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Introducing the DYNAMICS framework of moment-to-moment development in achievement motivation

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ABSTRACT

This article introduces a new theoretical and psychometric framework describing moment-to-moment development and inter-dependencies of achievement motivation in terms of the situated expectancy-value theory, by introducing dynamical systems concepts into this line of research. As a first empirical example of a study using this framework, we examined whether task values, costs, and success expectancies measured in a learning situation (time point t) predicted themselves and each other at the next situation (t + 1; 27 min later) within a weekly university lecture.

Situational task values, expectancies, and costs were assessed using the experience sampling method in 155 university teacher training students during weekly lectures for one semester, with three surveys during each weekly lesson. Data were analyzed with multilevel cross-lagged structural equation models.

There were significant auto-regressions from one learning situation to the next in success expectancies and effort costs, but not in intrinsic, utility, or attainment value nor emotional or opportunity costs. There were no significant cross-lagged effects from one situation to the next in any of the measured situated expectancy-value components.

As a framework to integrate dynamical systems concepts into the research on situated learning motivation, we expect the proposed DYNAMICS framework to have a substantial impact on further theory development.

1. Introduction

This article proposes a framework for the research of situation-specific learning motivation aiming to integrate insights provided by Eccles' situated expectancy-value theory of achievement motivation (e.g., Eccles & Wigfield, 2002; 2020), the control-value model of achievement motivation (e.g., Pekrun, 2006), and dynamical systems theories (e.g., Haslbeck & Ryan, 2021, pp. 1–32).

1.1. The situated expectancy-value theory

Eccles' expectancy-value theory of achievement motivation is one of the most influential theories about learning motivation, task choice, and the development of an achievement-related self-concept (e.g., Eccles & Wigfield, 2020; Wigfield & Eccles, 2000). Rather than attempting to give a comprehensive overview of its many assumptions, findings, and its vast impact on the field, this present study mainly focuses on the theory's core components (expectancies, values, and costs) and the recent reformulation of the theory as the situated expectancy value theory (Eccles & Wigfield, 2020). In a nutshell, Eccles' expectancy-value theory of achievement motivation states that individuals in achievement contexts (e.g., students in school) are more motivated and likely to choose and spend effort in a task if they ascribe a high value to that task and if they expect to be able to perform well at that task. According to the theory, individuals tend to choose tasks that they like (intrinsic value), find important and in line with their self-image and identity (attainment value), find useful to other goals (utility value), expect to be good at (success expectancy) and do not find overly costly (cost). All of these reasons to engage in a task can be divided into more specific facets (Flake, Barron, Hulleman, McCoach, & Welsh, 2015; Gaspard et al.,

Abbreviations: DYNAMICS, DYNamics of Achievement Motivation In Concrete Situations.

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2015; Gaspard, Häfner, Parrisius, Trautwein, & Nagengast, 2017; Perez, Cromley, & Kaplan, 2014; Watt, Bucich, & Dacosta, 2019).

While previous research on Eccles' expectancy-value theory of achievement motivation has focused on predicting broad choices, such as choosing a major or a career, the theory is also often used to examine how contextual factors determine the levels of expectancies and values and their associations with achievement. This focus on contextual factors is one of the reasons cited by Eccles and Wigfield (2020) for their recent reformulation of the situated expectancy value theory. The situated expectancy value theory focuses on learners' motivation and task choice in learning situations, reflecting that situations strongly determine the values and costs of learning tasks that learners perceive and the skills and resources that learners can choose from. While there is a large number of impactful studies on many aspects of the expectancy value theory in Education, its situation-specific aspects have only recently become a focus of interest (Dietrich, Moeller, Guo, Viljaranta, & Kracke, 2019; Dietrich, Viljaranta, Moeller, & Kracke, 2017; Kiuru et al., 2020; Moeller, Viljaranta, Kracke, & Dietrich, 2020; Parrisius, Gaspard, Zitzmann, Trautwein, & Nagengast, 2020; Tanaka & Murayama, 2014). Most previous longitudinal studies examined long-time development across weeks, months, or years (e.g., Watt, 2004), using situation-unspecific measures of task values and success expectancies that require participants to aggregate in their minds how they typically feel (e.g., I find solving math problems to be enjoyable; Eccles-Parsons, 1983). Therefore, little is known about the short-term development and short-term inter-dependencies among expectancy-value components from one learning situation to the next.

A few of the studies addressing situational aspects of expectancy-value experiences validated measures of situational task values, expectancies, and costs (Dietrich et al., 2017; Parrisius et al., 2020) and found that the experience of these situated motivational components predicted changes in rather stable motivational dispositions (Dietrich et al., 2017). Most studies addressing situational expectancy-value experiences seek to decompose the sources of variation by applying a multilevel model with situations nested in individuals (Dietrich et al., 2017, 2019; Moeller et al., 2020; Parrisius et al., 2020). These studies typically find substantial fluctuation of expectancy-value experiences among learning situations and seek to understand the relation between state and trait aspects of expectancy-value experiences (Dietrich et al., 2017; Parrisius et al., 2020). A recurrent topic in studies on situational expectancy-value experiences is the possibility of heterogeneity between situations (Dietrich et al., 2019) and between individuals (Moeller et al., 2020). Another recurrent topic is how fluctuating expectancy-value experiences relate to academic emotions (e.g., Tanaka & Murayama, 2014).

In this article, we propose a framework that we hope will help to systematize these recently emerging lines of research. We call it the DYNAMICS framework (see Fig. 1). Recent debates in the research on emotions, motivation, state-to-trait-relations and heterogeneity suggest that dynamical systems theories may offer insightful concepts and methods, and we expect that these perspectives will be fruitful for the research on situated expectancy-value experiences. Therefore, we introduce the relevant dynamical systems theory perspectives below, along with an explanation how they may contribute to new insights about situational achievement motivation.

1.2. Dynamical systems theory: Describing development in complex systems

Dynamical systems theory is a mathematical theory that aims to describe processes and mechanisms of development (e.g., Howe & Lewis, 2005, VanRoekel, Verhagen, Engels, & Kuppens, 2018). It describes development as change in a complex system and as the probable outcome of the reciprocal interrelations among the elements of that system. The change and interrelations among these elements of the

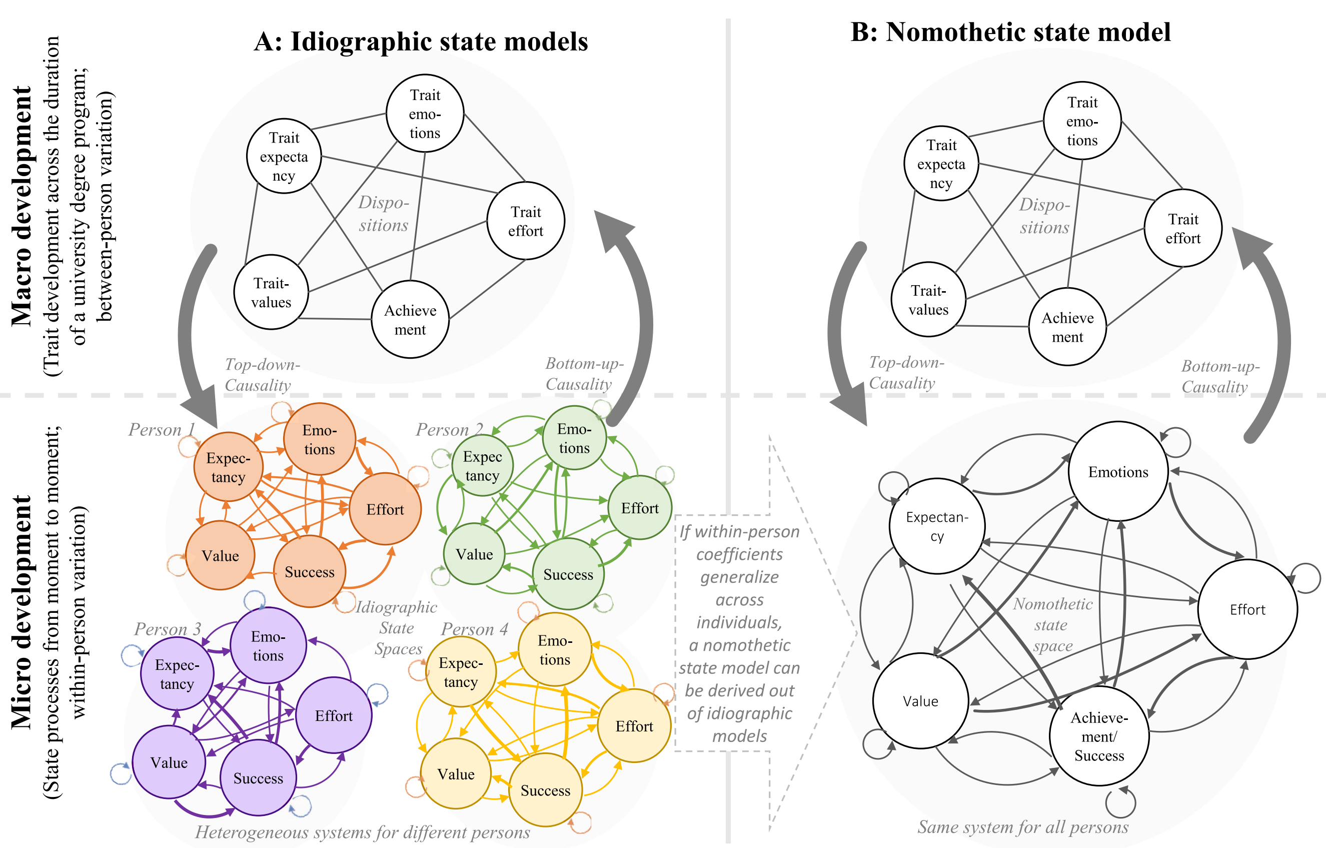

Fig. 1. The DYNAMICS framework (**DYN**amics of **A**chievement **M**otivation **I**n **C**oncrete **S**ituations).

system can happen on various levels (e.g., within and between individuals) and on various time scales (e.g., from moment to moment versus from one year to the next). Dynamical systems theory describes how interactions on a micro-level (e.g., in a situation) can ultimately lead to changes on a macro-level (e.g., development over years, or the emergence of traits that remain stable over years). This ability of dynamical systems theory to "coordinate moment-to-moment change with longer-term developmental transformations" (Newman & Newman, 2020, p. 12) is one of the features that we find helpful in our quest to understand better how situated experiences of expectancies and values may relate to trait-like motivational dispositions that have traditionally been assessed in previous studies on the expectancy-value theory of achievement motivation. Originating in Mathematics, Astronomy, Metereology and Biology, dynamical systems theory has elicited paradigm shifts in several disciplines, including climate research, economy, and evolutionary biology (Fogel, 2011). In Psychology, the theory is used to describe the emergence of new skills in young children, such as walking and speaking (e.g., Clark & Phillips, 1993), the development of emotions and psychopathological symptoms, as well as processes concerning approach and avoidance motivation in achievement contexts (e.g., Gernigon, Vallacher, Novak, & Conroy, 2015; Haslbeck, Ryan, Robinaugh, Waldorp, & Borsboom, 2019; Lange, Dalege, Borsboom, van Kleef, & Fischer, 2020; Mercer, 2012). Table 1 shows perspectives that the research on situational achievement motivation could borrow from the dynamical systems theory literature to further our understanding of the relations among expectancy-value experiences and their relevant predictors, correlates, and outcomes, concurrently within learning situations and over time, on a micro-level (e.g., within situations; from one moment to the next; within individuals), or macro-level (e.g., across months or years; across individuals; across contexts such as school classes or schools, regions, etc.). The main perspectives of dynamical systems theories that we propose to consider in future studies on situated learning motivation are: (1) The definition of the system as a whole, as opposed to the isolated study of a few variables outside of their systemic context, (2) the description of iterative feedback processes, along with the idea that some iterative feedback processes repeat in the ever-same ways (stable processes), whereas others lead to change and emerging new phenomena (emergent processes), and (3) the idea of heterogeneity, which may occur in the form of heterogeneity between individuals, or even in the form of heterogeneity between situations within individuals (see e.g., Dietrich et al., 2019). These aspects are described in more detail below.

1.2.1. Describing the system as a whole: Why we consider academic emotions to be core elements of the system of situated learning motivation

Among the lessons that dynamical systems theories, complex systems, and their applications in natural sciences teach us, is the one that development is best understood as development in context, and that such a context-aware perspective needs to describe the inter-dependent elements of the system (Haslbeck et al., 2019). This systemic understanding is very different from the common approach of looking at certain variables, or certain individuals, in isolation. For instance, the systematic covariation among the movements of the Earth and the Venus is difficult to understand if the set of variables examined does not include the sun. In Psychology, understanding -or treating- a child's behavior often requires a look at the family system surrounding that child. For instance, in Developmental Psychology, dynamical systems theory is used to describe the complex inter-dependencies of the development in one person being influenced -and reciprocally influencing- the development of other individuals in the same social system, for instance, the same family (e.g., Lichtwarck-Aschoff, Kunnen, & van Geert, 2009). These examles show that the frequent goal of psychological studies to examine the "pure" mechanistic relations between a few isolated variables (e.g., the related movement of Earth and Venus, or the stability in mood in one person) could and probably should be contrasted with the attempt to describe the complex reciprocal

Table 1
Features of dynamical systems theories promising to be insightful for the research on situated learning motivation.

Perspectives of dynamical systems theories that promise to be insightful for the research on situated learning motivation	Examples from the research on situational learning motivation and emotions
1. Describing a system of complex reciprocal inter-dependencies among the relevant elements of the system on multiple levels and time spans	Time levels: How do situational experiences of expectancies, values and costs in specific learning situations relate to long-term development of motivational traits that differ between individuals (see Dietrich et al., 2017)
1.1 Due to the iterative, multi-causal and reciprocal inter-relations in a complex system on various levels and time points, we cannot understand the multi-causal interactions in a complex system by ripping out a few of its variables to study the pure relation among them while controlling or disregarding other variables relevant to the development of these selected variables	e.g., we need to study the conceptual and empirical overlaps, as well as differences, among expectancy-value components and academic emotions, see section 1.3 in this article
1.2 Understanding development requires the understanding of iterative and reciprocal feedback processes in the forms of inertia/autocorrelation (a variable at time point 1 predicting its future state at time point 2) or cross-lagged relations (e.g., variable A at time 1 predicting variable B at time 2, variable B at time 1 predicting variable A at t2). Instead of the often-seen models in which variable A predicts variable B, a phenomenon A can be predictor and correlate and outcome of another phenomenon B (A at t1 predicting B at time 2 predicting A at t3, with A and B being correlated within each time point)	See the empirical study in this article.
1.3 How do micro-level fluctuations affect rather stable macro-level components (bottom-up causality) and vice versa, how to macro-level components affect phenomena on a micro-level (top-down causality)?	e.g., How do fluctuating motivational states in learning situations affect levels and development of trait-like motivational dispositions (bottom-up causality)? How do trait-like motivational dispositions affect a person's likelihood of experiencing certain motivational states in specific learning situations (top-down causality)?
2. Concepts helping to understand the relations -and developmental processes- between states and traits	Example for emergent processes: The relations between task values and success expectancies becoming stronger (more aligned) over the school years (Eccles & Wigfield, 2002; Wigfield et al., 1997). Example for stable processes: Concurrent in-the-moment correlation between task values and expectancies over time (see Dietrich et al., 2017).e.g., (How) does a well-developed personal interest develop out of repeated experiences of situational interest? How does a stable tendency of having a higher success expectancy in regard to Math develop out of the situational experiences made in Math lessons?
2.1 Iterative feedback loops	e.g., Does the repeated experience of situational interest/intrinsic task value in one school subject or area lead to the emergence of a stable well-developed personal interest for that school subject or area as suggested by Hidi and Renninger (2006)?
2.2 Difference between stable processes (i.e., processes with coefficients that remain stable over time) and	e.g., (How) does a well-developed personal interest develop out of repeated experiences of situational interest? How

(*continued on next page*)

Table 1 (*continued*)

Perspectives of dynamical systems theories that promise to be insightful for the research on situated learning motivation	Examples from the research on situational learning motivation and emotions
emergent processes (i.e., processes with coefficients that change over time)	does a stable tendency of having a higher success expectancy in regard to Math develop out of the situational experiences made in Math lessons?
3. Acknowledging possible heterogeneity, and findings ways to describe heterogeneity and possibly lacking ergodicity	What methods do we need to understand the within- versus between-person patterns of momentary motivation? e.g., different coefficients within- versus between individuals (e.g., Dietrich et al., 2017); heterogeneous profiles of expectancies, values, and costs in different learning situations (e.g., Dietrich et al., 2019);
3.1 Heterogeneity in regard to the different levels of motivation	How can we describe and predict differences between individuals in regard to their different levels of learning motivation in specific learning situations (e.g., Moeller et al., 2020)?
3.2 Heterogeneity in regard to different relations among expectancy-value components, either within a learning situation (correlations), or across time (lagged regression coefficients)	e.g., How do learning situations differ in regard to their patterns (in-the-moment profiles) of expectancies, values, and costs (see Dietrich et al., 2019)? Do individuals differ in regard to their moment-to-moment stabilities and inter-dependencies of situational expectancies, values, costs, and emotions (see Fig. 1, right panel, lower networks)?

dependencies of *all* the relevant elements in a complex system that influence the phenomenon of interest to a noteworthy degree.

Based on this insight, we suggest to work towards a systematic integration of the research on situational achievement motivation in terms of the situated expectancy-value theory (Eccles & Wigfield, 2020) with the research on situation-specific academic emotions in terms of the control-value theory (e.g., Pekrun, 2006), for the following reasons: Emotions and situational expectancies and values share many conceptual overlaps. For instance, the positive emotions of enjoyment and interest are inseparable elements of the definition of intrinsic task value. Vice versa, emotional costs are another term for the experience of negative emotions, such as frustration, stress, boredom, or anxiety (Perez et al., 2014). Moreover, both the situated expectancy-value theory and the control-value theory of academic emotions have roots in the same expectancy-value theory tradition by Atkinson (1957; 1964). Overlaps between these two theories have been addressed before (e.g., Lauermann, Eccles, & Pekrun, 2017; Goetz, Frenzel, Stoeger, & Hall, 2010; Pekrun, 2006) and are also being addressed in this special issue. For instance, , Goetz et al. (2010, p. 52) write about the control-value model of achievement emotions, that "Pekrun's theory is consistent with the expectancy-value tradition of motivation research (e.g., Atkinson, 1964) in that 'expectancy and value are assumed to combine in multiplicative ways, implying that both expectancy and value are necessary for a prospective emotion to be instigated' (Pekrun, 2006, p. 320). More generally, the model hypothesizes that 'for most academic emotions, both control and value are necessary antecedents' (Pekrun, Goetz, Titz, & Perry, 2002, p. 1010).". In line with this quote, academic emotions have been identified to be predictors, correlates, and outcomes, of expectancy and values and vice versa, expectancy and values have been described to be predictors, correlates, and outcomes, of academic emotions (e.g., Lauermann et al., 2017; Muis et al., 2018; Tamir, Bigman, Rhodes, Salerno, & Schreier, 2015; Tanaka & Murayama, 2014). The conceptual and empirical overlaps between both theories risk leading to jingle and jangle fallacies (jingle fallacy: same term coined for different phenomena; jangle fallacy: different terms used to describe the same phenomenon; see e.g., Block, 2000), if not reflected and disentangled in a clear framework that is able to explain which facet influences which other facet how at what point during a learning process.

An important reason to integrate insights from both theories is the fact that the expectancy-value research only recently has started to examine the situated nature of these motivational components (Eccles & Wigfield, 2020; Dietrich et al., 2017; 2019), whereas the research on the control-value model of achievement emotions has been using situational assessments for a longer time. Therefore, the research on situated learning motivation can learn much from the research on the control-value model of achievement emotions about intra- and inter-individual heterogeneity (e.g., Murayama et al., 2017; Pekrun et al., 2002), relations among situational measures of emotions and motivation (e.g., Pekrun et al., 2002), state-trait relations and the comparison of state-versus trait measures (e.g., Goetz, Bieg, Lüdtke, Pekrun, & Hall, 2013) and micro-level developmental processes. In these regards, the research on the control-value model of achievement emotions has ploughed the path and has provided instruments and analytical approaches for the new focus of the expectancy-value research on the situated nature and dynamics of motivational experiences.

For these reasons, we propose to integrate the facets described in both theories systematically in a joint theoretical and measurement framework in future studies and future theory development. The DYNAMICS framework therefore describes the (concurrent and time-lagged) inter-dependencies among situational measures of expectancies, values, costs, and different academic emotions. Further theory development and empirical findings could attempt to clarify the conceptual overlaps and differences between these constructs.

1.2.2. Describing the relations -and developmental processes-between states and traits

The second element that we propose to borrow from dynamical systems theories for the research of situated achievement motivation is the concept of iterative feedback processes. Iterative feedback loops occur when the outcome of one process (e.g., the mood of a daughter following a mother-daughter conflict) is fed back into the next prediction as a predictor (like in a vicious or virtuous circle; see also Stamovlasis, 2010, 2014). In the example of learning motivation, we wonder, for instance, whether a rewarding and interesting learning situation increases a person's likelihood of seeking out a similar task in the future, which may increase the chance of making further positive experiences with similar tasks, which over time may lead to a stabilizing personal interest for tasks related to similar topics (see Hidi & Renninger, 2006 four-phase model of interest development).

When studying the role of iterative feedback loops in developmental processes, it is important to distinguish between the case in which iterative feedback processes contribute to the stable versus emergent processes. Stable processes are defined as processes with parameters (e.g., regression weights) that do not change over time, such as the assumed stability of concurrent in-the-moment correlation between task values and expectancies over time (see Dietrich et al., 2017). In further examples for supposedly stable processes, the intra-individual concurrent correlation between expectancies for success and effort (Trautwein, Lüdtke, Roberts, Schnyder, & Niggli, 2009), and the intra-individual relations of values and expectancies to academic emotions (Bieg, Goetz, & Hubbard, 2013; Goetz et al., 2014; Goetz et al., 2010), are assumed, but not yet proven, to be invariant over time. In dynamical systems theories, stable processes are called stationary.

In contrast, emergent processes are defined as processes with parameters that change over time, such as the concurrent correlation between situational task values and success expectancies that becomes stronger from lower to higher school classes, due to increasing experience with the school subject; Eccles & Wigfield, 2002; Wigfield et al., 1997), or the assumed emergence of trait-like interests for a topic out of repeated experiences of situational interest, mentioned above and in Hidi and Renninger (2006). So far, no study used the concept of emerging processes to describe these motivation development processes.

A further concept borrowed from dynamical systems theories helping to understand the relation between motivational states and traits is the distinction between bottom-up and top-down causality (see e.g., Thelen & Smith, 2006). Bottom-up causality in this context describes the influence of states on traits (e.g., the repeated experience of situational interest leading eventually to the development of a stable personal interest; see Hidi & Renninger, 2006), whereas top-down causality describes the influence of rather stable personal traits (e.g., the rather stable expectancy of being a student who does well in Math) on the nature of certain situational experiences and the frequency thereof. A finding possibly supporting the notion of bottom-up causality is the observation that the frequency of experiencing certain situational profiles of expectancies and values was linked to the level (person-level mean score) and the change in dispositional measures of expectancies and values in University students (Dietrich et al., 2019). As an example for top-down processes, learners with a positive dispositional ability self-concept may tend to perceive learnings tasks as solvable and more challenging, i.e., more motivating, compared to learners with lower ability self-concepts, who may perceive the same tasks as more difficult, threatening, and less motivating.

1.2.3. Addressing possible heterogeneity in the experience of situated expectancies and values

That heterogeneity needs to be addressed is a lesson to be learned from the previous research on situated expectancy-value experiences, as well as from dynamical systems theories (Haslbeck & Ryan, 2021, pp. 1–32) and recent debates about a needed integration of idiographic and nomothetic methods (e.g., Beck & Jackson, 2020; Beltz, Wright, Sprague, & Molenaar, 2016; Block, 2000). For example, the relation (profile) among task values, success expectancies, and costs, differs between learning situations (Dietrich et al., 2019) and individuals (e.g., Bråten & Olaussen, 2005; Conley, 2012; Lazarides, Rubach, & Ittel, 2016; Viljaranta, Aunola, & Hirvonen, 2016; Dietrich & Lazarides, 2019). Because of such heterogeneity between and within individuals, it is important to examine the relation among expectancy-value components with methods that distinguish between the patterns to be found within specific individuals versus across a group of individuals (e.g., Dietrich et al., 2019, 2017; Moeller et al.., 2020; Parrisius et al., 2020). Addressing heterogeneity explicitly has become particularly important with the introduction of the situated aspects into the expectancy-value theory of achievement motivation, because the intensive longitudinal data needed to study these situated components add many more sources of heterogeneity, compared to the previously common trait-like assessments (see e.g., Moeller et al., 2022). Whereas the previously common trait-like measures of expectancies and values may differ in their levels and in their profiles between individuals, situated measures add the possibility of heterogeneous in-the-moment levels and heterogeneous in-the-moment profiles of expectancy-value experiences that differ between situations and occur with different (i.e., heterogeneous) frequencies in different individuals. Moreover, in intensive longitudinal data, individuals may differ in regard to their heterogeneous trajectories and cross-lagged relations among expectancy-value experiences over time. That heterogeneity is a likely and relevant issue to address when working with longitudinal data is acknowledged in mathematical theories of development such as the dynamical systems theories, which provide concepts and methods that help us understand how heterogeneity can be described both concurrently and in regard to heterogeneous trajectories over time (see e.g., Haslbeck & Ryan, 2021, pp. 1–32). For instance, the research on situated learning motivation owes dynamical systems theories its understanding of ergodicity and the consequences of a lack thereof (see e.g., Molenaar, 2004), which have led to the increasingly frequent distinction of within-person versus between-person coefficients (e.g., Voelkle, Brose, Schmiedek, & Lindenberger, 2014), as well as the recent re-emergence of idiographic network models and their systematic integration with nomothetic approaches (e.g., Beltz et al., 2016). Building upon dynamical systems theories, methods for describing heterogeneity have recently been introduced into the research on emotions (e.g., Haslbeck & Ryan, 2021, pp. 1–32), motivation (e.g., Gernigon, d'Arripe-Longueville, Delignières, & Ninot, 2004; Gernigon, Vallacher, Nowak, & Conroy, 2015; Rea, 1997), state-to-trait relations (e.g., Hamaker, Nesselroade, & Molenaar, 2007), and the work with intensive longitudinal data similar to those used in studies on situated expectancy-value experiences (e.g., Dietrich et al., 2019).

To build upon these insights, the DYNAMICS framework in Fig. 1 proposes to address heterogeneity explicitly. For instance, the lower left panel symbolizes the possibility that individuals may differ in regard to the cross-lagged and autoregressive relations among situated expectancy-value experiences from one measurement time point to the next. The DYNAMICS framework proposes to compare person-specific idiographic state systems (left panel) to the nomothetic state system (right panel), to find out what lagged coefficients can be generalized across individuals (for an example, see the GIMME method by Beltz et al., 2016) and what effects remain heterogeneous. As another angle to understanding heterogeneity -in this case the heterogeneity between different motivational experiences and their indicators-, the DYNAMICS framework proposes to consider a psychometric network perspective (e.g., Lange et al., 2020) to model the relations among specific facets of expectancies, values, costs, emotions, effort, and achievement, instead of applying the previously common higher-order factor models that tend to collapse all facets of one constructs into one higher-order factor (such as a factor for positive emotions, or one value factor for all value facets; e.g., Jiang, Rosenzweig, & Gaspard, 2018). The underlying reason for this suggestion is the insight that different facets of the same higher-order factor (e.g., different value components of the value factor) can show heterogeneous relations to relevant predictors, correlates and outcomes that are often insufficiently understood if facets are collapsed into higher-order factors (e.g., Lange et al., 2020).

1.3. Introducing the DYNAMICS framework

The DYNAMICS framework proposed in this article serves to integrate both theoretically and empirically insights from the situated expectancy-value theory (Eccles & Wigfield, 2020), with those from the control-value theory of achievement emotions (e.g., Pekrun, 2006), and insights from the above-mentioned elements of dynamical systems theories. DYNAMICS stands for DYNamics of Achievement Motivation In Concrete Situations. Please note that we choose the term framework, not model, to indicate that rather than proposing testable specific hypotheses, we propose a set of concepts and related methods that we hope will guide future studies aiming to test more specific hypotheses.

Fig. 1 visualizes the DYNAMICS framework. On the lower level, the Figure depicts moment-to-moment fluctuations (within-person variation). On the upper level, the figure depicts relations among stable traits (between-person variation). On the left side, there is the idiographic state system that allows for differences (heterogeneity) between individuals in regard to within-person relations on the right side there is the basic nomothetic model that assumes within-person coefficients to be invariant across individuals.

The core features proposed in this framework are (1) Relevant elements in the explanation of learning motivation include academic emotions and situated experiences of expectancies, values and cost, as well as effort and achievement. (2) The DYNAMICS framework distinguishes between, but integrates, the relations and development occurring on the micro-level (e.g., within specific learning situations or from one situation to the next) and the macro-level (e.g., within or across school years, with trait-like motivational dispositions differing between individuals). This distinction is included to inspire research on whether situational experiences, e.g., of situational interest, may lead to the emergence of stabilizing, trait-like motivational dispositions (e.g., in the form of well-developed personal interest, see Hidi & Renninger, 2006; called bottom-up causality), or whether traits may influence the prevalence or nature of situational motivational experiences. (3) The DYNAMICS framework proposes to systematically examine whether within-person coefficients (e.g., coefficients describing concurrent in-the-moment associations, or lagged changes from one moment to the next) differ between individuals (idiographic approach; left panel) or describe to all individuals in the sample (nomothetic approach; right panel). These two approaches are integrated here to enable future studies to build on the previous research that proposed integrating idiographic and nomothetic approaches to overcome the problem of lacking ergodicity/Simpson's paradox in the analysis of intensive longitudinal data (for the problem, see Kievit, Frankenhuis, Waldorp, & Borsboom, 2013; Molenaar, 2004, for solutions, see Beltz et al., 2016). (4) The DYNAMICS framework proposes to adopt a network perspective to enable the emerging research on the situated expectancy-value experiences to build upon the recent innovations and insights in the booming research on network models. The reason for this proposal are that network models have been found useful methods for the study of dynamical systems concepts (Haslbeck & Ryan, 2021, pp. 1–32), integrations of idiographic and nomothetic approaches (e.g., Beltz et al., 2016), situational measures of motivation and emotions (Lange et al., 2020), studies on the relation between states and traits (e.g., Beck & Jackson, 2020), and intensive longitudinal data/time series data (e.g., Beck & Jackson, 2020; Haslbeck & Ryan, 2021, pp. 1–32), measurement models for the relations among the facets of multi-facetted constructs (Lange et al., 2020; Moeller, 2020), as well as the various combinations of these aspects. Thus, the network research currently provides both the cutting-edge methods and the empirical findings relevant for the research desiderata described in the DYNAMICS framework.

For the sake of simplicity, Fig. 1 represents values and emotions with one node (circle) each, whereas we suggest to disentangle the facets (intrinsic value, attainment value, utility value, emotional costs, effort costs and opportunity costs, and discrete emotions) of these constructs in empirical studies (for reasons why discrete emotions should be distinguished rather than collapsed into higher-order factors, see e.g., Lange et al., 2020). Arrows originating in one construct A and ending in the same construct A represent lagged stabilities (autoregressive paths). Arrows originating in one construct A and leading to another construct B represent the cross-lagged regression paths of construct A at time point t predicting constructs B at the subsequent time point t+1. Since the figure is simplified and not much is known about these lagged and cross-lagged regression coefficients, the lines in Fig. 1 are currently placeholders for relations that warrant further investigation. We have formulated first hypotheses about these autoregressive and cross-lagged relations based on the previous research that could serve as a starting point for future research on this DYNAMICS framework proposed in this article. These hypotheses can be found here: https://osf.io/zdptf/).

Based on Eccles and Wigfield's (2020) situated expectancy-value theory of achievement motivation (see also Eccles & Wigfield, 2002), the DYNAMICS framework includes situational expectancy of success, three positive task value facets (intrinsic, utility, and attainment) and negative cost value facets (following the distinction between emotional, effort, and opportunity costs by Perez et al., 2014). To clarify the relations of these expectancy-value facets with relevant learning outcomes and mediators, the DYNAMICS framework includes as likely mediator the exerted effort (e.g., Martin et al., 2015) and as relevant outcome the achievement/learning success (e.g., Schmitz & Skinner, 1993). As discussed above, the DYNAMICS framework also includes academic emotions in terms of the control-value model (Pekrun, 2006) as concurrent correlates, predictors and outcomes of expectancies and values.

To narrow in on the idea of recursive, iterative processes and emergent processes, relations on the micro-level are examined as intra-individual time-lagged relations from one time point (t) to the next (t+1). Thus, the recursive paths in the dynamical system in Fig. 1 represent the idea that these constructs can be both outcomes and antecedents of learning in iterative learning processes. A core feature of the DYNAMICS framework is that it describes the relations (moment-to-moment cross-lagged predictions) between the specific facets of these constructs. The DYNAMICS framework considers facet-level relations to be potentially insightful, and is compatible with network approaches displaying such relations among facets (Lange et al., 2020).

1.4. How do task values and expectancies predict each other over time?

Since situation-specific expectancy-value measures have only recently been introduced (Dietrich et al., 2017; Xie, Heddy, & Greene, 2019), little is known about their inter-dependent development from one learning situation to the next. Previous longitudinal panel studies suggest that expectancies and values correlate with and predict each other across time lags (Eccles & Wigfield, 1995). Expectancies may increase the perception of a task as valuable, because individuals value activities they expect to be good and potentially successful at. Values may drive expectancies by increasing a person's likelihood to engage in, practice, and consequently become good at a task. Correlations between expectancies and values tend to become stronger over the school years (Fredricks & Eccles, 2002; Jacobs, Lanza, Osgood, Eccles, & Wigfield, 2002; Wigfield et al., 1997). Panel studies examining cross-lagged relations between dispositional expectancies and values are scarce and somewhat contradictory. Some studies have found that expectancies predicted later intrinsic value (Viljaranta, Tolvanen, Aunola, & Nurmi, 2014), whereas others found that these relations were reciprocal (Marsh, Trautwein, Lüdtke, Köller, & Baumert, 2005). Some studies reported a hardly observable relations (Spinath & Steinmayr, 2008) or no longitudinal relations at all (Spinath & Spinath, 2005).

None of these panel studies captured state-like expectancies and values or differentiated between inter-individual and intra-individual sources of variation (Hamaker, Kuiper, & Grasman, 2015). There are often discrepancies between such inter-individual findings and the structure and processes found within individuals (Molenaar, 2004). Consequently, it is unknown whether situation-specific expectancies and task values predict each other from one learning situation to the next, on the intra-individual state-level.

Similarly, it is largely unknown how stable or fluctuating values, costs, and success expectancies remain from one moment to the next, and how these components of achievement motivation are related to each other from one learning situation to the next within a lesson. This study therefore explores these relations and warrants systematic replications.

1.5. The present study

The present study examines a first aspect of the proposed dynamical situated expectancy-value framework (DYNAMICS framework), namely the moment-to-moment developmental dynamics among situational expectancies, value components and cost components from one learning situation to the next, 27 min later, within a 90-min university lecture (micro-level change, nomothetic approach; as represented by the lower right network in Fig. 1). While previous studies found that situation-specific expectancies and values differed greatly across learning situations and individuals (Dietrich et al., 2017; Martin et al., 2015), it is unknown how expectancy-value experiences change from one learning situation to the next. We study the reciprocal lagged relations among value facets, cost facets, and success expectancies as a first step, in the hope to prepare the ground for future studies to address further elements of the DYNAMICS framework (such as the possible heterogeneity between individuals in such micro-level change coefficients, or the relations of such micro-level coefficients with stable macro-level personality development).

Please note that this empirical study can only be a very first test of very limited aspects of the DYNAMICS framework, which includes many more components than those examined in this empirical study. With this article, we mainly intent to propose the DYNAMICS framework as a novel way to theoretically and methodologically integrate the situated expectancy-value theory with certain dynamical systems concepts and recent debates in the literature about network analyses. The following empirical study is not a test of this framework as such, but only one first example of how aspects of this framework (here: autoregressive and cross-lagged paths) can be studied. We hope that future studies will cumulatively provide more evidence helping to exactly quantify the network edges and their predicting moderators displayed in the networks in Fig. 1.

The research questions were:

RQ1: How stable are expectancies, task values, and costs, from one moment to another within one lesson of a university lecture? We expected low to moderate significant lagged stabilities.

RQ2: Do expectancies, task values, and costs predict each other from one learning situation to another? Due to the lack of prior studies on the moment-to-moment fluctuations of expectancies, values, and costs, they were explored without specific hypotheses, although theoretical considerations led us to expect cross-lagged relations, positive for the links between intrinsic, utility, and attainment values and expectancies and negative for the links between cost values and expectancies.

2. Methods

2.1. Sample and design

Participants were 155 German university teacher education students (51% female, on average 21.77 years). They were studying to become subject teachers of varying majors for secondary schools. Participants were surveyed over one semester (ten weeks) during an introductory Educational Psychology lecture with weekly 90-min lessons. In each lecture, each student answered three times to a 10-item situational motivation questionnaire, in the beginning, middle, and end of the lesson (27 min lag between measurements). The sample was divided into three equally large groups (A, B, and C) with different, rotating survey schedules (see Moeller et al., 2020, for details about the design). No distractions or motivational issues due to the interruptions of the lecture by to the surveys were reported by participants, nor observed by the researchers.

As is typical for intensive longitudinal studies, there were missing data on several levels. The analysis sample included 155 students providing data in at least one lesson. The number of participants declined over the course of the semester from 155 in the first lesson to 61 in the last lesson. The analysis sample included data from 809 lessons out of theoretically possible 1,550 lessons (155 students times 10 lessons). The number of lessons per student (i.e., response rate) was positively related to students' high school grades, but unrelated to gender, student-level expectancies and all value facts except opportunity cost (see Dietrich et al., 2017, for more details). The situation-level data comprised of 2,227 situational responses out of 4,650 possible replies (155 students times 10 lessons times three responses per lesson).

2.2. Instruments

Psychometric properties for all measures were reported in Dietrich et al. (2017); see also Dietrich et al. (2019), and Moeller et al. (2020). The situational motivation questionnaire consisted of eight items measuring expectancies and values, with the introduction "To what extent do the following statements apply to you in the present moment?". Students were asked to consider the lecture contents of the past couple of minutes and to respond to the questionnaire within 10 min. The response scale for all items was a 4-point Likert scale ranging from 1 = does not apply to 4 = fully applies.

Situational expectancies were measured with one item capturing success expectancies ("I will be good at these contents in the exam", adapted from Wigfield & Eccles, 2000) and one item addressing competence experience ("I understand these contents").

Situational task values items were adapted from the task value scale of Gaspard et al. (2015), including intrinsic value (two items: "I like these contents" and "I am interested in these contents", utility value (one item: "Knowing these contents well will be useful in my future occupation") and attainment value (one item: "It is important for me to know a lot about these contents"). We distinguished between emotional costs (one item: "I feel bad because I need to deal with these contents (e.g., I am annoyed and/or anxious and/or nervous)"), effort costs (one item: "Learning these contents exhausts me"), and opportunity costs (one item: "I have to give up other activities that I like in order to know these contents well"), in line with Perez et al., 2014; see also Flake et al., 2015). Psychometric properties for the items were reported in Dietrich et al. (2017).

Intra-class correlations for all measures for three levels (situation nested in weekly lectures, nested in person) are reported in Table 2.

Approximately half of the variation in the items was related to learning situations within lessons, indicating a considerable amount of fluctuation in students' situational experiences of expectations, (positive) values, and costs, on both intra-individual levels.

2.3. Analyses

Model estimation. Given the nested data structure, we applied multilevel structural equation models via the Mplus software (version

Table 2
ICCs of all measures, estimated with a three-level model.

Item	Variance between situations (Level 1)	Variance between weeks (Level 2)	Variance between individuals (Level 3)
Expectancies: I will be good at these contents in the exam.	.52	.21	.27
Expectancies: I understand these contents.	.52	.24	.24
Intrinsic value: I like these contents.	.48	.34	.18
Intrinsic value: I am interested in these contents.	.48	.28	.24
Utility value: Knowing these contents well will be useful in my future occupation.	.47	.23	.30
Attainment value: It is important for me to know a lot about these contents.	.44	.23	.33
Emotional costs: I feel bad because I need to deal with these contents (e.g., I am annoyed and/or anxious and/or nervous).	.35	.30	.35
Effort costs: Learning these contents exhausts me.	.41	.20	.39
Opportunity costs: I have to give up other activities that I like in order to know these contents well.	.22	.23	.55

Note**:** Intra-class correlations for all measures were estimated with three levels (situation nested in weekly lectures, nested in person). The $ICC_{situation}$ is 1-ICC_{week} - ICC_{person}. Although our cross-lagged models were estimated with two levels (situations nested in individuals), they took into account the meso-level of variation within the weekly 90-min lectures by estimating lags only within weekly lectures (from the beginning to the middle and from the middle to the end of the lecture). This dependency of measures within weekly lectures needed to be taken into account in the ICC calculation by adding the additional level 2 (variance between weeks).

8.4, Muthén & Muthén, 1998-2018) to separate the relations of expectancies and values on different levels and to focus on the intra-individual level. Full-information maximum likelihood estimation (FIML) was applied in all models for missing data handling. All models used the MLF estimator.

Model specification. Examples of two-level cross-lagged structural equation models[1] (SEM) used in this study are shown in Fig. 2. To reduce the number of parameters and keep models identifiable, the pairwise relations among pairs of expectancy-value components were examined in separate models. Thus, there were 21 models examining the pairwise relations among seven expectancy-value components (three value facets, three cost facets, and success expectancy; e.g., Model 1: intrinsic value with expectancy, Model 2: utility value with expectancy, Model 3: attainment value with expectancy, etc.).

In these models, Level 1 refers to lessons (n = 809) and Level 2 to students (n = 155). On Level 1, the three responses given at the beginning, middle, and end of a lesson were modeled as separate, auto-correlated variables. At Level 1, expectancy and intrinsic value items were set to load to separate latent factors, with factor loadings fixed to one to achieve local identification via the imposition of essentially tau-equivalent constraints. This was needed because we only had two indicators for each of these latent variables. Utility and attainment value and all costs facets were measured as single items and entered as manifest variables into the models. Autoregressive and cross-lagged associations from one learning situation to another (from time point t to t+1) were examined. We did not estimate lagged associations from the end of one lesson to the beginning of the next lesson, because they were spaced one week apart. Item-specific method factors were added to capture residual correlations between the measurement time point within one week/lesson ("W1 to W4"). The W-factors were allowed to correlate freely with each other (see Table 4). At Level 2, the manifest variables were allowed to freely correlate with each other (saturated model), because our research focus lied on the within-person level. A saturated model had the advantage that the model fit is not affected by potential misspecifications on the between level.

Set up in the present way, the models examined whether situational success expectancies and task values, including costs, were stable from one situation to another (beginning to middle, and middle to end of lesson), and whether there were lagged and/or concurrent relations between them. In other words, we tested to what extent the expectancy-value system can be described by stable (i.e., stationary) processes. Stationarity can be directly tested by implementing equality constraints (Cole & Maxwell, 2003; Morin et al., 2016). We tested stationarity in four consecutive steps via comparison of goodness of fit (Appendix A). Step 1 was a model with all autoregressive and cross-lagged paths, and all concurrent correlations being freely estimated. In Step 2 we set the autoregressive paths equal, in Step 3 additionally the cross-lagged paths, and in Step 4 additionally the concurrent correlations. If a given equality constraint does not lead to a substantial decrement in model fit, the more parsimonious model is retained. We used the descriptive fit indices to evaluate the change in model fit. In line with Chen (2007) we considered a CFI/TLI decline of 0.01 or less, and a RMSEA increase of 0.015 or less as no substantial decrement in model fit. As the final models we selected the ones that were as parsimonious as possible concerning Steps 1–4, but still showed adequate model fit. The results of these tests can be found in Table 4, last column.

[1] Usually, we would recommend using a dynamical structural equation model (Hamaker, Asparouhov, Brose, Schmiedek, & Muthén, 2018) or a vector autoregressive model (Bringmann et al., 2016) to test assumptions made by our theoretical model. In their current form, however, they were not well suited for the unequally spaced measurements varying from 30 min to one week in our data. Moreover, our chosen model had the advantage that we could distinguish between paths from the beginning to middle and middle to end of a lesson.

3. Results

The results from the final models are summarized in Table 3. The model fit indices are reported in Appendix A and the Mplus outputs in Appendix B.

3.1. How stable are expectancies and task values from one moment to another within one lesson of a university lecture? (RQ1)

There were significant intra-individual auto-correlations in expectancies from one situation to another, meaning the relative rank of expectancy at one situation, compared to all other situations in the same individual, was relatively stable from one learning situation to the next. This significant auto-regression in expectancies was found in four out of six models examining the links from the first to the second, and in three out of six models examining autocorrelations from the second to the third measurement time point within weekly lessons.

Effort costs showed a significant auto-regression in four out of six models, both from the beginning of the weekly lecture to its middle and from the middle to the end of the weekly lecture. In contrast, there was no significant auto-regression from one learning situation to the next in intrinsic, utility, or attainment value, emotional costs, or opportunity costs.

3.2. Do expectancies and task values predict each other from one learning situation to another (RQ2)?

There were no significant cross-lagged effects from one situation to the next.

Results of the equilibrium tests: That we found evidence of predictive equilibrium (equality of the cross-lagged path, autoregressive paths, and correlations) means that our predictions can be considered to be equal across all time lags for the models 1–15, 18, 19, and 21.

4. Discussion

4.1. Summary

This study introduced the DYNamics of Achievement Motivation In Concrete Situations (DYNAMICS) framework and tested some of its implications empirically. The DYNAMICS framework connects dynamical systems concepts with insights about short-term developmental dynamics among situational motivation components in terms of Eccles and Wigfield's (2020) situated expectancy-value theory, and academic emotions in terms of the control-value theory (Pekrun, 2006).

We hope that the DYNAMICS framework will guide future studies to systematically address in their theory development and choice of research methods the core components of 1) a systems-oriented understanding of development and inter-dependencies among situated motivational and emotional experiences, 2) the relations between motivational states to traits, 3) the possible heterogeneity between learning situations and between individuals in regard to the levels, developmental processes, and inter-relations of motivational and emotional experiences, and the need to integrate idiographic and nomothetic approaches, and 4) the possibility that network approaches might be useful methods to study the afore-mentioned points in the context of situated achievement motivation.

As a first step of formalizing and testing this framework's ideas, this study examined the micro-level development of situated expectancy-value components from one learning situation to the next situation 27 min later, within individuals and within weekly 90-min university lectures in a nomothetic approach (corresponding to the lower right network of the DYNAMICS framework in Fig. 1). We examined moment-to-moment auto-regressions of expectancies, values, and costs, as well as their cross-lagged effects and found such auto-correlations only for expectancies and effort costs, and only in a subset of the estimated models.

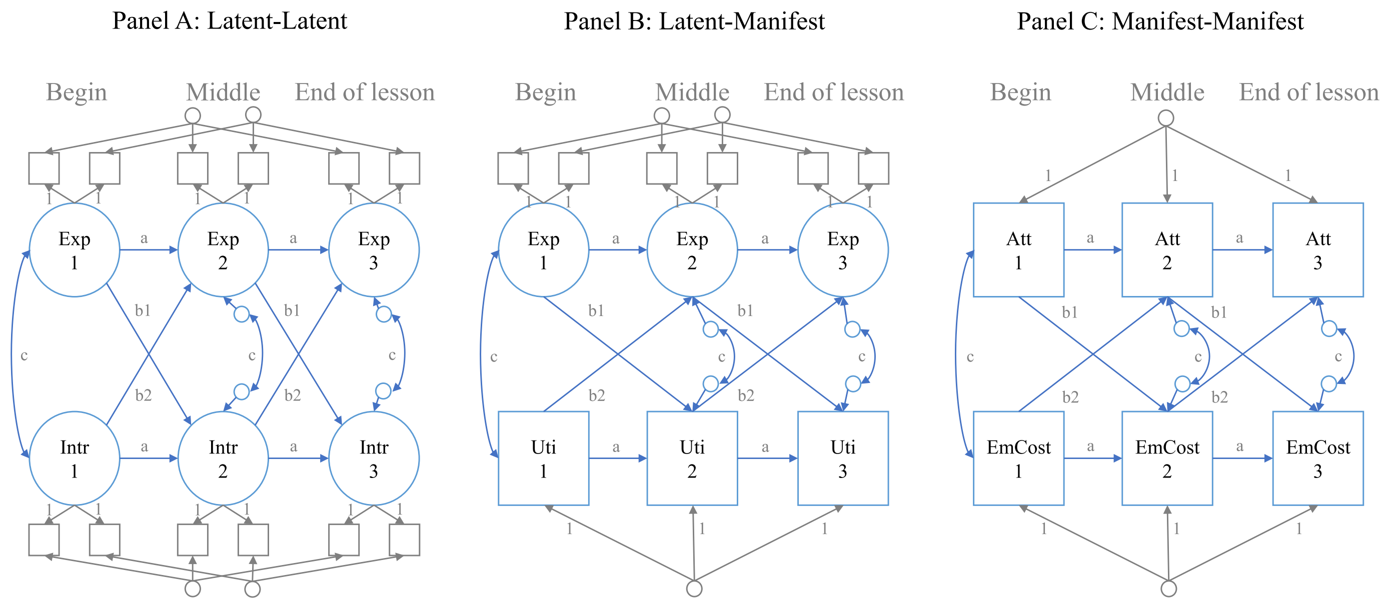

Fig. 2. Schematic representation of the estimated models at the within-person level. Panel A shows the model for expectancy and intrinsic value (Model 1), both measured as latent variables. Panel B shows the model for expectancy and utility value (Model 2) as example for the models with one latent and one manifest construct. Panel C shows the model for attainment value and emotional cost (Model 13) as example for the models involving manifest constructs only. The Figure also shows Steps 2 to 4 of the sequential equilibrium tests (Morin et al., 2016): In Step 2, the auto-regressive paths (a) were set equal. In Step 3, additionally the cross-lagged paths (b1 and b2, respectively) were set equal. In Step 4, additionally the concurrent correlations (c) were set equal. The freely estimated correlations between the method factors are not shown in this figure for the sake of simplicity. As the final model for each series of Model 1 to Model 21, we selected the model which was the most constrained compared to the freely estimated model (step 1) and at the same time showed no substantial worsening in model fit compared to step 1. When at least one fit index indicated a worsening in model fit, we selected the less constrained model. All method factors were allowed to correlate with each other, which is not shown in this schematic picture.

There were no cross-lagged effects from one time point to the next, 27 min apart. This again indicates that moment-to-moment associations among expectancy-value components measured 27 min apart may change across even such a short time period as a 90-min lecture.

It appears plausible to us that eventual lagged auto-regressions and cross-lagged effects could depend on stability versus change in the teaching style, taught topic, or class activities. We therefore suggest that future studies examine the effects between what happens in the class to the lagged effects examined in this study. Future studies should attempt to examine whether and how the nature of situations and contexts influence the moment-to-moment stability and cross-lagged paths in momentary learning motivation. It seems plausible that more stability and stronger cross-lagged coefficients could be found if the teaching situation and context remains stable, as opposed to the teaching situation and context changing. Our approach examined stabilities and cross-lagged paths averaged across weeks and across individuals. Future studies may want to look behind that curtain and examine which contextual, chronological and personal factors determine these coefficients.

4.2. Theoretical implications and directions for future research

The empirical tests of the moment-to-moment couplings among success expectancies, values, and costs are contributions to the situated expectancy-value theory (Eccles & Wigfield, 2020). To our knowledge, neither moment-to-moment autocorrelations of these situational motivation components, nor their cross-lagged relations from one learning situation to the next, were examined before from an expectancy-value perspective. The few existing studies examined such stable processes from one lesson (Malmberg & Martin, 2019) or one homework assignment to the next (Musher-Eizenman, Nesselroade, & Schmitz, 2002).

Interestingly, the insignificant cross-lagged relations looked nothing like the mostly significant concurrent correlations between the same constructs within the same learning situations (see Dietrich et al., 2017 and Table 3, last three columns). The mostly substantial correlations of expectancies with values and cost facets within learning situations contrasted with the mostly absent cross-lagged relations between these constructs from one learning situation to the next, only 27 min apart. This mirrors Malmberg and Martin's (2019) findings for the interplay of autonomous motivation (similar to intrinsic value) and competence beliefs (similar to expectancies). The discrepancy between the concurrent and short-term cross-lagged relations has interesting implications for debates about the structure, short-time processes, and possible determinants of expectancies and values. It appears that whatever drives the covariance between both constructs within a learning situation might not drive a similar coupling between these constructs from one learning moment to the next.

The absence of cross-lagged coupling from one learning situation to the next does contradict previous findings that expectancies and values may be coupled longitudinally across longer spans than the one examined here (lags of 27 min versus years as in Wigfield et al., 1997). As future studies attempt to replicate this finding, they should consider that autoregressive and cross-lagged parameters are likely to depend on the time lag (Voelkle, Oud, Davidov, & Schmidt, 2012). Using vastly different time spans might capture different developmental processes.

The here-presented empirical findings illustrate how the DYNAMICS framework can contribute to advancements in the research on the situated expectancy-value theory (Eccles & Wigfield, 2020) and its combination with the control-value model (e.g., Pekrun, 2006). While we could only take the first step of testing a few predictions of the DYNAMICS framework, we hope that future studies will contribute further insights about cross-lagged and concurrent relations among the facets of the situated expectancy-value model, the control-value model, and their relevant predictors, correlates, and outcomes, such as effort and success/achievement.

We expect the DYNAMICS framework to make substantial contributions to the further theory development and empirical findings of Eccles' situated expectancy-value theory. By introducing dynamical

Table 3
Standardized regression coefficients and significance levels for the lagged predictions from one time point (t) to the next (t+1) in the final models (for the model comparison and model decision, please see Appendix A).

	Beginning to middle (T1 to T2)				Middle to end (T2 to T3)				Concurrent correlations		
	Stability (auto-regression) Variable 1	Stability (auto-regression) Variable 2	Variable 1 predicting Variable 2	Variable 2 predicting Variable 1	Stability (auto-regression) Variable 1	Stability (auto-regression) Variable 2	Variable 1 predicting Variable 2	Variable 2 predicting Variable 1	T1	T2	T3
1. Expectancy (V1) & intrinsic value (V2)	.41	.19	.16	−.07	.49	.18	.16	−.08	.65	.69*	.74*
2. Expectancy (V1) & utility value (V2)	**.32***	.14	.11	.02	.40	.12	.11	.02	.45*	.39*	.44*
3. Expectancy (V1) & attainment value (V2)	.30	.06	.22	.08	.38	.06	.24	.09	.53*	.47*	.58*
4. Expectancy (V1) & emotional cost (V2)	**.33***	.09	−.10	−.02	**.43***	.09	−.12	−.02	−.30*	−.20	−.27
5. Expectancy (V1) & effort cost (V2)	**.36***	.22	−.00	.06	**.48***	.21	−.01	.07	−.27*	−.27*	−.35*
6. Expectancy (V1) & opportunity cost (V2)	**.34***	.09	.03	.03	**.45***	.09	.03	.03	−.08	−.10	−.12
7. Intrinsic (V1) & utility value (V2)	.29	.15	.09	.02	.30	.12	.09	.02	.49*	.52*	.51*
8. Intrinsic (V1) & attainment value (V2)	.33	.02	.22	−.01	.33	.02	.23	−.01	.63*	.59*	.58*
9. Intrinsic value (V1) & emotional cost (V2)	.28	.07	−.12	−.03	.29	.06	−.13	−.02	−.31*	−.30*	−.32*
10.Intrinsic value (V1) & effort cost (V2)	.31	.22	−.02	−.00	.33	.21	−.02	.00	−.32*	−.29*	−.30*
11.Intrinsic value (V1) & opportunity cost (V2)	.30	.07	−.04	.10	.32	.06	−.04	.10	−.07	−.21	−.19
12.Attainment value (V1) & utility value (V2)	.14	.19	.05	.10	.15	.17	.05	.10	.37*	.43*	.46*
13.Attainment value (V1) & emotional cost (V2)	.12	.10	.03	−.03	.12	.09	.03	−.02	−.08	−.12*	−.12*
14.Attainment value (V1) & effort cost (V2)	.13	**.20***	−.06	−.07	.13	**.19***	−.06	−.07	−.22*	−.28*	−.28*
15.Attainment value (V1) & opportunity cost (V2)	.14	.08	−.05	−.03	.14	.07	−.04	−.03	−.12	−.24*	−.23*
16.Utility value (V1) & emotional cost (V2)	.17	.15	−.06	−.10	.14	−.03	−.07	.01	−.20*	−.22	−.12
17.Utility value (V1) & effort cost (V2)	.17	**.21***	-.10	−.13	.15	**.20***	.07	.03	−.14	−.18	−.11
18.Utility value (V1) &	.19	.09	−.02	.08	.16	.08	−.01	.08	−.04	−.12	−.11

(*continued on next page*)

Table 3 (*continued*)

	Beginning to middle (T1 to T2)				Middle to end (T2 to T3)				Concurrent correlations		
	Stability (auto-regression) Variable 1	Stability (auto-regression) Variable 2	Variable 1 predicting Variable 2	Variable 2 predicting Variable 1	Stability (auto-regression) Variable 1	Stability (auto-regression) Variable 2	Variable 1 predicting Variable 2	Variable 2 predicting Variable 1	T1	T2	T3
opportunity cost (V2)											
19.Emotional costs (V1) & effort cost (V2)	.10	**.24***	−.05	.09	.10	**.23***	−.04	.10	.21*	.24*	.23*
20.Emotional costs (V1) & opportunity cost (V2)	.16	−.02	.02	−.02	.01	.14	.05	.09	.18	.09	.12
21.Effort costs (V1) & opportunity cost (V2)	**.23***	.06	−.02	−.09	**.22***	.06	−.02	−.09	.10	.12*	.11*

Note. Significant auto-correlations were marked bold.

Table 4
Correlations among method factors for all models and results of the invariance (stationary) tests (called "sequential equilibrium tests" in Morin et al., 2016).

	Correlations among method factors						Invariance (stationarity) test
	W1,W2	W2,W3	W1,W3	W1,W4	W2,W4	W3,W4	
1. Expectancy (V1) and intrinsic value (V2)	.40	.68	.68	.64	.62	.85*	Step 4
2. Expectancy (V1) and utility value (V2)	.46	.46	.39				Step 4
3. Expectancy (V1) and attainment value (V2)	.42	.29	.35				Step 4
4. Expectancy (V1) and emotional cost (V2)	−.43	.45	−.47*				Step 4
5. Expectancy (V1) and effort cost (V2)	−.39	.42	−.45				Step 4
6. Expectancy (V1) and opportunity cost (V2)	−.40	.43	−.43				Step 4
7. Intrinsic value (V1) and utility value (V2)	.85*	.75*	.58*				Step 4
8. Intrinsic value (V1) and attainment value (V2)	.69*	.84*	.83*				Step 4
9. Intrinsic value (V1) and emotional cost (V2)	.85*	−.42*	−.50*				Step 4
10.Intrinsic value (V1) and effort cost (V2)	.84*	−.29	−.41				Step 4
11.Intrinsic value (V1) and opportunity cost (V2)	.85*	−.37*	−.38*				Step 4
12.Attainment value (V1) and utility value (V2)	.70*						Step 4
13.Attainment value (V1) and emotional cost (V2)	−.54*						Step 4
14.Attainment value (V1) and effort cost (V2)	−.21						Step 4
15.Attainment value (V1) and opportunity cost (V2)	−.19						Step 4
16.Utility value (V1) and emotional cost (V2)	−.26						Step 1
17.Utility value (V1) and effort cost (V2)	−.17						Step 2
18.Utility value (V1) and opportunity cost (V2)	−.24						Step 4
19.Emotional costs (V1) and effort cost (V2)	.83*						Step 4
20.Emotional costs (V1) and opportunity cost (V2)	.62*						Step 1
21.Effort costs (V1) and opportunity cost (V2)	.77*						Step 4

systems concepts into the situated expectancy-value theory (and control-value theory), the DYNAMICS framework enables us to conceptualize learning-relevant motivation and emotion as both predictors and outcomes in iteratively repeating processes. A further innovation of the DYNAMICS framework that we expect to influence further theory development and studies is the distinction between stable and emerging processes. We hope that the concept of emerging processes will help testing the hypothesis that stable personal interests emerge out of the repeated experience of situational interest (Hidi & Renniger, 2006), or the idea that repeated experiences of situational success in learning moments may predict the development of stable, trait-like ability self-concept. Another example for assumed emerging processes is the assumption that expectancies and task values may become more strongly correlated over the school years (Fredricks & Eccles, 2002; Jacobs et al., 2002; Wigfield et al., 1997).

4.3. *The need for a debate about measurement models representing task values and success expectancies*

A further contribution of the DYNAMICS framework to theory and method development is its proposal to model relations as a system or network among facets of motivation and emotion. Such facet-based networks have recently been proposed in various fields of emotion and motivation research, including for situation-specific time-series data as those used here (Epskamp, 2020).

For instance, networks depicting relations among granular emotions have been proposed as novel and useful measurement models that may be more appropriate than other established measurement models, such as factor analyses (Lange et al., 2020). This suggestion for networks as measurement models comes at a time when we perceive that a debate about measurement models is imminent in the expectancy-value research, for the following reasons: The recent introduction of situation-specific measures and intra-individual analyses of expectancies and values have made debate about appropriate measurement models necessary, because the previously studied factor structures identified in inter-individual studies (Dietrich et al., 2019; Eccles, Wigfield, Harold, & Blumenfeld, 1993; Eccles & Wigfield, 1995; Gaspard et al., 2017; Parsons, 1980; Perez et al., 2014) does not necessarily generalize to the factors found in intra-individual analyses (due to discrepancies in construct structure on the within-versus between-level; see Dietrich et al., 2017).

For instance, the factor structure of costs differs between the level of situations (intra-individual variation, where unrestricted correlations between cost facets fitted the data best) and the level of individuals (inter-individual variation, where all cost items loaded on one factor; Dietrich et al., 2017; 2019). Similarly, profiles of expectancies and values differed between situations, within and between individuals (Dietrich et al., 2017, 2019; Conley, 2012; Lazarides et al., 2016; Viljaranta, Aunola, & Hirvonen, 2016). Likewise, other motivational constructs showed different structures intra-versus inter-individually (Ketonen, Dietrich, Moeller, Salmela-Aro, & Lonka, 2018; Schmukle, Egloff, & Burns, 2002; Vansteelandt, Van Mechelen, & Nezlek, 2005). Consequently, there is a need to identify appropriate measurement models that to account for such situation-specificity and inter-, as well as intra-individual heterogeneity in the structure of expectancies and values across situations (for options, see Beck & Jackson, 2020).

Possible measurement models for testing the DYNAMICS framework are for instance autoregressive network models for time-series data (Beck & Jackson, 2020; Epskamp, Deserno, & Bringmann, 2017) and particularly the GIMME method proposed by Beltz et al. (2016), which systematically compares idiographic models to one another to identify coefficients that generalize across individuals to find trustworthy nomothetic models.

Testing the hypothesized moment-to-moment changes assumed in the DYNAMICS framework requires intensive longitudinal data with many measurement time points and short, ideally equidistanced intervals between one measurement time point and the next (Dietrich et al., 2017, 2019; Moeller et al., 2020), or experimental data (Fogel, 2011). Methods for analyzing and visualizing such time series data under a dynamical systems perspective were discussed by Zou, Donner, Marwan, Donges, and Kurths (2019). We hope that the DYNAMICS framework will be used to examine the relations among all facets of the situated expectancy-value theory (Eccles & Wigfield, 2020), and the relations of these motivational components with relevant predictors, correlates, and outcomes, such as those described in Pekrun's (2006) control-value model. Testing the entire model exceeds the scope of a single study. Therefore, this study takes a first step to testing the DYNAMICS framework by examining the relation between task values and success expectancies across a time lag of 27 min.

4.4. Methodological challenges and other limitations

Please note that Fig. 1 is a schematic illustration of a framework introducing general ideas that we hope will inspire future studies, but that should not be interpreted as a literal blueprint excluding other approaches. Since little is known about moment-to-moment lagged autoregressions and cross-lagged relations among situational expectancy-value components, the paths (network edges) displayed in Fig. 1 are placeholders for relations that we propose should be studied and not yet proportional to actual effect sizes. Based on what is known so far, we have formulated hypothetical assumptions about these lagged autoregressive and cross-lagged pathways that we hope will serve future studies on the DYNAMICS framework as a stepping stone, and we will continue to update these hypotheses at https://osf.io/zdptf/.

We deviated from the framework with our empirical study ourselves by acknowledging that the lagged paths might vary between the first lag (begin to middle of weekly lecture) to the next (middle to end), whereas Fig. 1 only depicts one such lagged path for any variable at one time predicting another (or itself) at the next time point). We found, however, that the auto-regressive and cross-lagged paths were largely stationary across time, which can be depicted by the one lagged path shown in a network.

The DYNAMICS framework does not specify one single measurement model, it merely aims to remind of the many novel methodological insights that can be adopted from the research on dynamical systems, network models, time series analysis, and person-oriented methods for the research on situated learning motivation.

A limitation of this study is that our multilevel structural equation model, as well as the alternative available measurement models, ideally require more measurement time points than we had, less missing data than we had, and evenly spaced distances between measurement time points, which we lacked. While multiple imputation could be used to ameliorate the missing data problem, it is controversially discussed whether states can be imputed plausibly, particularly considering the possible lack of ergodicity, heterogeneous construct structure across situations, and the possible situation- and person-specific structure of psychological constructs. Since we surveyed university students in their lectures, our study was affected by their usual drop-out of the lecture over the course of the semester. The high amount of drop-out is a large problem for the trustworthiness of the results, particularly since responsiveness was correlated to students' high school grades, suggesting that the remaining students may represent a biased sample in terms of achievement, conscientiousness, or other aspects related to the motivation to respond in a certain way. We hope that future studies will test the replicability and generalizability of these findings systematically in further samples, although missing data are likely to limit most if not all experience sampling method studies.

Due to the necessary shortness of the ESM surveys, many expectancy-value facets and costs were measured with single items, which makes it difficult to obtain a measure of reliability. However, other psychometric properties, such as inter-correlations among the situational measures and their correlations with validated trait-like expectancy-value measures were examined in a previous study (Dietrich et al., 2017) and have so far supported the validity of the situational measures.

Since testing the entire DYNAMICS framework is beyond the scope of a single empirical study, many of its elements remain to be tested in future studies. This includes the question whether the lagged relations may differ between individuals with different traits or between different contexts, such as different lectures, for which the idiographic state systems (lower left panel of Fig. 1) should be examined in further studies. In this context, it should be noted that heterogeneity can hide behind a nomothetic approach such as the one we reported in this study, which could be addressed in future studies for instance by adopting an integrative approach such as the one proposed by Beltz et al. (2016) to find out which lagged coefficients can be generalized across individuals.

A further limitation of this study is that we do not know yet what caused the different stabilities and absence of cross-lagged relations among task values and costs and expectancies. Moderators predicting these paths could be explored in future studies. For instance, cross-lagged and concurrent relations between task value and success expectancies could differ by the age and expertise with a study subject (Wigfield et al., 1997) or the achievement level of students, which would be a top-down moderator in terms of the DYNAMICS framework.

Previous research has shown that autoregressive paths in emotions differ between individuals as a function of their mental health or other person characteristics. Emotional under-reactivity (i.e., increased moment-to-moment autocorrelations) predicted affective disorders and general psychological maladjustment, particularly increased moment-to-moment stability for negative emotions (Brose, Schmiedek, Koval, & Kuppens, 2015; VanRoekel, Verhagen, Engels, & Kuppens, 2018). Something similar might apply to the here examined moment-to-moment stabilities in emotional costs and to negative academic emotions states. In contrast, maintaining a high motivation independent of the current characteristics of a learning situation might be adaptive for students' learning, so that students with strong self-regulation skills might show higher moment-to-moment auto-correlations in motivational states than less self-regulated students. It remains a question for future studies to investigate what other moderators affect these auto-correlations from one moment to the next.

As a limitation and direction for future research, we would like to point out that with the models we were using, group-mean centering is used by default on the within-level. This should be unproblematic for multi-level cross-lagged panel models using data in wide format (Hamaker et al., 2015), but such group-mean centering can lead to underestimated autocorrelations in the analysis of multilevel data in long-format (Hamaker & Grasman, 2015). We used a data structure that was a bit out of the box. We have a mixture of a long- and a wide-format: The repeated measures per week were in wide format, meaning the variable for the lecture begin, the variable for the lecture middle, and the variable for the lecture end were three separate variables in three separate columns. However, the multiple weeks per person were in long format, meaning each person is represented with multiple lines, each line of which represents one week. Since our auto-correlations and cross-lagged paths are calculated from one within-week time point to the next, the analysis should refer to the data aspects that are in wide format, meaning T1 (lecture begin), T2 (lecture middle), and T3 (lecture end) are three separate variables in three separate columns. Therefore, we believe that the default centering should be no problem for this analysis, but we suggest that future studies address this question in detail if applying a similar analytical approach.

Further limitations are the sole reliance on self-reports, the fact that the sample comprised only one (large) university lecture classroom, and that this is the first study of this kind to our knowledge, which consequently requires systematic replications. A further reason why systematic replications are needed is the large number of significance tests in this study, which comes at a risk of spurious findings. We hope that future studies will test the DYNAMICS framework Appendix C in other student populations, other universities, university majors, and other lectures, to find out whether the findings replicate, and in what contexts. One question for such a study could be whether the auto-correlations and cross-lagged effects depend on the topic, or change in topic, or teaching style, since it seems plausible that fluctuations and stabilities in momentary measures of motivation and academic emotions could depend on what happens in the classroom. Ideally, a similar research design could be used in a variety of different classrooms in some sort of a collaborative data collection (see the ManyMoments Project; Moeller et al., in prep.), following the example of other crowdsourced research projects (e.g., Altschul et al., 2019; Klein et al., 2014; ManyBabies Consortium, 2020).

Author statement

The data collection was planned and conducted by Julia Dietrich, Julia Moeller, and Jaana Viljaranta and financial support by Bärbel Kracke, who was also the teacher giving the weekly university lectures studied here. Julia Dietrich and Julia Moeller conceived and described the DYNAMICS framework. Data were analyzed by Jaana Viljaranta, Asko Tolvanen supported by Julia Dietrich. Jaana Viljaranta wrote a first draft, Julia Moeller wrote all subsequent drafts. Bärbel Kracke contributed at every step along the way comments, edits, and support.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.learninstruc.2022.101653.

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