 (49%/81%)	14 (25%/63%)	9 (16%/53%)	9 (16%/53%)
It's a Blue World (3 notes)	26 (30%/60%)	14 (16%/44%)	8 (9%/32%)	8 (9%/32%)
It's a Blue World (4 notes)	19 (18%/42%)	11 (10%/32%)	7 (6%/24%)	4 (4%/16%)
Milestones (2 notes)	29 (71%/94%)	22 (54%/87%)	17 (41%/80%)	15 (37%/76%)
Milestones (3 notes)	32 (48%/83%)	25 (38%/76%)	18 (27%/66%)	13 (20%/56%)
Milestones (4 notes)	34 (35%/70%)	23 (24%/59%)	17 (18%/50%)	11 (11%/38%)
Moment's Notice (2 notes)	40 (59%/92%)	29 (43%/86%)	25 (37%/83%)	22 (32%/80%)
Moment's Notice (3 notes)	49 (46%/84%)	29 (27%/73%)	26 (24%/71%)	21 (20%/66%)
Moment's Notice (4 notes)	54 (34%/72%)	33 (21%/60%)	26 (16%/55%)	19 (12%/47%)
Mr. P.C. (2 notes)	39 (75%/97%)	30 (58%/92%)	24 (46%/87.5%)	20 (38%/83%)
Mr. P.C. (3 notes)	50 (62.5%/92%)	36 (45%/85%)	25 (31%/77%)	19 (24%/71%)
Mr. P.C. (4 notes)	65 (52%/84%)	44 (35%/74%)	28 (22%/61%)	20 (16%/53%)
Oleo (2 notes)	57 (61%/89%)	41 (44%/80%)	30 (32%/70%)	22 (23%/61%)
Oleo (3 notes)	70 (56%/82%)	46 (37%/69%)	27 (21%/52%)	17 (13%/41%)
Oleo (4 notes)	76 (46%/74%)	45 (27%/56%)	23 (14%/37%)	14 (9%/27%)
So What (2 notes)	28 (60%/92%)	22 (47%/86%)	15 (32%/77%)	11 (23%/70%)
So What (3 notes)	31 (50%/86%)	18 (29%/75%)	13 (21%/68%)	9 (15%/61%)
So What (4 notes)	36 (42%/78%)	20 (24%/64%)	14 (16%/56%)	11 (13%/51%)
Syedda's Song Flute (2 notes)	17 (63%/92%)	13 (48%/86%)	12 (44%/84%)	10 (37%/77%)
Syedda's Song Flute (3 notes)	23 (46%/79%)	15 (30%/66%)	10 (20%/55%)	6 (12%/42%)
Syedda's Song Flute (4 notes)	24 (38%/70%)	12 (19%/51%)	8 (13%/41%)	5 (8%/32%)
Tenor Madness (2 notes)	53 (61%/93%)	43 (49%/88%)	38 (44%/85%)	28 (32%/77%)
Tenor Madness (3 notes)	63 (55%/89%)	49 (43%/83%)	42 (37%/78%)	27 (23%/65%)
Tenor Madness (4 notes)	78 (47%/81%)	54 (33%/71%)	41 (25%/62%)	24 (14%/48%)
The Theme (2 notes)	28 (47%/75%)	14 (23%/52%)	8 (13%/38%)	6 (10%/32%)

Musical work (Paul Chambers)	At least 2 occurrences	At least 3 occurrences	At least 4 occurrences	At least 5 occurrences
The Theme (3 notes)	26 (33%/59%)	8 (10%/30%)	4 (5%/21%)	2 (3%/14%)
The Theme (4 notes)	22 (24%/46%)	8 (9%/24%)	4 (4%/14%)	2 (2%/8%)
Woody'n You (2 notes)	27 (59%/92%)	22 (48%/88%)	20 (43%/86%)	19 (41%/84%)
Woody'n You (3 notes)	34 (55%/89%)	23 (37%/80%)	21 (34%/77%)	19 (31%/74%)
Woody'n You (4 notes)	34 (44%/82%)	25 (32%/75%)	22 (28%/71%)	18 (23%/64%)
You'd Be So Nice to... (2 notes)	21 (40%/76%)	11 (21%/60%)	10 (19%/58%)	9 (17%/55%)
You'd Be So Nice to... (3 notes)	21 (31%/63%)	12 (18%/49%)	7 (10%/37.5%)	7 (10%/37.5%)
You'd Be So Nice to... (4 notes)	23 (28%/54%)	10 (12%/34%)	7 (9%/27%)	4 (5%/17%)
Musical work (Ron Carter)	At least 2 occurrences	At least 3 occurrences	At least 4 occurrences	At least 5 occurrences
Autumn Leaves (1961) (2 notes)	25 (36%/72.5%)	16 (23%/61%)	10 (14%/50%)	9 (13%/47.5%)
Autumn Leaves (1961) (3 notes)	23 (22%/49%)	11 (10%/34%)	6 (6%/24%)	4 (4%/19%)
Autumn Leaves (1961) (4 notes)	14 (11%/28%)	6 (5%/18%)	3 (2%/12.5%)	3 (2%/12.5%)
Autumn Leaves (1964) (2 notes)	33 (41%/75%)	20 (25%/61%)	13 (16%/50%)	9 (11%/42%)
Autumn Leaves (1964) (3 notes)	29 (24%/52%)	12 (10%/34%)	10 (8%/31%)	6 (5%/22%)
Autumn Leaves (1964) (4 notes)	24 (18%/40%)	10 (7%/25%)	7 (5%/21%)	4 (3%/14%)
Dolphin Dance (2 notes)	29 (57%/92%)	20 (39%/85%)	16 (31%/80%)	13 (25%/76%)
Dolphin Dance (3 notes)	43 (47%/81%)	20 (22%/64%)	14 (15%/59%)	11 (12%/52%)
Dolphin Dance (4 notes)	33 (25%/62%)	15 (11%/48%)	7 (5%/39%)	6 (4%/38%)
E.S.P. (2 notes)	52 (45%/79%)	31 (27%/66%)	21 (18%/56%)	15 (13%/48%)
E.S.P. (3 notes)	46 (25%/55%)	27 (15%/43%)	14 (8%/31%)	11 (6%/27%)
E.S.P. (4 notes)	32 (14%/36%)	16 (7%/25%)	10 (4%/20%)	8 (3%/17%)
Israel (2 notes)	22 (39%/71%)	13 (23%/55%)	9 (16%/45%)	6 (11%/35%)
Israel (3 notes)	20 (29%/58%)	11 (16%/43%)	8 (11%/35%)	5 (7%/25%)
Israel (4 notes)	17 (20%/44%)	10 (12%/32%)	5 (6%/19%)	2 (2%/9%)
Loose Bloose (2 notes)	22 (39%/66%)	9 (16%/41%)	5 (9%/30%)	3 (5%/22%)
Loose Bloose (3 notes)	11 (13%/28%)	6 (7%/18%)	1 (1%/4%)	0 (0%/0%)
Loose Bloose (4 notes)	4 (4%/9%)	1 (1%/3%)	0 (0%/0%)	0 (0%/0%)

Musical work (Ron Carter)	At least 2 occurrences	At least 3 occurrences	At least 4 occurrences	At least 5 occurrences
Mo' Joe (2 notes)	31 (31%/59%)	11 (11%/35%)	5 (5%/24%)	5 (5%/24%)
Mo' Joe (3 notes)	24 (20%/42%)	9 (7%/23%)	4 (3%/14%)	4 (3%/14%)
Mo' Joe (4 notes)	14 (10%/25%)	5 (4%/14%)	4 (3%/12%)	3 (2%/10%)
Oleo (2 notes)	43 (48%/79%)	20 (22%/57%)	16 (18%/52%)	12 (13%/44%)
Oleo (3 notes)	46 (38%/65%)	17 (14%/38%)	10 (8%/28%)	7 (6%/23%)
Oleo (4 notes)	33 (22%/46%)	12 (8%/26%)	9 (6%/22%)	7 (5%/19%)
Passion Dance (2 notes)	46 (51%/85%)	25 (28%/70%)	21 (23%/66%)	19 (21%/63%)
Passion Dance (3 notes)	49 (34%/67%)	25 (17%/51%)	15 (10%/40%)	12 (8%/36%)
Passion Dance (4 notes)	43 (23%/50%)	19 (10%/33%)	12 (6%/26%)	7 (4%/19%)
Pinocchio (2 notes)	33 (24%/54%)	17 (13%/40%)	8 (6%/28%)	5 (4%/22%)
Pinocchio (3 notes)	20 (11%/29%)	10 (6%/21%)	6 (3%/15%)	1 (1%/6%)
Pinocchio (4 notes)	17 (9%/20%)	6 (3%/10%)	3 (2%/6%)	1 (1%/2%)
Seven Steps to Heaven (2 notes)	54 (53%/84%)	32 (31%/69%)	20 (20%/57%)	17 (17%/53%)
Seven Steps to Heaven (3 notes)	48 (28%/59%)	28 (16%/45%)	19 (11%/36%)	10 (6%/24%)
Seven Steps to Heaven (4 notes)	41 (20%/45%)	23 (11%/33%)	14 (7%/24%)	13 (6%/14%)
Witch Hunt (2 notes)	38 (45%/81%)	22 (26%/68%)	19 (22%/64%)	14 (16%/56%)
Witch Hunt (3 notes)	36 (24%/55%)	15 (10%/38%)	10 (7%/33%)	7 (5%/28%)
Witch Hunt (4 notes)	23 (13%/37%)	10 (5%/27%)	7 (4%/23%)	6 (3%/21%)

*Note.* To keep this table readable, all percentages are reported without decimals (except for percentages that are exactly half such as 37.5%). The relative frequency of recurring chordal pitch class patterns is shown in parentheses. For example, the value 43 (47%/81%) in the 'min. 2 occurrences' column means that there were 43 different chordal pitch class patterns that were repeated at least twice in that particular bass line, the relative frequency of recurring chordal pitch class patterns in relation to the total number of different chordal pitch class patterns was 47% and the relative frequency of recurring chordal pitch class patterns in relation to the total number of all occurrences of chordal pitch class patterns was 81%.

TABLE 22 Removal of head sections

Musical work (Paul Chambers)	E (3 notes)	E (4 notes)	R (3 notes)	R (4 notes)	No. of bars
A Foggy Day (with themes)	0.692	0.738	48.00%/15.48%	54.84%/21.94%	155
A Foggy Day (no themes)	0.752	0.795	52.27%/22.77%	61.54%/31.68%	101
All of You (no themes)	0.803	0.862	74.12%/40.65%	81.55%/54.19%	155
All the Things You Are (with themes)	0.759	0.837	52.29%/20.73%	65.56%/36.00%	275
All the Things You Are (no themes)	0.770	0.836	55.43%/23.72%	66.39%/36.74%	215
Apothegm (with themes)	0.736	0.835	59.30%/23.08%	68.03%/37.56%	221
Apothegm (no themes)	0.771	0.865	54.29%/23.90%	68.37%/42.14%	159
Autumn Leaves (no themes)	0.664	0.722	55.56%/20.83%	66.67%/29.17%	96
Blues by Five (with themes)	0.784	0.859	53.57%/22.87%	70.98%/41.77%	328
Blues by Five (no themes)	0.802	0.877	54.20%/25.27%	73.60%/46.62%	281
Blue Train (no themes)	0.729	0.806	63.11%/22.57%	69.01%/34.03%	288
Chamber Mates (no themes)	0.703	0.779	43.48%/14.08%	54.69%/24.65%	142
Chasin' the Bird (no themes)	0.837	0.901	62.50%/35.16%	73.33%/51.56%	128
C-Jam Blues (with themes)	0.802	0.842	62.79%/29.56%	71.79%/40.88%	274
C-Jam Blues (no themes)	0.801	0.846	63.30%/30.26%	72.93%/42.54%	228
Cool Struttin' (no themes)	0.824	0.871	53.16%/27.27%	63.16%/38.96%	154
Cotton Tail (with themes)	0.783	0.840	56.03%/24.90%	63.83%/34.48%	261
Cotton Tail (no themes)	0.810	0.867	58.82%/29.41%	68.55%/41.67%	204
Crazy Rhythm (with themes)	0.811	0.890	66.67%/35.40%	75.64%/52.21%	113
Crazy Rhythm (no themes)	0.850	0.916	67.50%/42.19%	75.51%/57.81%	64
Excerpt (no themes)	0.842	0.902	64.49%/35.94%	77.94%/55.21%	192
Freddie Freeloader (with themes)	0.752	0.843	61.02%/25.00%	71.43%/41.67%	288
Freddie Freeloader (no themes)	0.761	0.849	57.84%/24.38%	70.83%/42.15%	242
Giant Steps (with themes)	0.564	0.612	38.46%/6.01%	47.06%/9.61%	333
Giant Steps (no themes)	0.572	0.619	44.90%/8.09%	53.23%/12.13%	272
I Can't Give You... (no themes)	0.907	0.934	78.87%/58.95%	85.90%/70.53%	95



Musical work (Paul Chambers)	E (3 notes)	E (4 notes)	R (3 notes)	R (4 notes)	No. of bars
I Could Write a Book (no themes)	0.781	0.832	65.59%/30.96%	73.45%/42.13%	197
If I Were a Bell (no themes)	0.815	0.847	64.96%/32.96%	70.37%/42.22%	270
It's a Blue World (with themes)	0.833	0.887	70.45%/40.26%	82.41%/57.79%	154
It's a Blue World (no themes)	0.876	0.922	77.27%/53.13%	88.31%/70.83%	96
Milestones (with themes)	0.703	0.794	51.52%/16.67%	64.58%/30.39%	204
Milestones (no themes)	0.718	0.804	53.85%/19.86%	64.79%/32.62%	141
Moment's Notice (with themes)	0.685	0.776	54.21%/15.72%	65.82%/28.18%	369
Moment's Notice (no themes)	0.695	0.786	57.43%/17.68%	69.33%/31.71%	328
Mr. P.C. (with themes)	0.646	0.767	37.50%/7.65%	48.41%/15.56%	392
Mr. P.C. (no themes)	0.638	0.749	40.00%/9.20%	47.54%/16.67%	348
Oleo (no themes)	0.767	0.831	44.44%/16.33%	53.66%/25.66%	343
So What (no themes)	0.617	0.718	50.00%/13.66%	57.65%/21.59%	227
Syedda's Song Flute (no themes)	0.720	0.785	54.00%/21.09%	61.90%/30.47%	128
Tenor Madness (with themes)	0.680	0.753	45.22%/11.18%	53.01%/18.92%	465
Tenor Madness (no themes)	0.685	0.758	43.75%/11.06%	53.09%/19.41%	443
The Theme (no themes)	0.854	0.902	66.67%/41.27%	75.56%/53.97%	126
Woody'n You (with themes)	0.653	0.701	45.16%/11.43%	56.41%/17.96%	245
Woody'n You (no themes)	0.634	0.680	39.58%/9.22%	54.84%/16.50%	206
You'd Be So Nice to... (no themes)	0.802	0.868	69.12%/36.72%	71.95%/46.09%	128

Musical work (Ron Carter)	E (3 notes)	E (4 notes)	R (3 notes)	R (4 notes)	No. of bars
Autumn Leaves (1961) (no themes)	0.865	0.926	78.10%/51.25%	89.15%/71.88%	160
Autumn Leaves (1964) (no themes)	0.861	0.901	75.83%/48.15%	82.48%/59.79%	189
Dolphin Dance (with themes)	0.677	0.743	53.26%/18.56%	75.37%/38.26%	264
Dolphin Dance (no themes)	0.722	0.788	54.32%/22.45%	77.39%/45.41%	196
E.S.P. (no themes)	0.855	0.913	75.00%/44.52%	86.15%/64.19%	310
Israel (no themes)	0.837	0.892	71.43%/42.02%	79.76%/56.30%	119
Loose Bloose (no themes)	0.940	0.985	87.21%/72.12%	95.96%/91.35%	104

Musical work (Ron Carter)	E (3 notes)	E (4 notes)	R (3 notes)	R (4 notes)	No. of bars
Mo' Joe (no themes)	0.905	0.943	80.17%/58.43%	89.93%/75.30%	166
Oleo (with themes)	0.848	0.897	62.30%/35.19%	78.00%/54.17%	216
Oleo (no themes)	0.894	0.941	70.64%/48.43%	83.72%/67.92%	159
Passion Dance (no themes)	0.806	0.878	65.73%/32.64%	77.13%/50.35%	288
Pinocchio (with themes)	0.924	0.963	88.76%/70.54%	91.37%/80.36%	224
Pinocchio (no themes)	0.971	0.995	98.06%/91.82%	98.15%/96.36%	110
Seven Steps to Heaven (with themes)	0.852	0.900	71.93%/41.41%	80.00%/55.22%	297
Seven Steps to Heaven (no themes)	0.861	0.905	74.85%/45.39%	80.40%/56.74%	282
Witch Hunt (with themes)	0.836	0.887	75.84%/44.84%	87.36%/63.10%	252
Witch Hunt (no themes)	0.889	0.928	80.70%/57.14%	90.84%/73.91%	161

*Note.* The first relative frequency value describes the relative frequency of non-recurring chordal pitch class patterns in relation to the total number of different chordal pitch class patterns. The second relative frequency value describes the relative frequency of non-recurring chordal pitch class patterns in relation to the total number of all occurrences of chordal pitch class patterns. In these results, harmonic context was considered. E = normalized entropy of melodic patterns; R = relative frequency of chordal pitch class patterns.

TABLE 23 Identification of segment boundaries

Tempo (bpm) + rank	Method A + rank	Method B + rank	Difference	Musical work (Paul Chambers)
293 (1.)	1184 (88.89%) (3.)	301 (90.39%) (1.)	-1.50	Giant Steps
283 (2.)	321 (71.02%) (23.)	61 (53.98%) (26.)	17.04	Crazy Rhythm
267 (3,5.)	491 (86.44%) (5.)	112 (78.87%) (6.)	7.57	Chamber Mates
267 (3,5.)	1187 (86.52%) (4.)	267 (77.84%) (7.)	8.68	Oleo
260 (5.)	1410 (89.92%) (2.)	339 (86.48%) (2.)	3.44	Mr. P.C.
257 (6.)	847 (86.43%) (6.)	205 (83.67%) (5.)	2.76	Woody'n You
253 (7.)	840 (80.46%) (10.)	186 (71.26%) (11.)	9.20	Cotton Tail
244 (8.)	1163 (78.79%) (12.)	274 (74.25%) (10.)	4.54	Moment's Notice
237 (9.)	671 (82.23%) (9.)	154 (75.49%) (9.)	6.74	Milestones
232 (10.)	854 (77.64%) (13.)	182 (66.18%) (16.)	11.46	All the Things You Are
229 (11.)	578 (73.35%) (20.)	120 (60.91%) (21.)	12.44	I Could Write a Book
221 (12.)	497 (64.71%) (26.)	105 (54.69%) (24,5.)	10.02	Excerpt
215 (13.)	514 (82.90%) (8.)	120 (77.42%) (8.)	5.48	A Foggy Day
211 (14.)	344 (68.25%) (24.)	68 (53.97%) (27.)	14.28	The Theme
191 (15.)	359 (58.28%) (30.)	68 (44.16%) (29.)	14.12	It's a Blue World
189 (16.)	331 (64.65%) (27.)	90 (70.31%) (13.)	-5.66	Syeeda's Song Flute
187 (17.)	797 (73.80%) (18.)	168 (62.22%) (20.)	11.58	If I Were a Bell
185 (18.)	238 (62.63%) (29.)	36 (37.89%) (30.)	24.74	I Can't Give You Anything but Love
179 (19.)	343 (66.99%) (25.)	70 (54.69%) (24,5.)	12.30	Chasin' the Bird
177 (20.)	1013 (77.21%) (14.)	211 (64.33%) (19.)	12.88	Blues by Five
175 (21.)	1684 (90.54%) (1.)	390 (83.87%) (4.)	6.67	Tenor Madness
171 (22.)	640 (72.40%) (21.)	143 (64.71%) (18.)	7.69	Apothegm
167 (23.)	326 (63.67%) (28.)	68 (53.13%) (28.)	10.54	You'd Be So Nice to Come Home to
166 (24,5.)	459 (74.03%) (16.)	85 (54.84%) (23.)	19.19	All of You
166 (24,5.)	817 (74.54%) (15.)	186 (67.88%) (15.)	6.66	C-Jam Blues
139 (26.)	771 (84.91%) (7.)	191 (84.14%) (3.)	0.77	So What

Tempo (bpm) + rank	Method A + rank	Method B + rank	Difference	Musical work (Paul Chambers)
133 (27.)	922 (80.03%) (11.)	197 (68.40%) (14.)	11.63	Blue Train
132 (28.)	284 (73.96%) (17.)	68 (70.83%) (12.)	3.13	Autumn Leaves
128 (29.)	826 (71.70%) (22.)	173 (60.07%) (22.)	11.63	Freddie Freeloader
110 (30.)	452 (73.38%) (19.)	100 (64.94%) (17.)	8.44	Cool Struttin'
Tempo (bpm) + rank	Method A + rank	Method B + rank	Difference	Musical work (Ron Carter)
298 (1.)	370 (55.72%) (7.)	57 (34.34%) (9.)	21.38	Mo' Joe
289 (2.)	690 (55.65%) (8.)	130 (41.94%) (7.)	13.71	E.S.P.
286 (3.)	863 (72.64%) (1.)	165 (55.56%) (3.)	17.08	Seven Steps to Heaven
244 (4.)	509 (58.91%) (6.)	106 (49.07%) (4.)	9.84	Oleo
240 (5.)	761 (66.00%) (2.)	178 (61.81%) (1.)	4.19	Passion Dance
212 (6.)	347 (38.73%) (11.)	62 (27.68%) (11.)	11.05	Pinocchio
148 (7.)	300 (63.03%) (3.)	58 (48.74%) (5.)	14.29	Israel
139 (8.)	465 (46.13%) (9.)	97 (38.49%) (8.)	7.64	Witch Hunt
136 (9.)	284 (44.38%) (10.)	50 (31.25%) (10.)	13.13	Autumn Leaves (1961)
133 (10.)	455 (60.19%) (5.)	89 (47.09%) (6.)	13.10	Autumn Leaves (1964)
122 (11.)	654 (61.93%) (4.)	162 (61.36%) (2.)	0.57	Dolphin Dance
115 (12.)	121 (29.09%) (12.)	23 (22.12%) (12.)	6.97	Loose Bloose

*Note.* The aim of this table is to compare the results from Method A (the relative frequency of notes that started a recurring 4-note interval pattern at any metrical location) and Method B (the relative frequency of recurring 4-note melodic patterns that started at the first beat of the bar). Number of notes that started a recurring 4-note interval pattern at any metrical location and the number of recurring melodic patterns using Method B are also presented. Difference = the difference between the relative frequency values. The most repetitive bass line reduction is ranked first. Regarding tempo values, the fastest tempo is ranked first.

### Appendix 3: Supplementary tables for Chapters 6.2.1 and 6.2.2

TABLE 24 Normalized entropy of melodic patterns in each bass line reduction

Musical work (Paul Chambers)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
A Foggy Day	0.620 (0.506)	0.692 (0.644)	0.738 (0.721)	155
A Foggy Day (x)	0.575 (0.454)	0.659 (0.601)	0.709 (0.689)	135
A Foggy Day (y)	0.737 (0.593)	0.760 (0.760)	0.797 (0.797)	20
All of You	0.716 (0.616)	0.803 (0.740)	0.862 (0.832)	155
All of You (x)	0.667 (0.508)	0.769 (0.686)	0.820 (0.783)	84
All of You (y)	0.875 (0.707)	0.906 (0.832)	0.987 (0.906)	16
All of You (z)	0.581 (0.527)	0.710 (0.641)	0.810 (0.789)	55
All the Things You Are	0.670 (0.566)	0.759 (0.727)	0.837 (0.825)	275
All the Things You Are (x)	0.606 (0.472)	0.718 (0.675)	0.790 (0.775)	199
All the Things You Are (y)	0.582 (0.522)	0.696 (0.680)	0.887 (0.879)	46
All the Things You Are (z)	0.797 (0.708)	0.797 (0.771)	0.895 (0.881)	30
Apothegm	0.686 (0.610)	0.736 (0.712)	0.835 (0.826)	221
Apothegm (x)	0.625 (0.518)	0.709 (0.676)	0.842 (0.825)	97
Apothegm (y)	0.586 (0.510)	0.615 (0.599)	0.683 (0.680)	56
Apothegm (z)	0.600 (0.509)	0.657 (0.619)	0.809 (0.797)	68
Autumn Leaves	0.591 (0.512)	0.664 (0.623)	0.722 (0.722)	96
Autumn Leaves (x)	0.611 (0.457)	0.716 (0.632)	0.737 (0.737)	54
Autumn Leaves (y)	0.198 (0.184)	0.266 (0.266)	0.469 (0.469)	30
Autumn Leaves (z)	0.544 (0.544)	0.628 (0.628)	0.628 (0.628)	12
Blues by Five	0.689 (0.564)	0.784 (0.721)	0.859 (0.828)	328
Blues by Five (x)	0.622 (0.486)	0.735 (0.661)	0.827 (0.788)	246
Blues by Five (y)	0.718 (0.567)	0.820 (0.756)	0.883 (0.848)	54
Blues by Five (z)	0.795 (0.591)	0.866 (0.804)	0.920 (0.920)	28

Musical work (Paul Chambers)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
Blue Train	0.646 (0.540)	0.729 (0.671)	0.806 (0.785)	288
Blue Train (x)	0.522 (0.485)	0.634 (0.626)	0.709 (0.709)	96
Blue Train (y)	0.635 (0.480)	0.721 (0.631)	0.812 (0.780)	192
Chamber Mates	0.659 (0.551)	0.703 (0.643)	0.779 (0.755)	142
Chamber Mates (x)	0.636 (0.520)	0.685 (0.622)	0.759 (0.738)	118
Chamber Mates (y)	0.538 (0.395)	0.592 (0.494)	0.735 (0.673)	24
Chasin' the Bird	0.752 (0.679)	0.837 (0.794)	0.901 (0.888)	128
Chasin' the Bird (x)	0.657 (0.583)	0.794 (0.751)	0.889 (0.871)	80
Chasin' the Bird (y)	0.738 (0.563)	0.844 (0.695)	0.844 (0.801)	16
Chasin' the Bird (z)	0.801 (0.696)	0.801 (0.759)	0.861 (0.861)	32
C-Jam Blues	0.689 (0.547)	0.802 (0.731)	0.842 (0.809)	274
C-Jam Blues (x)	0.624 (0.597)	0.712 (0.697)	0.759 (0.744)	46
C-Jam Blues (y)	0.667 (0.495)	0.795 (0.708)	0.837 (0.799)	228
Cool Struttin'	0.764 (0.658)	0.824 (0.772)	0.871 (0.861)	154
Cool Struttin' (x)	0.731 (0.589)	0.833 (0.772)	0.876 (0.868)	77
Cool Struttin' (y)	0.710 (0.570)	0.758 (0.689)	0.821 (0.795)	52
Cool Struttin' (z)	0.586 (0.511)	0.618 (0.542)	0.733 (0.733)	25
Cotton Tail	0.744 (0.597)	0.783 (0.698)	0.840 (0.802)	261
Cotton Tail (x)	0.651 (0.500)	0.680 (0.607)	0.823 (0.771)	58
Cotton Tail (y)	0.779 (0.570)	0.818 (0.703)	0.842 (0.792)	66
Cotton Tail (z)	0.662 (0.483)	0.719 (0.607)	0.781 (0.739)	137
Crazy Rhythm	0.740 (0.638)	0.811 (0.768)	0.890 (0.878)	113
Crazy Rhythm (x)	0.758 (0.596)	0.779 (0.701)	0.881 (0.860)	46
Crazy Rhythm (y)	0.552 (0.463)	0.721 (0.685)	0.819 (0.811)	49
Crazy Rhythm (z)	0.787 (0.611)	0.830 (0.782)	0.937 (0.910)	18
Excerpt	0.752 (0.623)	0.842 (0.788)	0.902 (0.886)	192
Excerpt (x)	0.708 (0.569)	0.823 (0.784)	0.881 (0.864)	94
Excerpt (y)	0.697 (0.524)	0.798 (0.707)	0.885 (0.864)	91

Musical work (Paul Chambers)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
Excerpt (z)	0.898 (0.898)	0.898 (0.898)	0.898 (0.898)	7
Freddie Freeloader	0.627 (0.509)	0.752 (0.708)	0.843 (0.834)	288
Freddie Freeloader (x)	0.588 (0.577)	0.665 (0.671)	0.770 (0.787)	48
Freddie Freeloader (y)	0.596 (0.451)	0.740 (0.684)	0.838 (0.825)	240
Giant Steps	0.492 (0.470)	0.564 (0.559)	0.612 (0.613)	333
Giant Steps (x)	0.319 (0.319)	0.417 (0.417)	0.489 (0.494)	125
Giant Steps (z)	0.485 (0.447)	0.557 (0.548)	0.602 (0.604)	208
I Can't Give You Anything...	0.847 (0.722)	0.907 (0.853)	0.934 (0.910)	95
I Can't Give You Anything... (x)	0.824 (0.710)	0.897 (0.862)	0.940 (0.918)	45
I Can't Give You Anything... (y)	0.736 (0.546)	0.830 (0.761)	0.854 (0.826)	33
I Can't Give You Anything... (z)	0.885 (0.622)	0.943 (0.747)	0.971 (0.903)	17
I Could Write a Book	0.690 (0.618)	0.781 (0.752)	0.832 (0.821)	197
I Could Write a Book (x)	0.568 (0.500)	0.666 (0.634)	0.729 (0.711)	101
I Could Write a Book (y)	0.827 (0.682)	0.867 (0.842)	0.975 (0.975)	19
I Could Write a Book (z)	0.666 (0.560)	0.805 (0.764)	0.859 (0.849)	77
If I Were a Bell	0.740 (0.615)	0.815 (0.755)	0.847 (0.844)	270
If I Were a Bell (x)	0.674 (0.539)	0.764 (0.718)	0.831 (0.818)	172
If I Were a Bell (y)	0.616 (0.575)	0.724 (0.694)	0.739 (0.739)	28
If I Were a Bell (z)	0.771 (0.550)	0.848 (0.688)	0.884 (0.830)	70
It's a Blue World	0.715 (0.640)	0.833 (0.810)	0.887 (0.883)	154
It's a Blue World (x)	0.639 (0.579)	0.779 (0.766)	0.844 (0.844)	86
It's a Blue World (y)	0.677 (0.534)	0.833 (0.778)	0.901 (0.887)	60
It's a Blue World (z)	0.802 (0.802)	0.802 (0.802)	0.802 (0.802)	8
Milestones	0.615 (0.409)	0.703 (0.591)	0.794 (0.741)	204
Milestones (y)	0.615 (0.409)	0.703 (0.591)	0.794 (0.741)	204
Moment's Notice	0.598 (0.502)	0.685 (0.654)	0.776 (0.767)	369
Moment's Notice (x)	0.488 (0.382)	0.628 (0.582)	0.687 (0.671)	139
Moment's Notice (z)	0.580 (0.470)	0.655 (0.626)	0.782 (0.775)	230

Musical work (Paul Chambers)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
Mr. P.C.	0.583 (0.493)	0.646 (0.613)	0.767 (0.755)	392
Mr. P.C. (x)	0.482 (0.417)	0.517 (0.482)	0.615 (0.615)	128
Mr. P.C. (y)	0.509 (0.402)	0.590 (0.555)	0.731 (0.714)	264
Oleo	0.701 (0.556)	0.767 (0.679)	0.831 (0.790)	343
Oleo (x)	0.948 (0.737)	0.948 (0.875)	0.948 (0.948)	11
Oleo (y)	0.757 (0.595)	0.827 (0.776)	0.878 (0.856)	88
Oleo (z)	0.626 (0.461)	0.707 (0.589)	0.784 (0.730)	244
So What	0.572 (0.395)	0.617 (0.525)	0.718 (0.671)	227
So What (y)	0.572 (0.395)	0.617 (0.525)	0.718 (0.671)	227
Syeeda's Song Flute	0.583 (0.525)	0.720 (0.702)	0.785 (0.780)	128
Syeeda's Song Flute (x)	0.561 (0.498)	0.704 (0.685)	0.775 (0.769)	120
Syeeda's Song Flute (z)	0.583 (0.583)	0.750 (0.750)	0.750 (0.750)	8
Tenor Madness	0.631 (0.535)	0.680 (0.633)	0.753 (0.743)	465
Tenor Madness (x)	0.567 (0.450)	0.634 (0.580)	0.706 (0.690)	236
Tenor Madness (y)	0.596 (0.447)	0.663 (0.580)	0.752 (0.741)	152
Tenor Madness (z)	0.446 (0.415)	0.446 (0.450)	0.589 (0.591)	77
The Theme	0.790 (0.648)	0.854 (0.783)	0.902 (0.866)	126
The Theme (x)	1.000 (0.833)	1.000 (1.000)	1.000 (1.000)	8
The Theme (y)	0.801 (0.701)	0.900 (0.853)	0.925 (0.891)	32
The Theme (z)	0.723 (0.533)	0.796 (0.697)	0.866 (0.819)	86
Woody'n You	0.603 (0.580)	0.653 (0.643)	0.701 (0.694)	245
Woody'n You (x)	0.528 (0.506)	0.584 (0.570)	0.644 (0.638)	147
Woody'n You (y)	0.353 (0.353)	0.471 (0.471)	0.571 (0.571)	50
Woody'n You (z)	0.669 (0.586)	0.685 (0.662)	0.685 (0.662)	48
You'd Be So Nice to...	0.726 (0.647)	0.802 (0.780)	0.868 (0.855)	128
You'd Be So Nice to... (x)	0.637 (0.520)	0.735 (0.701)	0.819 (0.791)	64
You'd Be So Nice to... (y)	0.701 (0.588)	0.844 (0.813)	0.908 (0.908)	40
You'd Be So Nice to... (z)	0.615 (0.597)	0.615 (0.615)	0.731 (0.731)	24



Musical work (Ron Carter)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
Autumn Leaves (1961)	0.745 (0.654)	0.865 (0.839)	0.926 (0.920)	160
Autumn Leaves (1961) (x)	0.667 (0.561)	0.809 (0.784)	0.876 (0.865)	100
Autumn Leaves (1961) (y)	0.762 (0.645)	0.903 (0.864)	0.986 (0.986)	50
Autumn Leaves (1961) (z)	0.699 (0.590)	0.880 (0.797)	1.000 (1.000)	10
Autumn Leaves (1964)	0.757 (0.619)	0.861 (0.810)	0.901 (0.869)	189
Autumn Leaves (1964) (x)	0.730 (0.529)	0.849 (0.770)	0.885 (0.837)	129
Autumn Leaves (1964) (y)	0.641 (0.600)	0.787 (0.787)	0.872 (0.872)	48
Autumn Leaves (1964) (z)	0.843 (0.732)	0.907 (0.861)	0.907 (0.861)	12
Dolphin Dance	0.536 (0.504)	0.677 (0.672)	0.743 (0.739)	264
Dolphin Dance (x)	0.528 (0.479)	0.757 (0.751)	0.879 (0.879)	94
Dolphin Dance (y)	0.349 (0.320)	0.491 (0.470)	0.539 (0.526)	137
Dolphin Dance (z)	0.628 (0.577)	0.751 (0.786)	0.854 (0.878)	33
E.S.P.	0.746 (0.629)	0.855 (0.810)	0.913 (0.903)	310
E.S.P. (x)	0.708 (0.578)	0.847 (0.794)	0.915 (0.898)	126
E.S.P. (y)	0.712 (0.557)	0.845 (0.792)	0.896 (0.888)	154
E.S.P. (z)	0.497 (0.412)	0.565 (0.497)	0.775 (0.775)	30
Israel	0.779 (0.624)	0.837 (0.750)	0.892 (0.846)	119
Israel (x)	0.748 (0.577)	0.853 (0.717)	0.878 (0.821)	30
Israel (y)	0.735 (0.529)	0.794 (0.691)	0.871 (0.812)	79
Israel (z)	0.639 (0.639)	0.699 (0.699)	0.797 (0.797)	10
Loose Bloose	0.812 (0.540)	0.940 (0.811)	0.985 (0.947)	104
Loose Bloose (z)	0.812 (0.540)	0.940 (0.811)	0.985 (0.947)	104
Mo' Joe	0.845 (0.678)	0.905 (0.824)	0.943 (0.919)	166
Mo' Joe (x)	0.796 (0.552)	0.878 (0.741)	0.921 (0.888)	72
Mo' Joe (y)	0.908 (0.642)	0.940 (0.798)	0.991 (0.921)	40
Mo' Joe (z)	0.743 (0.616)	0.841 (0.815)	0.896 (0.896)	54

Musical work (Ron Carter)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
Oleo	0.761 (0.614)	0.848 (0.801)	0.897 (0.886)	216
Oleo (x)	0.664 (0.436)	0.785 (0.763)	0.824 (0.824)	26
Oleo (y)	0.807 (0.666)	0.887 (0.851)	0.943 (0.937)	55
Oleo (z)	0.688 (0.506)	0.799 (0.731)	0.860 (0.843)	135
Passion Dance	0.694 (0.468)	0.806 (0.696)	0.878 (0.838)	288
Passion Dance (y)	0.694 (0.468)	0.806 (0.696)	0.878 (0.838)	288
Pinocchio	0.842 (0.661)	0.924 (0.864)	0.963 (0.944)	224
Pinocchio (x)	0.830 (0.628)	0.931 (0.864)	0.971 (0.953)	72
Pinocchio (y)	0.781 (0.559)	0.889 (0.811)	0.944 (0.918)	130
Pinocchio (z)	1.000 (0.748)	1.000 (0.959)	1.000 (0.980)	22
Seven Steps to Heaven	0.729 (0.568)	0.852 (0.772)	0.900 (0.866)	297
Seven Steps to Heaven (x)	0.682 (0.488)	0.822 (0.723)	0.882 (0.844)	202
Seven Steps to Heaven (z)	0.726 (0.593)	0.861 (0.797)	0.900 (0.864)	95
Witch Hunt	0.705 (0.594)	0.836 (0.805)	0.887 (0.883)	252
Witch Hunt (x)	0.879 (0.768)	0.935 (0.935)	1.000 (1.000)	26
Witch Hunt (y)	0.645 (0.520)	0.809 (0.766)	0.857 (0.852)	205
Witch Hunt (q)	0.810 (0.653)	0.840 (0.840)	0.978 (0.978)	21

*Note.* Values in parentheses refer to normalized entropy of interval patterns, whereas other values refer to normalized entropy of chordal pitch class patterns. Other abbreviations: (x) = one chord per bar harmonic rhythm only; (y) = one chord per at least two bars harmonic rhythm only; (z) = two chords per one bar harmonic rhythm only; (q) = one chord per one and a half bars harmonic rhythm only.

TABLE 25 Relative frequency of non-recurring chordal pitch class patterns and interval patterns

Musical work (Paul Chambers)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
A Foggy Day	46%/12% (25%/4%)	48%/15% (52%/15%)	55%/22% (58%/23%)	155
A Foggy Day (x)	40%/9% (24%/3%)	39%/11% (44%/11%)	49%/18% (53%/19%)	135
A Foggy Day (y)	64%/35% (29%/10%)	75%/45% (75%/45%)	77%/50% (77%/50%)	20
All of You	60%/25% (31%/7%)	74%/41% (63%/27%)	82%/54% (74%/45%)	155
All of You (x)	62%/25% (27%/5%)	77%/43% (63%/26%)	87.5%/58% (80%/48%)	84
All of You (y)	67%/50% (37.5%/19%)	77%/62.5% (64%/44%)	86%/75% (77%/62.5%)	16
All of You (z)	53%/16% (33%/7%)	68%/31% (62%/24%)	70%/42% (65%/36%)	55
All the Things You Are	42%/11% (17%/3%)	52%/21% (48%/16%)	66%/36% (64%/34%)	275
All the Things You Are (x)	33%/7% (6%/0.5%)	46%/16% (39%/11%)	61%/29% (62%/28%)	199
All the Things You Are (y)	38%/11% (20%/4%)	62%/28% (60%/26%)	70%/50% (66%/46%)	46
All the Things You Are (z)	67%/40% (31%/13%)	67%/40% (65%/37%)	78%/60% (73%/53%)	30
Apothegm	47%/14% (25%/5%)	59%/23% (53%/18%)	68%/38% (67%/35%)	221
Apothegm (x)	45%/13% (25%/4%)	57.5%/24% (54%/20%)	70%/43% (68%/40%)	97
Apothegm (y)	44%/12.5% (18%/4%)	58%/20% (68%/23%)	67%/29% (71%/30%)	56
Apothegm (z)	52%/16% (31%/6%)	63%/25% (38%/12%)	66%/37% (61%/32%)	68
Autumn Leaves	54%/16% (37%/7%)	56%/21% (45%/14%)	67%/29% (67%/29%)	96
Autumn Leaves (x)	50%/17% (30%/6%)	54%/24% (35%/11%)	67%/33% (67%/33%)	54
Autumn Leaves (y)	60%/10% (25%/3%)	50%/10% (50%/10%)	67%/20% (67%/20%)	30
Autumn Leaves (z)	60%/25% (60%/25%)	67%/33% (67%/33%)	67%/33% (67%/33%)	12
Blues by Five	41%/11% (22%/3%)	54%/23% (51%/17%)	71%/42% (68%/36%)	328
Blues by Five (x)	38%/8% (25%/2%)	48%/17% (49%/14%)	66%/35% (63%/30%)	246
Blues by Five (y)	45%/19% (17%/4%)	58%/33% (50%/24%)	79%/57% (71%/46%)	54
Blues by Five (z)	44%/25% (22%/7%)	70%/50% (59%/36%)	83%/68% (83%/68%)	28
Blue Train	45%/10% (39%/5%)	63%/23% (61%/18%)	69%/34% (68%/32%)	288
Blue Train (x)	64%/15% (53%/9%)	66%/22% (65%/21%)	67.5%/28% (67.5%/28%)	96
Blue Train (y)	36%/8% (29%/3%)	62%/23% (59%/17%)	70%/37% (69%/33%)	192

Musical work (Paul Chambers)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
Chamber Mates	35%/9% (20%/3%)	43%/14% (37%/9%)	55%/25% (52%/21%)	142
Chamber Mates (x)	31%/8% (0%/0%)	36%/11% (32%/8%)	51%/22% (49%/19%)	118
Chamber Mates (y)	50%/17% (67%/17%)	70%/29% (57%/17%)	69%/37.5% (64%/29%)	24
Chasin' the Bird	52%/22% (42%/12.5%)	62.5%/35% (59%/28%)	73%/52% (68%/45%)	128
Chasin' the Bird (x)	52%/17.5% (42%/10%)	70%/37.5% (65%/30%)	79%/56% (72%/47.5%)	80
Chasin' the Bird (y)	56%/31% (50%/19%)	55%/37.5% (50%/25%)	55%/37.5% (50%/31%)	16
Chasin' the Bird (z)	50%/28% (38%/16%)	50%/28% (50%/25%)	68%/47% (68%/47%)	32
C-Jam Blues	44%/12% (25%/3%)	63%/30% (58%/22%)	72%/41% (64%/32%)	274
C-Jam Blues (x)	47%/15% (38%/11%)	62%/28% (60%/26%)	62.5%/33% (61%/30%)	46
C-Jam Blues (y)	43%/12% (17%/2%)	63%/30% (57%/21%)	73%/43% (65%/32%)	228
Cool Struttin'	40%/16% (20%/5%)	53%/27% (49%/21%)	63%/39% (59%/35%)	154
Cool Struttin' (x)	50%/21% (19%/4%)	58%/34% (50%/23%)	63%/42% (57%/36%)	77
Cool Struttin' (y)	30%/12% (17%/4%)	52%/25% (52%/21%)	68%/40% (66%/37%)	52
Cool Struttin' (z)	25%/8% (29%/8%)	33%/12% (37.5%/12%)	54%/28% (54%/28%)	25
Cotton Tail	50%/18% (19%/3%)	56%/25% (47.5%/15%)	64%/34% (61%/29%)	261
Cotton Tail (x)	50%/19% (38%/9%)	56%/24% (65%/22%)	71%/43% (70%/36%)	58
Cotton Tail (y)	58%/29% (7%/2%)	59%/33% (36%/14%)	60%/36% (61%/33%)	66
Cotton Tail (z)	44%/13% (12.5%/1%)	54%/21% (46%/12%)	62%/30% (56%/23%)	137
Crazy Rhythm	60%/27% (24%/6%)	67%/35% (65%/30%)	76%/52% (70%/46%)	113
Crazy Rhythm (x)	50%/24% (25%/7%)	58%/30% (60%/26%)	76%/54% (71%/48%)	46
Crazy Rhythm (y)	56%/18% (20%/4%)	65%/31% (60%/24%)	66%/39% (61%/35%)	49
Crazy Rhythm (z)	83%/56% (29%/11%)	85%/61% (83%/56%)	94%/83% (87%/72%)	18
Excerpt	52%/21% (25%/5%)	64%/36% (63%/30%)	78%/55% (69%/45%)	192
Excerpt (x)	59%/24% (17%/3%)	67%/38% (60%/31%)	79%/55% (73%/48%)	94
Excerpt (y)	37.5%/13% (12.5%/2%)	60%/31% (62%/25%)	77%/54% (64%/41%)	91
Excerpt (z)	83%/71% (83%/71%)	83%/71% (83%/71%)	83%/71% (83%/71%)	7
Freddie Freeloader	47%/11% (26%/3%)	61%/25% (61%/22%)	71%/42% (71%/40%)	288
Freddie Freeloader (x)	56%/19% (36%/10%)	73%/33% (73%/33%)	74%/42% (75%/44%)	48

Musical work (Paul Chambers)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
Freddie Freeloader (y)	44%/10% (19%/2%)	58%/23% (57%/20%)	71%/42% (70%/39%)	240
Giant Steps	17%/1.5% (17%/1%)	38%/6% (39%/6%)	47%/10% (46%/10%)	333
Giant Steps (x)	20%/2% (20%/2%)	20%/2% (20%/2%)	45%/8% (41%/7%)	125
Giant Steps (z)	15%/1% (14%/1%)	46%/8% (47%/8%)	48%/11% (49%/11%)	208
I Can't Give You Anything...	67%/41% (40%/15%)	79%/59% (68%/42%)	86%/71% (82%/62%)	95
I Can't Give You Anything... (x)	71%/44% (47%/20%)	79%/60% (74%/51%)	84%/71% (83%/67%)	45
I Can't Give You Anything... (y)	59%/30% (33%/9%)	73%/48% (61%/33%)	83%/61% (77%/52%)	33
I Can't Give You Anything... (z)	69%/53% (29%/12%)	87%/76% (60%/35%)	94%/88% (86%/71%)	17
I Could Write a Book	48%/16% (38%/9%)	66%/31% (60%/25%)	73%/42% (71%/39%)	197
I Could Write a Book (x)	44%/11% (39%/7%)	58%/21% (53%/17%)	61%/27% (59%/24%)	101
I Could Write a Book (y)	69%/47% (60%/32%)	71%/53% (62%/42%)	94%/89% (94%/89%)	19
I Could Write a Book (z)	43%/16% (24%/5%)	70%/39% (66%/32%)	76%/51% (73%/47%)	77
If I Were a Bell	45%/16% (22%/4%)	65%/33% (53%/21%)	70%/42% (68%/38%)	270
If I Were a Bell (x)	35%/10% (12.5%/2%)	57%/25% (48%/18%)	63%/35% (62%/33%)	172
If I Were a Bell (y)	45%/18% (33%/11%)	81%/46% (64%/32%)	88%/54% (88%/54%)	28
If I Were a Bell (z)	59%/29% (31%/7%)	73%/47% (59%/24%)	78%/56% (72%/44%)	70
It's a Blue World	51%/19% (34%/8%)	70%/40% (67.5%/35%)	82%/58% (81%/56%)	154
It's a Blue World (x)	37%/12% (21%/5%)	69%/36% (67%/34%)	80%/52% (80%/52%)	86
It's a Blue World (y)	58%/23% (31%/7%)	70%/43% (65%/33%)	85%/65% (82%/60%)	60
It's a Blue World (z)	83%/62.5% (83%/62.5%)	83%/62.5% (83%/62.5%)	83%/62.5% (83%/62.5%)	8
Milestones	29%/6% (19%/1%)	52%/17% (51%/12%)	65%/30% (62%/25%)	204
Milestones (y)	29%/6% (19%/1%)	52%/17% (51%/12%)	65%/30% (62%/25%)	204
Moment's Notice	41%/8% (9%/1%)	54%/16% (51%/12%)	66%/28% (63%/26%)	369
Moment's Notice (x)	53%/12% (14%/1%)	62%/20% (59%/16%)	70%/27% (70%/25%)	139
Moment's Notice (z)	32%/5% (6%/0.4%)	48%/13% (44%/10%)	64%/29% (59%/26%)	230
Mr. P.C.	25%/3% (14%/1%)	37.5%/8% (35%/6%)	48%/16% (45%/14%)	392
Mr. P.C. (x)	12.5%/2% (0%/0%)	19%/3% (20%/3%)	39%/10% (39%/10%)	128
Mr. P.C. (y)	31%/4% (22%/2%)	44%/10% (42%/8%)	52%/18% (48%/15%)	264

Musical work (Paul Chambers)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
Oleo	39%/11% (25%/3%)	44%/16% (43%/11%)	54%/26% (54%/22%)	343
Oleo (x)	90%/82% (71%/45%)	90%/82% (89%/73%)	90%/82% (90%/82%)	11
Oleo (y)	43%/18% (26%/6%)	51%/27% (47.5%/22%)	67%/44% (67%/42%)	88
Oleo (z)	26%/5% (6%/0.4%)	33%/9% (27.5%/5%)	42%/16% (39%/12%)	244
So What	40%/8% (24%/2%)	50%/14% (52%/10%)	58%/22% (52%/16%)	227
So What (y)	40%/8% (24%/2%)	50%/14% (52%/10%)	58%/22% (52%/16%)	227
Syeeda's Song Flute	37%/8% (21%/3%)	54%/21% (47%/16%)	62%/30% (61%/30%)	128
Syeeda's Song Flute (x)	35%/7% (13%/2%)	56%/21% (47.5%/16%)	64%/31% (63%/30%)	120
Syeeda's Song Flute (z)	50%/25% (50%/25%)	40%/25% (40%/25%)	40%/25% (40%/25%)	8
Tenor Madness	39%/7% (26%/2%)	45%/11% (41%/8%)	53%/19% (49%/16%)	465
Tenor Madness (x)	40%/7% (21%/2%)	43%/11% (37%/7%)	59%/22% (54%/18%)	236
Tenor Madness (y)	32%/7% (21%/2%)	45%/12.5% (41%/9%)	46%/18% (42%/16%)	152
Tenor Madness (z)	54%/9% (40%/5%)	54%/9% (54%/9%)	47%/12% (47%/12%)	77
The Theme	53%/25% (25%/6%)	67%/41% (57%/27%)	76%/54% (72.5%/46%)	126
The Theme (x)	100%/100% (67%/50%)	100%/100% (100%/100%)	100%/100% (100%/100%)	8
The Theme (y)	63%/37.5% (23%/9%)	67%/50% (57%/37.5%)	77%/62.5% (75%/56%)	32
The Theme (z)	36%/14% (8%/1%)	61%/33% (45%/16%)	71%/47% (67%/37%)	86
Woody'n You	41%/8% (23%/3%)	45%/11% (40%/9%)	56%/18% (54%/16%)	245
Woody'n You (x)	36%/5% (18%/2%)	44%/10% (38%/7%)	59%/18% (57%/16%)	147
Woody'n You (y)	17%/2% (17%/2%)	27%/6% (27%/6%)	47%/14% (47%/14%)	50
Woody'n You (z)	56%/21% (33%/8%)	58%/23% (53%/19%)	58%/23% (53%/19%)	48
You'd Be So Nice to...	60%/24% (32%/9%)	69%/37% (71%/36%)	72%/46% (74%/47%)	128
You'd Be So Nice to... (x)	67%/25% (23%/5%)	75%/37.5% (77%/37.5%)	68%/41% (73%/42%)	64
You'd Be So Nice to... (y)	50%/22.5% (33%/10%)	65%/42.5% (67%/40%)	77%/60% (77%/60%)	40
You'd Be So Nice to... (z)	60%/25% (44%/17%)	60%/25% (60%/25%)	69%/37.5% (69%/37.5%)	24

Musical work (Ron Carter)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
Autumn Leaves (1961)	64%/27.5% (36%/9%)	78%/51% (68%/39%)	89%/72% (87%/69%)	160
Autumn Leaves (1961) (x)	62%/23% (29%/6%)	78%/46% (65%/34%)	83%/59% (79%/54%)	100
Autumn Leaves (1961) (y)	65%/34% (37.5%/12%)	79%/60% (71%/48%)	96%/92% (96%/92%)	50
Autumn Leaves (1961) (z)	67%/40% (60%/30%)	75%/60% (71%/50%)	100%/100% (100%/100%)	10
Autumn Leaves (1964)	59%/25% (37%/8%)	76%/48% (67%/35%)	82%/60% (80%/53%)	189
Autumn Leaves (1964) (x)	57%/24% (30%/5%)	79%/51% (67%/33%)	84%/60% (82%/52%)	129
Autumn Leaves (1964) (y)	53%/19% (36%/10%)	65%/35% (65%/35%)	79%/56% (79%/56%)	48
Autumn Leaves (1964) (z)	78%/58% (57%/33%)	80%/67% (67%/50%)	80%/67% (67%/50%)	12
Dolphin Dance	43%/8% (34%/5%)	53%/19% (52%/17%)	75%/38% (76%/39%)	264
Dolphin Dance (x)	43%/10% (25%/4%)	57%/27% (58%/27%)	77%/53% (77%/53%)	94
Dolphin Dance (y)	50%/7% (53%/6%)	48%/11% (46%/9%)	69%/23% (70%/23%)	137
Dolphin Dance (z)	33%/12% (20%/6%)	53%/27% (44%/24%)	83%/61% (84%/64%)	33
E.S.P.	55%/21% (20%/3%)	75%/45% (62%/29%)	86%/64% (82%/58%)	310
E.S.P. (x)	61%/25% (14%/2%)	73%/46% (62.5%/32%)	91%/73% (84%/63%)	126
E.S.P. (y)	47%/17% (19%/3%)	76%/46% (60%/29%)	84%/61% (81%/57%)	154
E.S.P. (z)	70%/23% (43%/10%)	75%/30% (70%/23%)	72%/43% (72%/43%)	30
Israel	61%/29% (34%/8%)	71%/42% (57%/25%)	80%/56% (79%/51%)	119
Israel (x)	76%/43% (33%/10%)	86%/63% (60%/30%)	87%/67% (80%/53%)	30
Israel (y)	57%/25% (33%/6%)	64%/34% (53%/22%)	78%/53% (80%/51%)	79
Israel (z)	40%/20% (40%/20%)	67%/40% (67%/40%)	71%/50% (71%/50%)	10
Loose Bloose	61%/34% (30%/6%)	87%/72% (69%/38%)	96%/91% (91%/78%)	104
Loose Bloose (z)	61%/34% (30%/6%)	87%/72% (69%/38%)	96%/91% (91%/78%)	104
Mo' Joe	69%/41% (36%/10%)	80%/58% (70%/39%)	90%/75% (85%/66%)	166
Mo' Joe (x)	60%/33% (29%/7%)	81%/58% (68%/35%)	90%/74% (86%/64%)	72
Mo' Joe (y)	77%/60% (50%/17.5%)	85%/72.5% (75%/45%)	97%/95% (88%/72.5%)	40
Mo' Joe (z)	71%/37% (31%/9%)	74%/48% (69%/41%)	83%/63% (83%/63%)	54
Oleo	52%/21% (25%/5%)	62%/35% (60%/29%)	78%/54% (76%/51%)	216
Oleo (x)	45%/19% (43%/12%)	69%/42% (67%/38%)	78%/54% (78%/54%)	26

Musical work (Ron Carter)	2-note melodic patterns	3-note melodic patterns	4-note melodic patterns	No. of bars
Oleo (y)	55%/31% (22%/7%)	61%/42% (60%/38%)	80%/67% (78%/64%)	55
Oleo (z)	51%/18% (21%/3%)	62%/31% (58%/24%)	77%/49% (75%/45%)	135
Passion Dance	49%/15% (14%/1%)	66%/33% (60%/21%)	77%/50% (69%/38%)	288
Passion Dance (y)	49%/15% (14%/1%)	66%/33% (60%/21%)	77%/50% (69%/38%)	288
Pinocchio	76%/46% (31%/8%)	89%/71% (78%/50%)	91%/80% (88%/72%)	224
Pinocchio (x)	64%/37.5% (26%/7%)	86%/71% (82%/57%)	92%/85% (92%/81%)	72
Pinocchio (y)	75%/42% (22%/4%)	88%/65% (71%/40%)	89%/75% (84%/65%)	130
Pinocchio (z)	100%/100% (58%/32%)	100%/100% (90%/82%)	100%/100% (95%/91%)	22
Seven Steps to Heaven	47%/16% (19%/3%)	72%/41% (59%/24%)	80%/55% (73%/44%)	297
Seven Steps to Heaven (x)	47%/15% (17%/2%)	68%/36% (51%/18%)	78%/51% (68%/40%)	202
Seven Steps to Heaven (z)	47%/19% (21%/4%)	79%/53% (70%/37%)	85%/63% (81%/55%)	95
Witch Hunt	55%/19% (45%/9%)	76%/45% (66%/35%)	87%/63% (87%/62%)	252
Witch Hunt (x)	68%/50% (67%/38%)	82%/69% (82%/69%)	100%/100% (100%/100%)	26
Witch Hunt (y)	44%/11% (13%/1%)	74%/40% (60%/28%)	84%/56% (83%/54%)	205
Witch Hunt (q)	79%/52% (82%/43%)	80%/57% (80%/57%)	95%/90% (95%/90%)	21

*Note.* To keep this table readable, all percentages are reported without decimals (except when the percentage is exactly half as in 37.5%). The first two percentages refer to the relative frequency of non-recurring chordal pitch class patterns in relation to the total number of different chordal pitch class patterns and the relative frequency of non-recurring chordal pitch class patterns in relation to the total number of all occurrences of chordal pitch class patterns, respectively. The percentages in parentheses refer to the relative frequency of non-recurring interval patterns in relation to the total number of different interval patterns and the relative frequency of non-recurring interval patterns in relation to the total number of all occurrences of interval patterns, respectively. Other abbreviations: (x) = one chord per bar harmonic rhythm only; (y) = one chord per at least two bars harmonic rhythm only; (z) = two chords per one bar harmonic rhythm only; (q) = one chord per one and a half bars harmonic rhythm only.



## Appendix 4: Supplementary tables for Chapters 6.2.3 to 6.2.5

TABLE 26 Normalized entropy of target notes

Musical work (Paul Chambers)	4-beat harmonic rhythm	8-beat harmonic rhythm	2-beat harmonic rhythm	All
A Foggy Day	0.254 (135)	0.291 (20)	-	0.240 (155)
All of You	0.307 (84)	0.535 (16)	0.242 (55)	0.290 (155)
All the Things You Are	0.244 (199)	0.265 (46)	0.434 (30)	0.239 (275)
Apothegm	0.269 (97)	0.299 (56)	0.282 (68)	0.242 (221)
Autumn Leaves	0.282 (54)	0.086 (30)	0.370 (12)	0.208 (96)
Blues by Five	0.264 (246)	0.321 (54)	0.439 (28)	0.268 (328)
Blue Train	0.116 (96)	0.265 (192)	-	0.219 (288)
Chamber Mates	0.326 (118)	0.312 (24)	-	0.311 (142)
Chasin' the Bird	0.240 (80)	0.224 (16)	0.379 (32)	0.236 (128)
C-Jam Blues	0.250 (46)	0.309 (228)	-	0.284 (274)
Cool Struttin'	0.323 (77)	0.290 (52)	0.195 (25)	0.277 (154)
Cotton Tail	0.276 (58)	0.393 (66)	0.312 (137)	0.298 (261)
Crazy Rhythm	0.430 (46)	0.303 (49)	0.477 (18)	0.324 (113)
Excerpt	0.315 (94)	0.309 (91)	0.695 (7)	0.281 (192)
Freddie Freeloader	0.163 (48)	0.264 (240)	-	0.252 (288)
Giant Steps	0.131 (125)	-	0.164 (208)	0.141 (333)
I Can't Give You Anything but Love	0.281 (45)	0.413 (33)	0.565 (17)	0.339 (95)
I Could Write a Book	0.219 (101)	0.633 (19)	0.302 (77)	0.262 (197)
If I Were a Bell	0.256 (172)	0.247 (28)	0.371 (70)	0.255 (270)
It's a Blue World	0.215 (86)	0.326 (60)	0.583 (8)	0.250 (154)
Milestones	-	0.330 (204)	-	0.330 (204)
Moment's Notice	0.243 (139)	-	0.253 (230)	0.232 (369)
Mr. P.C.	0.193 (128)	0.263 (264)	-	0.242 (392)

Musical work (Paul Chambers)	4-beat harmonic rhythm	8-beat harmonic rhythm	2-beat harmonic rhythm	All
Oleo	0.570 (11)	0.340 (88)	0.296 (244)	0.285 (343)
So What	-	0.300 (227)	-	0.300 (227)
Syeeda's Song Flute	0.237 (120)	-	0.181 (8)	0.235 (128)
Tenor Madness	0.256 (236)	0.281 (152)	0.174 (77)	0.232 (465)
The Theme	0.719 (8)	0.332 (32)	0.365 (86)	0.367 (126)
Woody'n You	0.090 (147)	0.177 (50)	0.440 (48)	0.191 (245)
You'd Be So Nice to Come Home to	0.230 (64)	0.295 (40)	0.257 (24)	0.229 (128)
Musical work (Ron Carter)	4-beat harmonic rhythm	8-beat harmonic rhythm	2-beat harmonic rhythm	All
Autumn Leaves (1961)	0.232 (100)	0.317 (50)	0.141 (10)	0.251 (160)
Autumn Leaves (1964)	0.348 (129)	0.308 (48)	0.442 (12)	0.305 (189)
Dolphin Dance	0.122 (94)	0.080 (137)	0.142 (33)	0.094 (264)
E.S.P.	0.308 (126)	0.302 (154)	0.198 (30)	0.267 (310)
Israel	0.411 (30)	0.387 (79)	0.413 (10)	0.352 (119)
Loose Bloose	-	-	0.450 (104)	0.450 (104)
Mo' Joe	0.431 (72)	0.554 (40)	0.308 (54)	0.361 (166)
Oleo	0.470 (26)	0.303 (55)	0.338 (135)	0.321 (216)
Passion Dance	-	0.344 (288)	-	0.344 (288)
Pinocchio	0.435 (72)	0.422 (130)	0.699 (22)	0.382 (224)
Seven Steps to Heaven	0.305 (202)	-	0.294 (95)	0.275 (297)
Witch Hunt	0.337 (26)	0.226 (205)	0.478 (21) *	0.226 (252)

*Note.* Number of bars is presented in parentheses. Harm. = harmonic rhythm. \* One chord per one and a half bars harmonic rhythm.

TABLE 27 Relative frequency of root notes and consonant target notes (root notes, major thirds, minor thirds, and perfect fifths combined)

Musical work (Paul Chambers)	Root notes	Consonant target notes	No. of bars
A Foggy Day	56.77%	87.74%	155
All of You	57.42%	78.06%	155
All the Things You Are	53.82%	91.64%	275
Apothegm	61.99%	90.05%	221
Autumn Leaves	72.92%	96.88%	96
Blues by Five	48.78%	84.76%	328
Blue Train	52.78%	90.28%	288
Chamber Mates	47.18%	80.99%	142
Chasin' the Bird	64.84%	91.41%	128
C-Jam Blues	47.45%	80.66%	274
Cool Struttin'	55.19%	85.06%	154
Cotton Tail	49.43%	83.52%	261
Crazy Rhythm	49.56%	84.07%	113
Excerpt	50.52%	91.15%	192
Freddie Freeloader	37.85%	86.81%	288
Giant Steps	69.37%	97.30%	333
I Can't Give You Anything but Love	51.58%	83.16%	95
I Could Write a Book	59.39%	83.25%	197
If I Were a Bell	55.19%	90.00%	270
It's a Blue World	58.44%	94.16%	154
Milestones	31.86%	63.73%	204
Moment's Notice	59.08%	86.99%	369
Mr. P.C.	55.36%	88.27%	392
Oleo	45.48%	81.05%	343
So What	39.21%	77.53%	227
Syedda's Song Flute	53.91%	96.88%	128

Musical work (Paul Chambers)	Root notes	Consonant target notes	No. of bars
Tenor Madness	54.62%	87.96%	465
The Theme	42.86%	74.60%	126
Woody'n You	68.57%	91.43%	245
You'd Be So Nice to Come Home to	69.53%	91.41%	128
Musical work (Ron Carter)	Root notes	Consonant target notes	No. of bars
Autumn Leaves (1961)	70.00%	88.13%	160
Autumn Leaves (1964)	55.03%	80.42%	189
Dolphin Dance	89.77%	95.08%	264
E.S.P.	56.45%	73.23%	310
Israel	52.10%	74.79%	119
Loose Bloose	29.81%	56.73%	104
Mo' Joe	45.78%	68.07%	166
Oleo	51.39%	70.37%	216
Passion Dance	32.99%	64.93%	288
Pinocchio	40.18%	60.27%	224
Seven Steps to Heaven	51.85%	78.11%	297
Witch Hunt	55.56%	82.54%	252

TABLE 28 Average and maximum length of recurring melodic patterns after the overlapping melodic patterns removal process

Musical work (Paul Chambers)	Aver. length (int.)	Aver. length (sec.)	Max. length (int.)	Max. length (sec.)
A Foggy Day (after stage 1)	9.74 (7.72)	2.72	40	11.16
A Foggy Day (after stage 2)	11.29 (9.04)	3.15	40	11.16
A Foggy Day (after stage 3)	10.69 (9.50)	2.98	40	11.16
All of You (after stage 1)	4.59 (3.48)	1.66	18	6.51
All of You (after stage 2)	5.47 (3.86)	1.98	18	6.51
All of You (after stage 3)	5.26 (3.80)	1.90	18	6.51
All the Things You Are (after stage 1)	6.65 (6.63)	1.72	38	9.83
All the Things You Are (after stage 2)	6.55 (6.15)	1.69	38	9.83
All the Things You Are (after stage 3)	5.53 (5.14)	1.43	38	9.83
Apothegm (after stage 1)	5.80 (4.99)	2.04	26	9.12
Apothegm (after stage 2)	6.16 (5.25)	2.16	26	9.12
Apothegm (after stage 3)	5.25 (4.90)	1.84	26	9.12
Autumn Leaves (after stage 1)	8.78 (6.81)	3.99	31	14.09
Autumn Leaves (after stage 2)	9.84 (8.17)	4.47	31	14.09
Autumn Leaves (after stage 3)	8.65 (8.92)	3.93	31	14.09
Blues by Five (after stage 1)	4.41 (3.42)	1.49	20	6.78
Blues by Five (after stage 2)	5.39 (3.62)	1.83	20	6.78
Blues by Five (after stage 3)	5.17 (3.56)	1.75	20	6.78
Blue Train (after stage 1)	5.93 (5.32)	2.68	29	13.08
Blue Train (after stage 2)	6.49 (5.34)	2.93	29	13.08
Blue Train (after stage 3)	5.83 (4.81)	2.63	29	13.08
Chamber Mates (after stage 1)	11.92 (10.01)	2.68	48	10.79
Chamber Mates (after stage 2)	12.61 (11.40)	2.83	48	10.79
Chamber Mates (after stage 3)	9.83 (10.75)	2.21	48	10.79
Chasin' the Bird (after stage 1)	3.45 (2.44)	1.16	13	4.36
Chasin' the Bird (after stage 2)	4.19 (2.68)	1.40	13	4.36

Musical work (Paul Chambers)	Aver. length (int.)	Aver. length (sec.)	Max. length (int.)	Max. length (sec.)
Chasin' the Bird (after stage 3)	4.15 (2.82)	1.39	13	4.36
C-Jam Blues (after stage 1)	4.95 (4.11)	1.80	23	8.36
C-Jam Blues (after stage 2)	5.55 (4.32)	2.02	23	8.36
C-Jam Blues (after stage 3)	5.29 (4.31)	1.92	23	8.36
Cool Struttin' (after stage 1)	5.49 (5.20)	2.97	28	15.14
Cool Struttin' (after stage 2)	5.66 (4.96)	3.06	28	15.14
Cool Struttin' (after stage 3)	5.28 (4.37)	2.85	28	15.14
Cotton Tail (after stage 1)	6.40 (5.27)	1.52	28	6.67
Cotton Tail (after stage 2)	7.16 (5.77)	1.70	28	6.67
Cotton Tail (after stage 3)	6.37 (5.82)	1.52	28	6.67
Crazy Rhythm (after stage 1)	4.23 (3.08)	0.89	15	3.16
Crazy Rhythm (after stage 2)	5.14 (3.47)	1.08	15	3.16
Crazy Rhythm (after stage 3)	5.04 (3.68)	1.06	15	3.16
Excerpt (after stage 1)	3.64 (2.91)	0.99	18	4.91
Excerpt (after stage 2)	4.26 (2.94)	1.16	18	4.91
Excerpt (after stage 3)	4.06 (2.83)	1.11	18	4.91
Freddie Freeloader (after stage 1)	3.77 (2.75)	1.77	16	7.50
Freddie Freeloader (after stage 2)	4.60 (2.99)	2.16	16	7.50
Freddie Freeloader (after stage 3)	4.58 (2.16)	2.15	16	7.50
Giant Steps (after stage 1)	9.74 (8.46)	1.99	50	10.24
Giant Steps (after stage 2)	11.84 (8.87)	2.42	50	10.24
Giant Steps (after stage 3)	11.41 (8.42)	2.34	50	10.24
I Can't Give You Anything... (after stage 1)	3.34 (2.48)	1.08	13	4.22
I Can't Give You Anything... (after stage 2)	3.75 (2.70)	1.22	13	4.22
I Can't Give You Anything... (after stage 3)	3.68 (2.70)	1.19	13	4.22
I Could Write a Book (after stage 1)	6.96 (5.86)	1.82	30	7.86
I Could Write a Book (after stage 2)	7.20 (6.44)	1.89	30	7.86
I Could Write a Book (after stage 3)	6.20 (6.37)	1.62	30	7.86

Musical work (Paul Chambers)	Aver. length (int.)	Aver. length (sec.)	Max. length (int.)	Max. length (sec.)
If I Were a Bell (after stage 1)	4.41 (3.37)	1.41	20	6.42
If I Were a Bell (after stage 2)	5.36 (3.64)	1.72	20	6.42
If I Were a Bell (after stage 3)	5.30 (3.69)	1.70	20	6.42
It's a Blue World (after stage 1)	4.26 (3.82)	1.34	21	6.60
It's a Blue World (after stage 2)	4.33 (3.73)	1.36	21	6.60
It's a Blue World (after stage 3)	3.94 (3.48)	1.24	21	6.60
Milestones (after stage 1)	5.09 (3.81)	1.29	22	5.57
Milestones (after stage 2)	6.51 (4.17)	1.65	22	5.57
Milestones (after stage 3)	6.37 (4.28)	1.61	22	5.57
Moment's Notice (after stage 1)	5.80 (4.42)	1.43	23	5.66
Moment's Notice (after stage 2)	6.95 (5.05)	1.71	23	5.66
Moment's Notice (after stage 3)	6.51 (5.42)	1.60	23	5.66
Mr. P.C. (after stage 1)	8.64 (6.66)	1.99	35	8.08
Mr. P.C. (after stage 2)	11.02 (7.63)	2.54	35	8.08
Mr. P.C. (after stage 3)	10.24 (8.31)	2.36	35	8.08
Oleo (after stage 1)	8.40 (8.21)	1.89	49	11.01
Oleo (after stage 2)	9.06 (7.83)	2.04	49	11.01
Oleo (after stage 3)	7.93 (6.78)	1.78	49	11.01
So What (after stage 1)	7.03 (5.68)	3.03	31	13.38
So What (after stage 2)	8.50 (6.23)	3.67	31	13.38
So What (after stage 3)	8.15 (6.43)	3.52	31	13.38
Syedda's Song Flute (after stage 1)	4.23 (3.36)	1.34	19	6.03
Syedda's Song Flute (after stage 2)	4.92 (3.56)	1.56	19	6.03
Syedda's Song Flute (after stage 3)	4.78 (3.49)	1.52	19	6.03
Tenor Madness (after stage 1)	10.06 (8.95)	3.45	46	15.77
Tenor Madness (after stage 2)	11.27 (9.42)	3.86	46	15.77
Tenor Madness (after stage 3)	9.58 (8.94)	3.28	46	15.77

Musical work (Paul Chambers)	Aver. length (int.)	Aver. length (sec.)	Max. length (int.)	Max. length (sec.)
The Theme (after stage 1)	5.25 (4.08)	1.49	18	5.12
The Theme (after stage 2)	5.75 (4.66)	1.64	18	5.12
The Theme (after stage 3)	5.05 (4.73)	1.44	18	5.12
Woody'n You (after stage 1)	13.80 (12.04)	3.22	61	14.24
Woody'n You (after stage 2)	14.71 (13.25)	3.43	61	14.24
Woody'n You (after stage 3)	11.19 (12.86)	2.61	61	14.24
You'd Be So Nice to... (after stage 1)	3.79 (2.80)	1.36	16	5.75
You'd Be So Nice to... (after stage 2)	4.50 (3.07)	1.62	16	5.75
You'd Be So Nice to... (after stage 3)	4.35 (3.16)	1.56	16	5.75
Musical work (Ron Carter)	Aver. length (int.)	Aver. length (sec.)	Max. length (int.)	Max. length (sec.)
Autumn Leaves (1961) (after stage 1)	3.09 (2.50)	1.36	13	5.74
Autumn Leaves (1961) (after stage 2)	3.25 (2.51)	1.43	13	5.74
Autumn Leaves (1961) (after stage 3)	3.06 (2.41)	1.35	13	5.74
Autumn Leaves (1964) (after stage 1)	12.04 (14.06)	5.43	63	28.42
Autumn Leaves (1964) (after stage 2)	6.19 (10.25)	2.79	63	28.42
Autumn Leaves (1964) (after stage 3)	3.82 (5.57)	1.72	63	28.42
Dolphin Dance (after stage 1)	6.19 (5.51)	3.04	30	14.75
Dolphin Dance (after stage 2)	6.06 (5.68)	2.98	30	14.75
Dolphin Dance (after stage 3)	5.25 (5.31)	2.58	30	14.75
E.S.P. (after stage 1)	3.22 (2.49)	0.67	13	2.70
E.S.P. (after stage 2)	3.68 (2.55)	0.76	13	2.70
E.S.P. (after stage 3)	3.55 (2.54)	0.74	13	2.70
Israel (after stage 1)	9.32 (10.08)	3.78	47	19.05
Israel (after stage 2)	6.55 (8.55)	2.66	47	19.05
Israel (after stage 3)	4.94 (7.12)	2.00	47	19.05
Loose Bloose (after stage 1)	2.00 (1.18)	1.04	7	3.65
Loose Bloose (after stage 2)	2.35 (1.24)	1.23	7	3.65



Musical work (Ron Carter)	Aver. length (int.)	Aver. length (sec.)	Max. length (int.)	Max. length (sec.)
Loose Bloose (after stage 3)	2.35 (1.24)	1.23	7	3.65
Mo' Joe (after stage 1)	2.65 (1.70)	0.53	9	1.81
Mo' Joe (after stage 2)	3.37 (1.78)	0.68	9	1.81
Mo' Joe (after stage 3)	3.36 (1.82)	0.68	9	1.81
Oleo (after stage 1)	11.32 (11.79)	2.78	52	12.79
Oleo (after stage 2)	6.99 (10.14)	1.72	52	12.79
Oleo (after stage 3)	4.29 (6.56)	1.05	52	12.79
Passion Dance (after stage 1)	3.48 (2.53)	0.87	14	3.50
Passion Dance (after stage 2)	4.20 (2.73)	1.05	14	3.50
Passion Dance (after stage 3)	4.10 (2.75)	1.03	14	3.50
Pinocchio (after stage 1)	2.21 (1.41)	0.63	9	2.55
Pinocchio (after stage 2)	2.67 (1.42)	0.76	9	2.55
Pinocchio (after stage 3)	2.66 (1.42)	0.75	9	2.55
Seven Steps to Heaven (after stage 1)	4.37 (3.64)	0.92	21	4.41
Seven Steps to Heaven (after stage 2)	4.91 (3.73)	1.03	21	4.41
Seven Steps to Heaven (after stage 3)	4.54 (3.58)	0.95	21	4.41
Witch Hunt (after stage 1)	3.23 (2.79)	1.39	16	6.91
Witch Hunt (after stage 2)	3.39 (2.66)	1.46	16	6.91
Witch Hunt (after stage 3)	3.16 (2.49)	1.36	16	6.91

*Note.* Standard deviations are presented in parentheses. Aver. length (int.) = average length (in intervals); Aver. length (sec.) = average length in seconds; Max. length (int.) = maximum length (in intervals); Max. length (sec.) = maximum length in seconds.

TABLE 29 Normalized entropy of interval size and average interval size

Musical work (Paul Chambers)	Norm. interval size	Average interval size	No. of bars
A Foggy Day	0.303	2.52	155
All of You	0.326	2.55	155
All the Things You Are	0.339	3.09	275
Apothegm	0.335	2.92	221
Autumn Leaves	0.415	3.04	96
Blues by Five	0.309	2.81	328
Blue Train	0.305	2.88	288
Chamber Mates	0.353	2.82	142
Chasin' the Bird	0.384	3.27	128
C-Jam Blues	0.327	3.13	274
Cool Struttin'	0.361	2.94	154
Cotton Tail	0.301	2.62	261
Crazy Rhythm	0.364	2.51	113
Excerpt	0.361	3.17	192
Freddie Freeloader	0.324	2.99	288
Giant Steps	0.360	3.71	333
I Can't Give You Anything but Love	0.370	2.81	95
I Could Write a Book	0.332	2.91	197
If I Were a Bell	0.316	3.08	270
It's a Blue World	0.368	3.22	154
Milestones	0.290	2.42	204
Moment's Notice	0.336	3.19	369
Mr. P.C.	0.298	2.50	392
Oleo	0.317	3.10	343
So What	0.289	2.72	227
Syedda's Song Flute	0.384	3.26	128

Musical work (Paul Chambers)	Norm. interval size	Average interval size	No. of bars
Tenor Madness	0.282	2.85	465
The Theme	0.410	3.42	126
Woody'n You	0.282	2.17	245
You'd Be So Nice to Come Home to	0.403	3.38	128
Musical work (Ron Carter)	Norm. interval size	Average interval size	No. of bars
Autumn Leaves (1961)	0.429	4.12	160
Autumn Leaves (1964)	0.407	4.73	189
Dolphin Dance	0.369	3.79	264
E.S.P.	0.373	4.12	310
Israel	0.411	2.89	119
Loose Bloose	0.488	5.14	104
Mo' Joe	0.376	3.11	166
Oleo	0.398	4.08	216
Passion Dance	0.342	3.10	288
Pinocchio	0.411	4.19	224
Seven Steps to Heaven	0.328	3.21	297
Witch Hunt	0.389	3.91	252

*Note.* Norm. interval size = normalized entropy of interval size.

## Appendix 5: Supplementary tables for Chapters 6.3.2 to 6.3.4

TABLE 30 Normalized entropy of melodic contour patterns and relative frequency of non-recurring melodic contour patterns

Musical work (Paul Chambers)	Norm. entropy (F)	Norm. entropy (P)	Rel. frequency (F)	Rel. frequency (P)
A Foggy Day	0.591	0.344	59.09%/16.77%	0%/0%
All of You	0.629	0.347	62.26%/21.29%	11.11%/0.65%
All the Things You Are	0.713	0.383	46.81%/16.00%	26.67%/1.45%
Apothegm	0.679	0.368	46.27%/14.03%	20.00%/0.90%
Autumn Leaves	0.630	0.401	44.44%/12.50%	12.50%/1.04%
Blues by Five	0.685	0.383	47.52%/14.63%	7.69%/0.30%
Blue Train	0.640	0.353	50.63%/13.89%	0%/0%
Chamber Mates	0.677	0.411	35.71%/10.56%	0%/0%
Chasin' the Bird	0.759	0.405	59.65%/26.56%	11.11%/0.78%
C-Jam Blues	0.706	0.386	55.79%/19.34%	7.69%/0.36%
Cool Struttin'	0.713	0.407	50.85%/19.48%	25.00%/1.95%
Cotton Tail	0.626	0.355	48.48%/12.26%	18.18%/0.77%
Crazy Rhythm	0.690	0.447	60.00%/23.89%	23.08%/2.65%
Excerpt	0.755	0.394	55.00%/22.92%	16.67%/1.04%
Freddie Freeloader	0.714	0.370	59.65%/23.61%	21.43%/1.04%
Giant Steps	0.571	0.351	39.62%/6.31%	18.18%/0.60%
I Can't Give You Anything but Love	0.748	0.411	69.39%/35.79%	11.11%/1.05%
I Could Write a Book	0.703	0.375	55.41%/20.81%	0%/0%
If I Were a Bell	0.702	0.372	54.26%/18.89%	23.08%/1.11%
It's a Blue World	0.770	0.406	61.64%/29.22%	20.00%/1.30%
Milestones	0.600	0.357	60.71%/16.67%	20.00%/0.98%

Musical work (Paul Chambers)	Norm. entropy (F)	Norm. entropy (P)	Rel. frequency (F)	Rel. frequency (P)
Moment's Notice	0.666	0.366	47.87%/12.20%	14.29%/0.54%
Mr. P.C.	0.628	0.360	40.28%/7.40%	0%/0%
Oleo	0.671	0.357	35.44%/8.16%	10.00%/0.29%
So What	0.525	0.312	44.19%/8.37%	18.18%/0.88%
Syeeda's Song Flute	0.710	0.381	56.25%/21.09%	0%/0%
Tenor Madness	0.602	0.323	39.51%/6.88%	11.11%/0.22%
The Theme	0.750	0.439	60.00%/26.19%	18.18%/1.59%
Woody'n You	0.573	0.381	46.65%/8.57%	23.08%/1.22%
You'd Be So Nice to Come Home to	0.745	0.415	63.79%/28.91%	9.09%/0.78%

Musical work (Ron Carter)	Norm. entropy (F)	Norm. entropy (P)	Rel. frequency (F)	Rel. frequency (P)
Autumn Leaves (1961)	0.841	0.504	71.88%/43.13%	20.00%/2.50%
Autumn Leaves (1964)	0.768	0.431	62.07%/28.57%	37.50%/3.17%
Dolphin Dance	0.687	0.493	67.62%/26.89%	13.04%/1.14%
E.S.P.	0.779	0.394	51.54%/21.61%	17.65%/0.97%
Israel	0.756	0.485	68.97%/33.61%	28.57%/3.36%
Loose Bloose	0.908	0.479	82.05%/61.54%	15.38%/1.92%
Mo' Joe	0.785	0.407	58.44%/27.11%	18.18%/1.20%
Oleo	0.809	0.452	59.80%/28.24%	36.84%/3.24%
Passion Dance	0.747	0.396	52.21%/20.49%	25.00%/1.74%
Pinocchio	0.830	0.427	65.57%/35.71%	5.88%/0.45%
Seven Steps to Heaven	0.762	0.374	53.39%/21.21%	46.67%/2.36%
Witch Hunt	0.819	0.460	65.67%/34.92%	20.83%/1.98%

*Note.* The first relative frequency value refers to the relative frequency of non-recurring melodic contour pattern classes in relation to the total number of melodic contour pattern classes, whereas the second relative frequency value refers to the relative frequency of non-recurring melodic contour pattern classes in relation to the total number of all occurrences of melodic contour patterns. F = fuzzy interval patterns; P = Parsons's code patterns.

TABLE 31 Average length and maximum length of recurring fuzzy interval patterns and Parsons's code patterns

Musical work (Paul Chambers)	Aver. length (F)	Aver. length (P)	Max. length (F)	Max. length (P)
A Foggy Day	9.67 (2.70 s)	10.72 (2.99 s)	40 (11.16 s)	41 (11.44 s)
All of You	4.81 (1.74 s)	6.52 (2.36 s)	18 (6.51 s)	19 (6.87 s)
All the Things You Are	6.65 (1.72 s)	7.53 (1.95 s)	38 (9.83 s)	38 (9.83 s)
Apothegm	6.16 (2.16 s)	7.61 (2.67 s)	30 (10.53 s)	30 (10.53 s)
Autumn Leaves	10.00 (4.47 s)	10.67 (4.85 s)	33 (15.00 s)	37 (16.82 s)
Blues by Five	4.70 (1.59 s)	6.84 (2.32 s)	20 (6.78 s)	30 (10.17 s)
Blue Train	6.21 (2.80 s)	7.73 (3.49 s)	32 (14.44 s)	38 (17.14 s)
Chamber Mates	12.44 (2.80 s)	12.09 (2.72 s)	48 (10.79 s)	48 (10.79 s)
Chasin' the Bird	4.08 (1.37 s)	5.89 (1.97 s)	16 (5.36 s)	18 (6.03 s)
C-Jam Blues	5.11 (1.85 s)	7.10 (2.57 s)	23 (8.31 s)	31 (11.20 s)
Cool Struttin'	5.69 (3.10 s)	7.21 (3.93 s)	28 (15.27 s)	33 (18.00 s)
Cotton Tail	6.44 (1.53 s)	7.75 (1.84 s)	28 (6.64 s)	33 (7.83 s)
Crazy Rhythm	4.98 (1.06 s)	6.22 (1.32 s)	19 (4.03 s)	23 (4.88 s)
Excerpt	4.04 (1.10 s)	8.54 (2.32 s)	18 (4.89 s)	45 (12.22 s)
Freddie Freeloader	4.29 (2.01 s)	6.79 (3.18 s)	20 (9.38 s)	28 (13.13 s)
Giant Steps	10.45 (2.14 s)	13.03 (2.67 s)	50 (10.24 s)	66 (13.52 s)
I Can't Give You Anything but Love	3.79 (1.23 s)	5.57 (1.81 s)	13 (4.22 s)	15 (4.86 s)
I Could Write a Book	6.90 (1.81 s)	8.50 (2.23 s)	30 (7.86 s)	40 (10.48 s)
If I Were a Bell	4.68 (1.50 s)	6.51 (2.09 s)	20 (6.42 s)	26 (8.34 s)
It's a Blue World	4.27 (1.34 s)	6.19 (1.94 s)	21 (6.60 s)	24 (7.54 s)
Milestones	5.58 (1.41 s)	7.24 (1.83 s)	23 (5.82 s)	23 (5.82 s)
Moment's Notice	5.95 (1.46 s)	7.57 (1.86 s)	23 (5.66 s)	28 (6.89 s)
Mr. P.C.	9.45 (2.18 s)	11.38 (2.63 s)	35 (8.08 s)	42 (9.69 s)
Oleo	8.46 (1.90 s)	9.33 (2.10 s)	49 (11.01 s)	49 (11.01 s)
So What	7.37 (3.18 s)	9.75 (4.21 s)	31 (13.38 s)	36 (15.54 s)
Syedda's Song Flute	4.46 (1.42 s)	6.29 (2.00 s)	19 (6.03 s)	23 (7.30 s)

Musical work (Paul Chambers)	Aver. length (F)	Aver. length (P)	Max. length (F)	Max. length (P)
Tenor Madness	10.07 (3.45 s)	11.60 (3.98 s)	46 (15.77 s)	54 (18.51 s)
The Theme	5.32 (1.51 s)	6.63 (1.89 s)	18 (5.12 s)	23 (6.54 s)
Woody'n You	19.20 (4.48 s)	18.76 (4.38 s)	84 (19.61 s)	85 (19.84 s)
You'd Be So Nice to Come Home to	3.89 (1.40 s)	5.62 (2.02 s)	16 (5.75 s)	16 (5.75 s)
Musical work (Ron Carter)	Aver. length (F)	Aver. length (P)	Max. length (F)	Max. length (P)
Autumn Leaves (1961)	4.53 (2.00 s)	5.39 (2.38 s)	25 (11.03 s)	25 (11.03 s)
Autumn Leaves (1964)	10.96 (4.94 s)	11.31 (5.10 s)	63 (28.42 s)	71 (32.03 s)
Dolphin Dance	6.54 (3.22 s)	6.73 (3.31 s)	30 (14.75 s)	30 (14.75 s)
E.S.P.	3.71 (0.77 s)	6.08 (1.26 s)	16 (3.32 s)	25 (5.19 s)
Israel	8.95 (3.63 s)	8.43 (3.42 s)	47 (19.05 s)	47 (19.05 s)
Loose Bloose	2.36 (1.23 s)	5.37 (2.80 s)	7 (3.65 s)	17 (8.87 s)
Mo' Joe	3.09 (0.62 s)	5.33 (1.07 s)	10 (2.01 s)	15 (3.02 s)
Oleo	10.65 (2.62 s)	10.33 (2.54 s)	52 (12.79 s)	55 (13.52 s)
Passion Dance	3.81 (0.95 s)	6.34 (1.59 s)	14 (3.50 s)	30 (7.50 s)
Pinocchio	2.74 (0.78 s)	5.19 (1.47 s)	11 (3.11 s)	16 (4.53 s)
Seven Steps to Heaven	4.39 (0.92 s)	6.42 (1.35 s)	24 (5.03 s)	26 (5.45 s)
Witch Hunt	3.59 (1.55 s)	5.38 (2.32 s)	19 (8.20 s)	19 (8.20 s)

*Note.* Aver. length = average length; Max. length = maximum length; F = fuzzy interval patterns; P = Parsons's code patterns.

TABLE 32 Normalized entropy of approach-note patterns and relative frequency of non-recurring approach-note patterns

Musical work (Paul Chambers)	2-note approach-note patterns	3-note approach-note patterns	2-note interval patterns	3-note interval patterns
A Foggy Day	0.316 (25%/1%)	0.579 (34%/7%)	0.506 (25%/4%)	0.644 (52%/15%)
All of You	0.304 (12.5%/1%)	0.616 (39%/10%)	0.616 (31%/7%)	0.740 (63%/27%)
All the Things You Are	0.375 (19%/1%)	0.671 (46%/13%)	0.566 (17%/3%)	0.727 (48%/16%)
Apothegm	0.363 (25%/2%)	0.680 (43%/12%)	0.610 (25%/5%)	0.712 (53%/18%)
Autumn Leaves	0.445 (25%/3%)	0.675 (53%/18%)	0.512 (37%/7%)	0.623 (45%/14%)
Blues by Five	0.286 (29%/1%)	0.597 (41%/8%)	0.564 (22%/3%)	0.721 (51%/17%)
Blue Train	0.303 (15%/1%)	0.566 (44%/9%)	0.540 (39%/5%)	0.671 (61%/18%)
Chamber Mates	0.304 (14%/1%)	0.612 (34%/8%)	0.551 (20%/3%)	0.643 (37%/9%)
Chasin' the Bird	0.324 (33%/2%)	0.632 (44%/13%)	0.679 (42%/12.5%)	0.794 (59%/28%)
C-Jam Blues	0.345 (27%/1%)	0.593 (52%/12%)	0.547 (25%/3%)	0.731 (58%/22%)
Cool Struttin'	0.338 (23%/2%)	0.617 (45%/12%)	0.658 (20%/5%)	0.772 (49%/21%)
Cotton Tail	0.271 (18%/1%)	0.551 (48%/9%)	0.597 (19%/3%)	0.698 (47.5%/15%)
Crazy Rhythm	0.392 (20%/2%)	0.699 (42%/14%)	0.638 (24%/6%)	0.768 (65%/30%)
Excerpt	0.402 (42%/4%)	0.703 (61%/22%)	0.623 (25%/5%)	0.788 (63%/30%)
Freddie Freeloader	0.370 (32%/2%)	0.637 (56%/15%)	0.509 (26%/3%)	0.708 (61%/22%)
Giant Steps	0.379 (19%/1%)	0.577 (33%/5%)	0.470 (17%/1%)	0.559 (39%/6%)
I Can't Give You Anything but Love	0.376 (40%/4%)	0.650 (69%/27%)	0.722 (40%/15%)	0.853 (68%/42%)
I Could Write a Book	0.327 (40%/3%)	0.609 (47%/12%)	0.618 (38%/9%)	0.752 (60%/25%)
If I Were a Bell	0.306 (33%/1.5%)	0.595 (42%/9%)	0.615 (22%/4%)	0.755 (53%/21%)
It's a Blue World	0.365 (33%/3%)	0.647 (58%/20%)	0.640 (34%/8%)	0.810 (67.5%/35%)
Milestones	0.391 (25%/2%)	0.585 (42%/10%)	0.409 (19%/1%)	0.591 (51%/12%)
Moment's Notice	0.357 (36%/2%)	0.675 (40%/10%)	0.502 (9%/1%)	0.654 (51%/12%)
Mr. P.C.	0.293 (8%/0.3%)	0.553 (32%/4%)	0.493 (14%/1%)	0.613 (35%/6%)
Oleo	0.299 (27%/1%)	0.580 (47%/8.5%)	0.556 (25%/3%)	0.679 (43%/11%)
So What	0.404 (25%/2%)	0.594 (45%/9%)	0.395 (24%/2%)	0.525 (52%/10%)



Musical work (Paul Chambers)	2-note approach-note patterns	3-note approach-note patterns	2-note interval patterns	3-note interval patterns
Syeeda's Song Flute	0.401 (31%/4%)	0.749 (49%/20%)	0.525 (21%/3%)	0.702 (47%/16%)
Tenor Madness	0.241 (27%/1%)	0.503 (37%/4%)	0.535 (26%/2%)	0.633 (41%/8%)
The Theme	0.413 (42%/4%)	0.707 (51%/18%)	0.648 (25%/6%)	0.783 (57%/27%)
Woody'n You	0.207 (62.5%/2%)	0.504 (37.5%/5%)	0.580 (23%/3%)	0.643 (40%/9%)
You'd Be So Nice to Come Home to	0.404 (38%/4%)	0.706 (62.5%/24%)	0.647 (32%/9%)	0.780 (71%/36%)
Musical work (Ron Carter)	2-note approach-note patterns	3-note approach-note patterns	2-note interval patterns	3-note interval patterns
Autumn Leaves (1961)	0.460 (39%/6%)	0.767 (66%/30%)	0.654 (36%/9%)	0.839 (68%/39%)
Autumn Leaves (1964)	0.447 (33%/4%)	0.741 (59%/24%)	0.757 (37%/8%)	0.861 (67%/35%)
Dolphin Dance	0.504 (28%/3%)	0.722 (65%/27%)	0.504 (34%/5%)	0.672 (52%/17%)
E.S.P.	0.426 (26%/2%)	0.739 (58%/24%)	0.629 (20%/3%)	0.810 (62%/29%)
Israel	0.437 (44%/6%)	0.710 (64%/26%)	0.624 (34%/8%)	0.750 (57%/25%)
Loose Bloose	0.561 (48%/11%)	0.847 (77%/49%)	0.540 (30%/6%)	0.811 (69%/38%)
Mo' Joe	0.465 (12%/1%)	0.767 (60%/28%)	0.678 (36%/10%)	0.824 (70%/39%)
Oleo	0.434 (30%/3%)	0.766 (61%/27%)	0.614 (25%/5%)	0.801 (60%/29%)
Passion Dance	0.394 (19%/1%)	0.649 (53%/16%)	0.468 (14%/1%)	0.696 (60%/21%)
Pinocchio	0.536 (23%/3%)	0.860 (75%/48%)	0.661 (31%/8%)	0.864 (78%/50%)
Seven Steps to Heaven	0.352 (33%/2%)	0.599 (48%/12%)	0.568 (19%/3%)	0.772 (59%/24%)
Witch Hunt	0.471 (24%/3%)	0.755 (68%/31%)	0.594 (45%/9%)	0.805 (66%/35%)

*Note.* To keep this table readable, all percentages are reported without decimals (except when the percentage is exactly half as in 37.5%). Relative frequency of non-recurring approach-note patterns are presented in parentheses. Relative frequency of non-recurring interval patterns that started at the first beat of the bar are also presented.