# EXAMINING THE INTENDED USAGE BEHAVIOUR OF CONSUMERS WHEN ACCESSING AND USING SMART DEVICES

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**Author: Phil Maly**
**Discipline: Marketing**
**Supervisor: Aijaz A. Shaikh**

JYVÄSKYLÄN YLIOPISTO

# ABSTRACT

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| Author<br>Phil Maly | |
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| Abstract<br>In 2020, more than two third of the world’s population are using mobile phones or other internet devices. Researchers already found out that there are differences in the user’s motivation to use different internet devices, and numerous studies are conducted about the technology adoption of new devices. However, there is only little research about the motivations of users to continue to use a certain device and in which context a device is preferably used. This is highly important for marketers and managers to better understand the usage behaviour of costumers and users to improve all online marketing efforts. Therefore, this study examines technological, psychological, and behavioural drivers of users’ intention to continue to use mobile phones and personal computers, which are the two most used connected devices worldwide. More specifically, the effect of perceived ubiquity on continuance intention is explored, which is a relatively new concept and refers to technologies, which are available anytime and everywhere. Additionally, the effect of habit as a behavioural driver as well as perceived self-efficacy, perceived enjoyment and personal innovativeness as psychological drivers were included into the research. The study is conducted with a quantitative approach. The data is collected with the help of an online survey (N=121), which was distributed to participants of different countries. The collected information is analysed by partial least square structural equitation modelling (PLS-SEM). Based on this study, perceived enjoyment is the only driver which affects the continuance intention to use both, a personal computer and a mobile phone. Also, the relatively new concept of perceived ubiquity is the most relevant factor for the continued use of mobile phones, while habit is the strongest predictor of the continuance intention of personal computers. All the other antecedents of continuance intention were found to have no significant effect whether on the continued intention to use personal computers nor on the continued intention to use mobile phones. | |
| Keywords<br>post-adoption use of technology, information system continuance intention, drivers of using internet devices | |
| Location Jyväskylä University Library | |

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# 1 INTRODUCTION

## 1.1 Research background

In 2020, according to a global study from *We Are Social Inc.* (Kemp, 2020), 67% of the world's population are using mobile phones which are 5.19 billion users (Kemp, 2020.) This number is showing that the internet is part of most people's life around the world which they access with different devices for different needs and at different times. Because of that, it is important for marketers to understand the context and reasons why and when a device is used to be successful.

Much research has been done to find out about the general effects of mobile devices and especially the use of the internet on shopping behaviour. Most of the studies focused on different online and offline channels and confirmed that channel attributes, either digital or others, are affecting the customer's choice of channels in the buying process (e.g. Gensler et al., 2012). Furthermore, literature shows that internet search affects in-store purchases (Verhoef et. al, 2007) which is underlined by a study from 2019 in Germany: 92% of in-store shoppers used digital services before or during their store visit which is equivalent to €126 billion (Deloitte, 2019).

Nevertheless, shopping apps are only the third most used apps per month with 66% of internet users are using them. Chat Apps as well as social networking apps are used by 89% of the users. Entertainment and video apps (65%), music apps (52%) and map apps (65%) are also used by more than 50% of the users. (Kemp, 2020). These numbers are highlighting the fact that mobile devices are used for different online activities, but there is little research about the reasons why users are using a specific device for a certain activity. Similar to the studies of different channels, digital devices should be differentiated as well because of their different characteristics such as screen size, capacity, and portability (Rodríguez-Torrico et al., 2017).

Academic research in information system continuance, which is defined as the user's decision to continue to use an information system (Bhattacharjee, 2001), focuses on technology acceptance-related models to find out about the user's initial adoption and their acceptance (Gao et. al., 2015) of one information system (IS). One of the earliest theoretical models is the expectation-confirmation model (Bhattacharjee, 2001) which is partly based on the technology acceptance model (Davis et. al., 1989) and explains user's continuance intention with the user's satisfaction with the IS use and perceived usefulness.

Based on these early findings, the model has been extended in numerous other studies for different contexts, such as internet usage (e.g. Limayem et al., 2007) and mobile internet usage (e.g. Hong et al., 2006; Thong et al., 2006). Another important theory in technology adoption is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) which is used in numerous studies and got revised multiple times (e.g. Venkatesh et. al, 2012).

## 1.2 Research gap

The need for further research about cross-device consumer behaviour has gotten more attention during the last years (e.g. Kannan & Li, 2017). The Marketing Science Institute (MSI) prioritize different aspects of cross-device consumer behaviour in their 'Research Priorities 2020-2022'. According to that, research will be done about integrated customer experience, distribution and demand, communication messages as well as capturing exposure across devices (MSI Research Priorities 2020-2022). Also, there is much more research about the initial adoption of technology than about the post-adoption stage after a technology is adopted.

Figure 1 shows in greater detail the different adoption stages of a technology user. The focus of this study is on the post-adoption stage, more precisely, about the user's intention to continue to use a technology, e.g. mobile devices or personal computers.

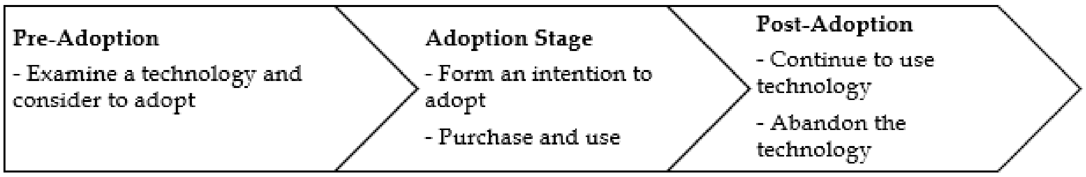


FIGURE 1 Technology adoption process (Kim & Crowston, 2011)

This study aims to examine a proposed research model which is based on existing literature for different mobile devices to find out whether there are differences in the continued use of each device. Many studies found out that hedonic and utilitarian motivations are influencing the continuance intention (e.g. Leon, 2018; Susanto et al., 2016). Additionally, recent studies (e.g., Cruz-Cárdenas et al., 2019; Elliott er al., 2012) are showing the influence of technology optimism and innovativeness towards continuance intention. Parasuraman (2000) defines optimism as a positive attitude towards technology and the benefits it offers. Innovativeness is the tendency of consumers to be among the first ones who are accepting and use new technology (Parasuraman, 2000). In this study, the focus will be more on personal innovativeness because studies showed positive influence of it on continuance intention of mobile devices (e.g. Hong et al., 2016; Lu, 2014).

However, the literature about continuance intention of information technology shows that numerous factors can possibly influence continuance intention, which can be divided into psychological factors, technology factors, behavioural factors, social factors, as well as different moderators and mediators (Yan et al., 2021). This study focuses mainly on psychological factors, such as perceived enjoyment, self-efficacy, and personal innovativeness. Nevertheless, the model is complemented with a technological factor, perceived ubiquity, and one behavioural factor, habit, in order to get a more holistic understanding of the research questions.

## 1.3 Research objective

The objective of this research is to further examine motivations of usage behaviour in a post-adoption context and contribute to existing theories about users' continuance intention. Furthermore, this study aims to shed light on consumers' cross-device usage behaviour by examines drivers of user's continuance intention for different connected devices. The study aims to identify the most relevant drivers for a user to use a specific device as well as the differences compared to other devices. In order to do so, the relationships between psychological drivers, namely perceived enjoyment, personal innovativeness and self-efficacy as well as perceived ubiquity as a technological factor and habit as a behavioural factor towards the continuance intention will be analysed. This approach allows a more detailed examination of the relationships between user's continuance intention and its antecedents.

Different recent studies (e.g. Deloitte, 2019; Kemp, 2020) are showing that computers and laptops as well as mobile phones, or interchangeably so called smartphones, are by far the most used connected devices worldwide. Therefore, following research questions are applied:

Primary research questions:
- What factors motivate the usage behaviour of consumers when accessing and using smart devices and personal computers?
- How vary these factors between these two devices?

This research is highly relevant to study differences in the usage behaviour of different devices. Studies are indicating that certain factors which are relevant in technology acceptance models are not necessarily affecting the continuance intention of a specific device, e.g. perceived enjoyment does not affect the continuance intention of smartwatches (Nascimento et al., 2018) while literature suggests that it is one of the most important predictors of technology adoption and continuance (e.g., Venkatesh et al., 2003; Brunar & Kumar, 2005).

Thus, this study aims to reveal these differences among the two most used connected devices (Kemp, 2020). Furthermore, the concept of perceived ubiquity is not integrated in many studies yet, therefore it will bring valuable insights of the role of perceived ubiquity in a post-adoption context.

## 1.4 Research structure

The research consists of five different chapters. In chapter 2, theoretical knowledge is discussed and leads to the development of different hypotheses. The methodology is introduced afterwards in chapter 3. The results of the study are reported in chapter 4, which is leading to theoretical and managerial implications in chapter 5.

These implications also include limitations of the study as well as recommendations for further research. Figure 2 shows the details of the structure of the research.

**1 Introduction**

- Research background
- Research objectives
- Research structure

**2 Theoretical knowledge and hypotheses development**

- Continuance intention of connected devices
- Perceived Ubiquity
- Perceived enjoyment
- Habit
- Perceived Self-efficacy
- Consumer innovativeness

**3 Methodology**

- Quantitative research
- Data collection and implementation
- Data analysis

**4 Results**

- Demographic and background information
- Measurement model
- Structural model

**5 Discussion**

- Theoretical contributions
- Managerial implications
- Limitations of the research
- Recommendations for future research

FIGURE 2 Structure of the study

# 2 THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

The theoretical background which is fundamental to this study is explained in this chapter. Moreover, concepts of continuance intention and drivers of it, especially perceived ubiquity, perceived enjoyment, habit, perceived IT self-efficacy and personal innovativeness, are introduced. Ultimately, hypotheses are developed which will be integrated into a proposed research model.

## 2.1 Global state of mobile device usage

According to a worldwide digital report in 2020 (Kemp, 2020), more 4.54 billion people around the world are using the internet. Also, 5.19 billion people are using mobile phones and these numbers are growing. Furthermore, 6 hours and 43min is the average time that an internet user spends online during one day which is equivalent to more than 40% of the time awake with 8 hours of sleep in one day. (Kemp, 2020).

These numbers are highlighting that the majority of people are connected with the internet for most of their time and that it is highly important for everyone. However, for marketers it is important to know which devices their customers are using when accessing the internet (Kannan & Li, 2017). The share of web traffic shows that the device, which was mostly used in 2019, is the mobile phone with 53,3%. Personal computers, such as laptops and desktops, are accountable for 44% of the web traffic. Tablets and other devices are in total only used by less than 3% to be connected with the internet. (Kemp, 2020).

These statistics are showing that mobile phones as well as personal computers (PC) are the two most relevant devices when examining the usage behaviour of different smart devices in a post-adoption context. Therefore, these two devices are subject of this study.

## 2.2 Post-adoption theories and models

The concept of information systems continuance was first discussed in 2001 (Bhattacherjee, 2001). The background and the concept of continuance intention is briefly introduced and how it differs from technology adoption. Finally, the importance of information systems continuance intention is discussed.

During the last two decades, an increasing number of studies in the field of information technology (IT) adoption and usage examined post-adoption behaviours, especially information systems (IS) continuance. IS continuance is defined as user’s decision to continue using an IS over the long run, while IT acceptance is the initial or first-time use of IT (Bhattacherjee, 2001). IS continuance of an individual user is especially important for many businesses, such as online retailers, online banks, internet service providers and many more, which are depending on new customers as well as continued users (Bhattacherjee et al., 2008).

Therefore, continuance intention has been studied in numerous different contexts, for example in the context of e-learning (e.g. Roca & Gagné, 2008), mobile apps (e.g. Amoroso & Lim, 2017), online banking (Bhattacherjee, 2001), sharing economy platforms (Wang et al., 2020), and online services (Lin & Filieri, 2015).

One of the first studies about IS continuance introduced the technology continuance model or also called expectation-confirmation model (ECM), which adapted the expectation-disconfirmation theory from Oliver (1980) and examined the relations between confirmation, perceived usefulness, satisfaction and IS continuance intention (Bhattacherjee, 2001). The model is partly based on the Technology Acceptance Model (Davis et. al, 1989), which found out that perceived usefulness as well as perceived ease-of-use are significantly correlated with the usage of the system in the past and the expected usage in the future of an information system. In 2008, the model was extended with the concepts of post-usage usefulness, IT self-efficacy, facilitating conditions as well as the distinction between continuance intention and the actual continuance behaviour (Bhattacherjee et al., 2008).

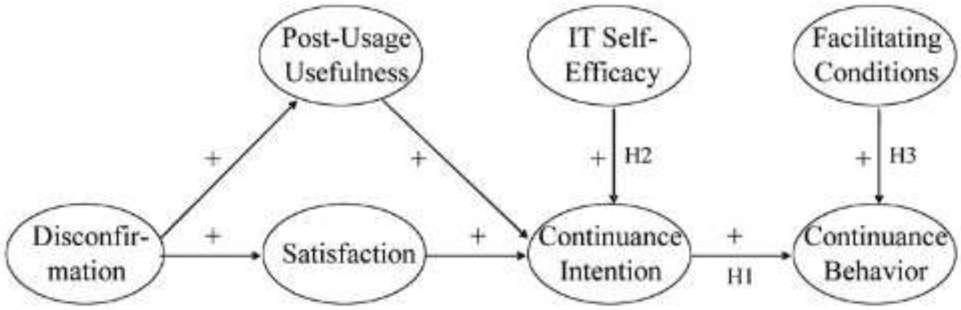


FIGURE 3 Extended model of IS Continuance (Bhattacherjee et al., 2008)

Another important study about IT continuance is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Like the expectation-confirmation model, UTAUT uses utilitarian-type motivations such as perceived usefulness and performance expectance. This type of motivation includes task orientation, convenience in consumption and fulfilment of concrete goals (Babin et al., 1994). Hedonic motivations, which is associated with fun, pleasure, and enjoyment (Holbrook & Hirschmann, 1982), are more subjective compared to utilitarian motivations and harder to measure (Babin et al., 1994). It combines the most critical concepts of eight models and theories, such as TAM and Theory of Planned Behaviour (Ajzen, 1991).

In 2012, Venkatesh et. al reviewed the model and proposed a new theory called UTAUT2. The model can explain approximately 74% of the variance in behavioural intention to use technology compared to 56% of the previous model (Venkatesh et. al, 2012).

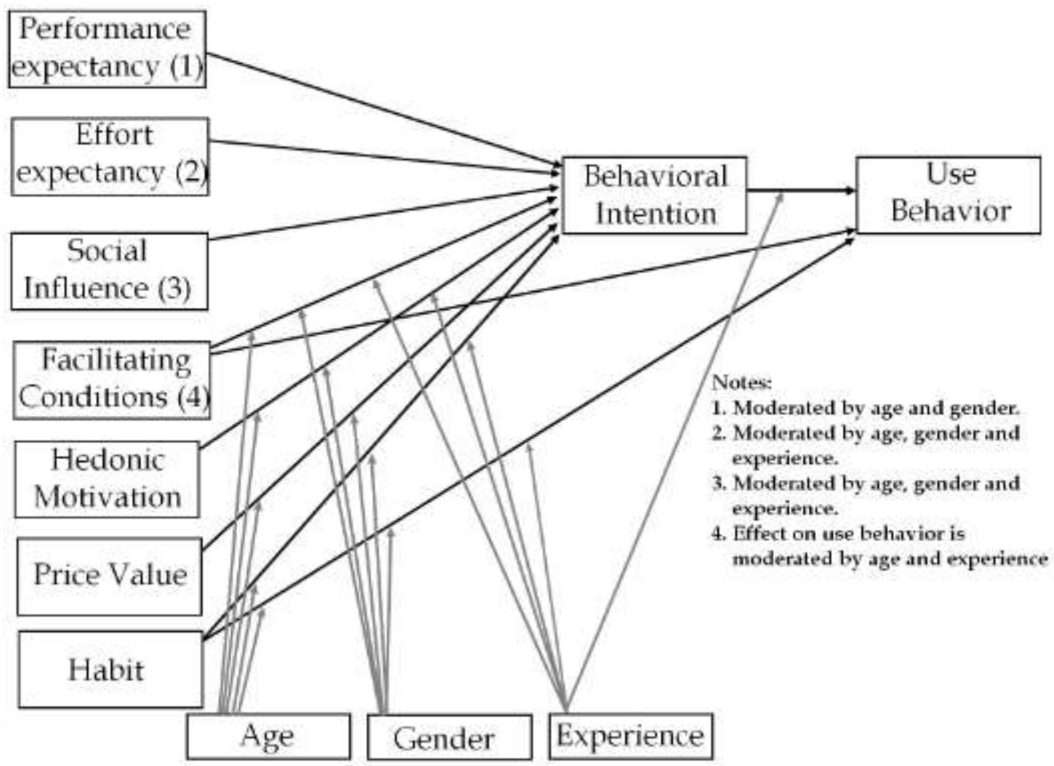


FIGURE 4 UTAUT2 framework (Venkatesh et al., 2012)

According to Yan, Filieri and Gorton (2021), more than 30 different theories, frameworks, and models, which are trying to examine the concept of IS continuance intention, exist. Besides TAM (Davies et al, 1989), UTAUT (Venkatesh et al., 2003) and the expectation & confirmation theory of IS continuance intention (Bhattacherjee et al., 2008), the literature uses other IT related theories, psychology, and socio-psychology theories as well as process and logic models (Yan et al., 2021). Examples are the Uses and Gratifications Theory (UGT) (Katz et al., 1973), task-technology fit model (TTF) from Goodhue and Thompson (1995) and the Technology Readiness Index (TRI) from Parasuraman (2000).

In the recent years, it is common practice that researchers are using these models and theories to study user's continuance intention in a specific context. Some are using one model or an extended version of it, such as TAM (e.g. Joo et al., 2018) or ECM (e.g. Dai et al., 2020; Jo et al., 2017). Other researchers are combining two different models or theories, such as ECM combined with UTAUT2 (e.g., Tam et. al, 2020) or TTF combined with TAM (e.g., Wu & Chen, 2017).

## 2.3 Antecedents of IS continuance intention

Resulting from the numerous studies about IS continuance intention, there are countless antecedents of continuance intention. According to Yan et al. (2021), 85 potential antecedents are present in the literature which can be classified into psychological, technological, social, and behavioural factors. Few examples of the most used antecedents are satisfaction, trust and attitude as psychological factors, perceived usefulness and perceived ease of use as technology factors, subjective norms and social influence as social factors as well as habit and frequency as behavioural factors. (Yan et al., 2021).

However, this study tries to avoid using antecedents of continuance intention which are extensively researched constructs, e.g. perceived usefulness and satisfaction, in order to further examine the role of other variables in users continuance intention of connected devices. According to Yan et al. (2021), compared to the other categories, psychological factors are the ones which are used the most in continuance intention studies. Therefore, this study wants to explore the role of psychological factors which did not received a sufficient amount of attention yet. Nevertheless, this study also wants to explore how established factors in IS research affect the continuance intention of a specific device.

Moreover, due to the fast development of information technologies, the relatively new technology factor, perceived ubiquity, is going to be introduced. The technological environment, when most of the theories and models about IS adoption and continuance intention were introduced, is different to the current one. That is why it is important to investigate concepts which are might affecting IS continuance intention in the current environment. Furthermore, habit as one behavioural antecedent is added into the model.

A brief overview over the antecedents used in this study is given in table 1.

TABLE 1 Definitions of antecedents

| Antecedent | Definition |
|---|---|
| **Continuance intention** | user's decision to continue using an IS over a long time (Bhattacherjee, 2001) |
| **Perceived Ubiquity** | possibility of using mobile services anytime and anywhere (Kleijnen et al., 2007) |
| **Perceived enjoyment** | "the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use" (Venkatesh, 2000, p.351) |
| **Personal innovativeness** | the degree to which an individual is adopting innovations earlier compared to his social community (Rogers & Shoemaker, 1971) |
| **Perceived Self-efficacy** | user's confidence in his or her capability to use a new technology (Bandura, 1977, 2011) |
| **Habit** | the extent to which people perform a behaviour automatically because of learning (Limayem et al., 2007) |

### 2.3.1 Perceived Ubiquity

The construct of perceived ubiquity has become more popular among researchers with the advent of mobile phones and other portable connected devices in the early 2000's. Therefore, the concept developed intensively in the recent years. In the literature, the possibility of using mobile services anytime and anywhere is referred as ubiquity and was used in different studies (e.g. Kleijnen et al., 2007; Nysveen et al, 2005; Okazaki et al., 2009). Thought leaders were expecting a paradigm change of marketing due to the nature of ubiquitous mobile services, especially in retailing (e.g., Shankar & Balasubramanian, 2009), but nevertheless, no formal instrument of measurement was developed and validated until 2013 (Okazaki & Mendez, 2013).

Okazaki and Mendez (2013) refined the concept of ubiquity by an extensive literature review and introduced four pairs of dimensions of mobile user's experiences with ubiquitous devices: continuity and simultaneity, immediacy and speed, portability, and mobility, and searchability and reachability.

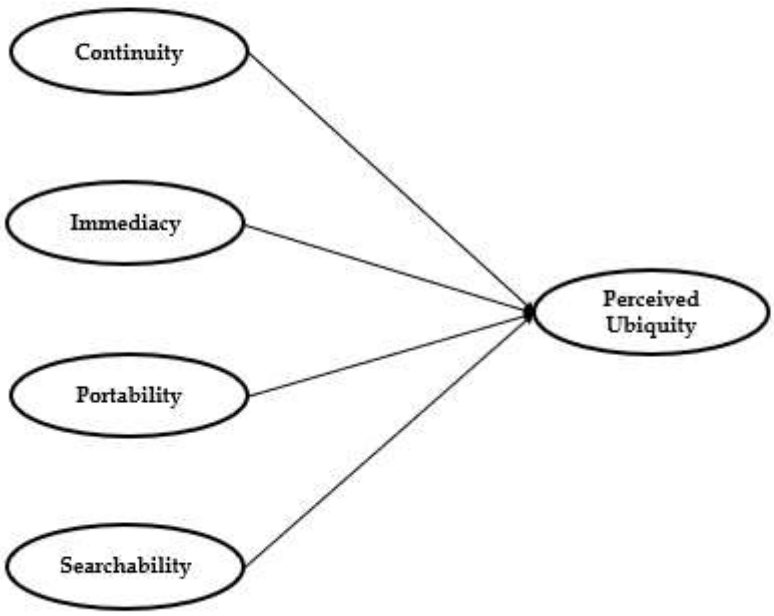


FIGURE 5 The concept of perceived ubiquity

The concept of continuity relates to the state of "being continuous" or "always on" (Okazaki & Mendez, 2013). Continuous access to services is a unique ability of mobile devices which traditional channels cannot offer (Kleijnen et al., 2007). Similarly, Leung and Wei (2000) defined the concept of simultaneity as happening, existing, or doing at the same time. In practice, the ubiquitous nature of devices allows the user to engage in different tasks simultaneously and seamlessly (Okazaki & Mendez, 2013).

Immediacy means effortless, light and easy dislocation (Okazaki & Mendez, 2013) and is defined as the perceived amount of time between an action and the consequences which are resulting from it (Crano, 1995). Speed is defined as the state of fast motion which is in between arrival and departure or desire and fulfillment (Tomlinson, 2004). Both, the concepts of immediacy and speed, are directly connected to the matters of timing, customer wait times and responsiveness (Smith et al., 1999). Other studies referred to immediacy as the "speed of mobile devices as instant connectivity" (e.g., Ko et al., 2009) or ubiquitous availability (e.g., Gao et al., 2009).

The quality of being light enough to be carried is called portability and relates to the physical characteristics of devices (e.g., Kleijnen et al., 2007; Barnes, 2002). Junglas and Watson (2006) defined portability as the "physical aspect of mobile devices that enable them to be readily carried for long periods of time" (p 573). Furthermore, portability is linked to the use and effectiveness of mobile devices and therefore mirrors the high level of mobility in our social lives (Garfield, 2005). In literature, the extend of portability of an IS is recognized as a key factor for the use and satisfaction of an information system (Kuziemsky et al., 2005).

Synonymously to portability, mobility has been used as a predictor of time-place independence as well (Chatterjee et al., 2009) and is defined as "people's independence from geographical constraints" (Makimoto, 2013). Additionally, it can be divided into three categories: traveling, wandering, and visiting. Traveling refers to an extensive mobility from one place to another and visiting refers to going to a particular location for a certain period of time. Wandering relates to the movement in a building or local area (Kristoffersen & Ljungberg, 2000).

Searchability has been defined from Kim and Garrison (2009) as the extent to which one user can "reach" another one "anytime and anywhere" using mobile devices. They used the term reachability interchangeably. Pascoe et al. (2000) referred to searchability as the capability of making a thorough examination while reachability is defined by Junglas and Watson (2006, 573) as the ability to "be in touch with and reached by other people 24 h per day, 7 days a week, assuming that the mobile network coverage is sufficient, and the mobile device is switched on".

However, the study of Okazaki and Mendez (2013) proofed that perceived ubiquity is relevant for a hypermedia environment. It shows that perceived ubiquity directly influences flow, which influences continuance intention itself. Furthermore, they concluded that there is a big discrepancy between desktop PC's and mobile devices because the relation between perceived ubiquity and focused attention was not statistically relevant, which means that users of mobile devices does not need to be mentally prepared to use them, because the use of these devices is flexible and easy.

Different studies are highlighting the importance and relevance of perceived ubiquity of the usage behaviour of mobile devices and PC's. Hubert et al. (2017) proved the effect of ubiquitous mobile phones on usefulness and the ease of use of mobile shopping, while the study from Ashraf et al. (2017) showed that ubiquity positively affects the intention of the consumer to take part in mobile commerce. Furthermore, Okazaki & Mendez (2013) showed that trust and attitude towards mobile ads is positively related to perceived ubiquity, and that it is an important predictor of the users' decision-making behaviour towards mobile commerce.

These results suggest that marketers should engage in services which are available at anytime and anywhere, such as mobile shopping or mobile payments.

Additionally, Okazaki et al. (2009) discovered that perceived ubiquity plays an important moderating role for trust in the context of mobile advertising.

Based on these findings, following hypothesises are proposed:

H1: In the context of PCs, the perceived ubiquity has a positive effect on User's continuance intention.

H6: In the context of smartphones, the perceived ubiquity has a positive effect on User's continuance intention.

### 2.3.2 Perceived enjoyment

Studies have shown that users are not always making a rational decision and emotions play a big role in the user acceptance of technology (Zhang & Li, 2005). In order to include this aspect into technology acceptance research, three related approaches have been introduced: perceived enjoyment, flow, and perceived playfulness (Padilla-Meléndez et al., 2013). Perceived enjoyment is defined as "the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use" (Venkatesh, 2000, 351). The theory of flow highlights the important role of a specific context rather than the differences of each individual user in explaining human motivated behaviours, and playfulness is a concept to measure it (Byoung-Chan et al., 2009).

While gaining more experience by using an incumbent technology, the general computer playfulness is expected to lessen, but the attributes of enjoyment are likely to be reflected because it relates to the user-system interaction (Venkatesh, 2000). In the literature, motivation theory distinguishes between intrinsic and extrinsic motivations. Extrinsic motivation is related to an activity which is the instrument to achieve a valued outcome (Ryan & Deci, 2000). In an information technology context, perceived usefulness is considered to be an example of extrinsic motivation while perceived enjoyment is an example of intrinsic motivation (Davis et al., 1992).

A study from Thong et al. (2006) shows that perceived enjoyment could affect user satisfaction of technology, because many technologies are used for fun and pleasure instead of improving performance. Davis et al. (1992) discovered that perceived enjoyment is one of the most important motivators for the intention to use a computer. Many other studies are showing that perceived enjoyment is one of the most important determinants of behavioural intention to use specific systems or services as well (Park et al., 2014). For instance, perceived enjoyment is a significant determinant of behavioural intention to use internet services (Teo et al., 1999). Furthermore, Ha et al. (2007) found that perceived enjoyment is the most important determinant of attitudes of users towards internet services. Consistent with the results of this study, perceived enjoyment also influences the adoption of mobile commerce (Dai & Palvi, 2009). Most importantly, Brunar and

Kumar (2005) stated that perceived enjoyment is the biggest factor on consumer attitude towards mobile internet devices.

Other TAM related studies are also showing the importance of perceived enjoyment for IT usage (e.g. Venkatesh et al., 2003) but recent studies are stating, that perceived enjoyment does not have a significant direct effect on continuance intention. Nascimento et al. (2018) found out that there is no direct effect on continuance intention of using smartwatches and Joo et al. (2017) are stating the same in their study of continuance intention of digital textbooks among middle school students.

Summing it up, it seems that users of information technology are spending more time and effort on a task when it creates a high level of enjoyment, even if recent studies are stating differently. Hence, following hypotheses were created:

> H2: In the context of PCs, perceived enjoyment has a positive effect on User's continuance intention.
>
> H7: In the context of smartphones, perceived enjoyment has a positive effect on User's continuance intention.

### 2.3.3 Personal innovativeness

The concept of innovativeness is defined as the degree to which an individual is adopting innovations earlier compared to his social community (Rogers & Shoemaker, 1971). Foxall, Goldsmith and Brown (1998) described consumer innovativeness as the consumer's tendency to buy new products relatively soon after they emerge in the market compared to other buyers. This means, that consumers with a higher innovativeness towards a product are more likely to be early adopters of the innovation than others (Strutton, Lumpkin & Vittell, 1994). Yi, Fiedler and Park (2006) are stating that some people are more unwilling to try out new technology than others, who are open to test new innovations.

Furthermore, personal innovativeness is studied as a personality trait (Bartels & Reinders, 2011) including psychological factors such as rationality, curiosity and ambition as well as sociological factors, for instance searching for sources of information about exposure to media (Midgley & Dowling, 1978). Li, Zhang and Wang (2015) are claiming that personal innovativeness is an important concept in understanding the adoption of new products as well as to predict consumer's innovative buying behaviour, because it apprehends the natural tendency of a consumer to test a new technology (Lu, 2014).

However, there is relatively little research about personal innovativeness in a post-adoption context, but some researchers believe that users can discover and adopt new features and functions of an incumbent system (Jasperson et al., 2005). Furthermore, Hong et al. (2011) found out that innovative users are more likely to use future features of agile IS.

A study from Hong, Lin and Hsieh (2016) showed that personal innovativeness can predict continuance intention, mediated by hedonic and utilitarian value, towards smartwatch usage. It means that a more innovative person is more likely to continue using a smartwatch. Moreover, Lu (2014) showed that personal innovativeness is an important determinant of continuance intention, which was even stronger than social influence.

As such, following hypotheses were proposed:

H3: In the context of PCs, the personal innovativeness has a positive effect on User's continuance intention.

H8: In the context of smartphones, the personal innovativeness has a positive effect on User's continuance intention.

### 2.3.4 Perceived self-efficacy

In the 70's, it has been discussed that computer self-efficacy is the greatest predictor of behavioural change in individuals (Bandura, 1977). Research about IT usage used the Social-Cognitive Theory (SCT) model (Bandura, 1986) which tries to understand and predict human behaviour. It advocates that behavioural change is influenced by personal factors and environmental conditions. One central factor of SCT is self-efficacy which is the extend of confidence and skills of a person to complete a task or reach a goal (Bandura, 1986). In terms of IT usage, it refers to the confidence in the capabilities of the user to use new technology and it is an important predictor for technology acceptance (Bandura, 1977, 2011; Compeau & Higgins, 1995).

In the literature, computer self-efficacy consists of three interrelated dimensions: psychological confidence/motivation, generalizability/specificity and skill/knowledge (Compeau & Higgins, 1995). The forethought and the extend of importance of the outcome to the individual user is the psychological confidence and motivation aspect of self-efficacy (Brief & Aldag, 1981). It extends or the reduces the performance of the user's skills and helps to overcome problems or difficult situations (Thatcher et al., 2008). Generalizability refers to the situation and the context to which the user needs to respond. It is the main argument for separating specific computer self-efficacy and a general concept of self-efficacy (Gupta & Thompson, 2019). The reason for that is the complexity of computer programs, which each is a skill by themselves and cannot be transferred to other programs (Agarwal, Sambamurthy, & Stair, 2000). The third dimension, skill or knowledge, refers to the level of skill and knowledge a user's thinks he possesses (Compeau & Higgins, 1995). In this research, the influence of perceived self-efficacy for a specific device is analysed instead of general computer self-efficacy.

Liew et al. (2014) found out that computer self-efficacy influences the decisions, goals, and amount of effort for completing a task as well as the amount of time a user would carry on if he or she faces challenges or complications. Furthermore, computer self-efficacy is the user's "motivational base" in navigating in computer-based environments (Deimann & Keller, 2006). Gan and Balakrishan (2017) showed in their study on mobile technology acceptance that computer self-efficacy predicts behavioural intention as a mediator. Moreover, computer self-efficacy was found to be encouraging on technology acceptance for learning purposes in education related literature (e.g., Alqurashi, 2016; Chester et al., 2011). Also, Lew et al. (2019) stated that self-efficacy as well as enjoyment are significantly affecting student's continuance intention of using cloud e-learning applications.

Thus, following hypotheses were formulated:

> H4: In the context of PCs, the perceived self-efficacy has a positive effect on User's continuance intention.

> H9: In the context of smartphones, the perceived self-efficacy has a positive effect on User's continuance intention.

### 2.3.5 Habit

Research examining the continued use of information systems detected that frequently performed behaviour can become a habit which is an essential part in IS research (e.g., Kim & Malhotra, 2005; Limayem et al., 2007). Habit is defined as the extent to which people perform a behaviour automatically because of learning (Limayem et al., 2007). Similarly, De Guinea and Markus's (2009) defined habit as learned sequences which are repeated without conscious intention. Consequently, researchers added habit in their research models as a learned and then unconscious repeated behaviour which influences technology usage and continuance intention (e.g., Venkatesh et al., 2012; Hong et al., 2008).

Cheung and Limayem (2005) found out that habit limits the predictive power of the intention to use a technology on the actual usage behaviour, and that past online behaviour has a strong effect on continued usage. Furthermore, Liao et al. (2006) determined online purchase behaviour by testing habit, perceived usefulness, and trust. Besides, it was found that habit has a moderating effects on the relationship between purchase intention and perceived value, satisfaction, and trust (Hsu et al., 2015).

Analogously to habit is inertia which is based on Status Quo Bias (SQB) (Amoroso & Lim, 2017). It says that people will maintain an existing action even if there is a superior one (Samuelson & Zeckhauser, 1988). Kim and Kankanhalli (2009) used SQB to explain the resistance of a user to a new one. Inertia might be driven by cognitive misperceptions, loss aversion, uncertainty, or psychological commitment (Lee & Joshi, 2016) which means that habit and inertia are cognitive and affective at the same time (Polites & Karahanna, 2012). While habit is a learned sequence which is repeated unconsciously caused by environmental influences, inertia "is a conscious choice to stay with the status quo" (de Guinea & Markus, 2009).

Cognitive inertia therefore implies that a user consciously decides to stick with an incumbent system, even if they know that there is a superior one. Affective inertia means that a user uses a system continuously because a change would be too stressful (Amoroso & Lim, 2017). Both, habit and inertia, are used in the marketing literature to explain user's continuance intention as well as brand loyalty (e.g., McMullan, 2005; Polites & Karahanna, 2012).

However, Amoroso and Ogawa (2013) have also found that habit is a "push" variable for consumers loyalty and their repeat buys as well as for higher level of satisfaction. Consumers may prefer the path of least effort which means they prefer repetition. If they affix themselves to a brand that meets their needs, rationally or emotionally, habit may surpass loyalty and satisfaction with regard to the prediction of costumer's continuance intention (e.g. Gefen, 2003; Lafley & Martin, 2017). Therefore, following hypotheses were formulated based on the existing literature:

*H5: In the context of PCs, habit has a positive effect on User's continuance intention.*

*H10: In the context of smartphones, habit has a positive effect on User's continuance intention.*

## 2.4 Research Model

The model of this research is shown in Figure 3. The impact of five independent variables will be examines on one dependent variable, namely continuance intention, in the context of smartphone and personal computer usage. Okazaki and Mendez (2013) developed a measurable concept of perceived ubiquity of mobile devices, which was used in the context of mobile services, and studies are showing that perceived ubiquity might influence continuance intention of information technology (Kim & Garrison, 2009).

Furthermore, TAM related studies showed effects of perceived enjoyment on continuance intention, even though recent studies are stating, that these effects are not significant in the context of smartwatches (Nascimento et al., 2018) and digital textbooks (Joo et al., 2017). The impact of personal innovativeness is well researched for technology adoption (e.g., Li, Zhang and Wang, 2015), but there is relatively little research about the effect of personal innovativeness in a post-adoption context (Hong, Lin and Hsieh, 2016). This study aims to shed light on whether there is a significant effect on the continued usage of smartphones and computers.

Moreover, different studies are showing that IT self-efficacy is influencing the adoption of mobile technology and technology for learning purposes (e.g., Gan & Balakrishan, 2017; Alqurashi, 2016; Chester et al., 2011). Studies about the effect of IT self-efficacy on continuance intention (e.g., Lew et al., 2019) are relatively scarce which is the reason why it is included in the model.

Also, habit is included in the model because of the effect on continuance intention (e.g., Cheung & Limayem, 2005; Lafley & Martin, 2017). Lastly, perceived enjoyment was added to the model because of the stated effect on continuance intention (e.g., Lu, 2014) of smartwatches (Hong, Lin & Hsieh, 2016), which indicates that it might affect the post-adoption stage in the usage of smartphones and computers as well.

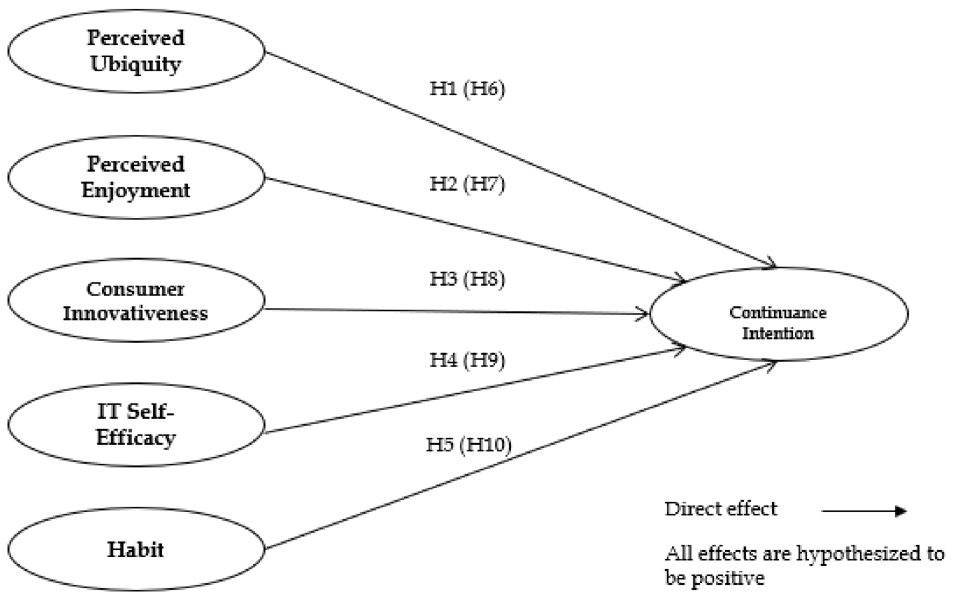


FIGURE 6 Research Model

All of the hypotheses proposed in the research model are summarized together with literature that supports these hypotheses in table 2.

TABLE 2 Key supporting literature for hypotheses (hypotheses regarding use of smartphone are in parentheses)

| Hypotheses | Key supporting literature |
|---|---|
| **H1 (H6):** Perceived Ubiquity → Continuance Intention | Kleijnen et al., 2007; Okazaki & Mendez, 2013; Hubert et al. 2017 |
| **H2 (H7):** Perceived Enjoyment → Continuance Intention | Davis et al., 1992; Venkatesh, 2000; Venkatesh et al., 2003; Brunar and Kumar, 2005 |
| **H3 (H8):** Personal Innovativeness → Continuance Intention | Rogers & Shoemaker, 1971; Lu, 2014; Li et al., 2015; Hong, Lin et al., 2016 |
| **H4 (H9):** Perceived Self-efficacy → Continuance Intention | Bandura, 1977; Compeau & Higgins, 1995; Liew et al., 2014; Gan and Balakrishan (2017) |
| **H5 (H10):** Habit → Continuance Intention | Limayem et al., 2007; De Guinea & Markus, 2009; Venkatesh et al., 2012; Lafley & Martin, 2017 |

# 3 METHODOLOGY

This section discusses the methodological choices which were made for this study. First, the quantitative research method is discussed and explained why it is the most appropriate for this study. Second, data collection and practical implementation are explained. Finally, the process of the data analysis is discussed.

## 3.1 Quantitative research

Quantitative research can be defined as the explanation of existing phenomena by collecting numerical data that are analysed using mathematically based methods (statistics) (Aliaga & Gunderson, 2002). It is used for research questions which are aiming to find quantitative answers, numerical changes, explanations of phenomena or tests of hypotheses (Muijs, 2011).

Characteristically, quantitative research has a systematic logic and linear path, hard data (e.g., numbers), it measures variables and tests hypotheses as well as verify or falsify relationships or hypotheses (O'Gorman & McIntosh, 2014). It quantifies the problem and tries to understand "how widespread it is by seeking projectable outcomes for a larger population" (O'Gorman & McIntosh, 2014, 154). In other words, quantitative research systematically observes hypothesized connections among variables which creates, expands, or refines existing theory (Allen et al., 2009). The researcher uses operational variables which are created through surveys or intentional manipulation, and precisely analyses the data (Allen et al., 2009).

Nevertheless, quantitative research is also criticised, for instance that it cannot explore a problem in depth because it would need ethnographic methods, interviews, or other qualitative methods (Allen et al., 2009). Furthermore, quantitative methods can test theories and hypotheses, but it cannot create them. It needs a thorough literature review or exploratory qualitative research to do so (Allen et al., 2009).

Moreover, quantitative research can only look at a limited number of variables which the researcher defines to be studied, while in qualitative studies unexpected variables can emerge (Allen et al., 2009). Finally, quantitative methods are used to look at the causality of a problem, but it cannot explain the meaning of specific events or circumstances (Allen et al., 2009).

Considering the nature of quantitative research questions, its benefits, and that there is satisfactory amount of literature covering this research topic, a quantitative method was selected in order to continue with this study.

## 3.2 Data collection and practical implementation

Surveys are a common method in quantitative research to work with large samples and to form numerical comparisons (O'Gorman & McIntosh, 2014). In general, surveys are a "structured method of asking the same questions in the same order, to different respondents" (O'Gorman & McIntosh, 2014, 158). Researchers are benefitting from higher response rates and larger amount of data from samples of respondents (O'Gorman & McIntosh, 2014) at reasonably low cost and effort, compared to other methods such as observation (Muijs, 2011).

Furthermore, researchers can guarantee respondent's anonymity which might lead to more honest answers than less anonymous methods, for instance in an interview (Muijs, 2011). Moreover, standardized questions allow an easy comparability between the answers of different respondents as well as between different groups of respondents (Muijs, 2011).

Surveys are a self-completion method of collecting quantitative data including mail surveys, internet or other electronic surveys, and drop-off and pick-up surveys (Hair et al., 2015, p. 208). Surveys are frequently completed without the researcher being presents which means that the respondents need to have the knowledge and motivation to complete them by their own (Hair et al., 2015, p. 210). Therefore, the topic, design, and format must be sufficiently appealing that the respondents are completing and returning the survey (Hair et al., 2015, p. 210). Besides, digital surveys, especially online self-completion surveys, provide quicker responses compared to mail or other types of surveys and yield high quality data (Hair et al., 2015, p. 210).

Nevertheless, there are some major disadvantages when conducting a survey study. One of them is the loss of researcher control, which means that the researcher does not know whether the respondents completed the survey, answered the questions in the formatted sequence, or if they asked others for input (Hair et al., 2015, p. 211). Self-completed surveys also have a higher chance of missing data or misinterpretation of questions by the respondents (O'Gorman & McIntosh, 2014). All these aspects can initiate response bias. Additionally, the researcher cannot control if the respondents are representative of the target population or not (Hair et al., 2015, p.211).

Based on the evaluation of benefits and disadvantages about self-completed questionnaires, especially about online surveys, and the topic of this research, online surveys were considered to be an appropriate data collection method for this study.

The questionnaire was created in the English language using the online survey platform Webropol 3.0. The data was collected using convenience sampling which means that the participants are people who were conveniently available to participate in this study (Hair et al., 2015, p. 183). The data was collected from 1) available contacts of the researcher, 2) private Facebook groups and Instagram followers, and 3) Amazon mTurk research platform.

The first page of the questionnaire included background information of the study, e.g. who conducts the study and how long does it take to complete it. Furthermore, contact details were provided in case the participant wants to ask further questions.

The data was gathered between the 03.02.2021 and 16.03.2021. In total, 156 participants submitted their answers while 375 persons opened the survey. Therefore, the effective response rate was 41,6%. Nevertheless, the actual response rate might be slightly higher because this method does not consider that one participant could access the survey more than one time.

According to Podsakoff, MacKenzie, Lee & Podsakoff (2003), Common Method Variance (CMV) could be a potential problem in behavioural research. In order to avoid CMV in this study, different procedures were implemented. First, the order of the items in the questionnaire were altered, the predictor and the criterion variables were separated, and the identities of the participants were hidden. Second, according to Kock (2015), a full collinearity test was executed. All factor-level VIF's were lower than 3.3, which means that CMV was successfully minimized, and it can be concluded that CMV should not affect the research (Kock, 2015).

## 3.3 The questionnaire

The questionnaire used established scales to measure each construct of the study. The minimum number of measured items per scale is three to ensure reliability (Hair et al., 2015). Furthermore, all constructs were reflective measurement scales (Hair et al., 2014).

Perceived Ubiquity was measured with adapted scales from Okazaki & Mendez (2013). These included scales of three items each for Continuity, Immediacy, Portability and Searchability since Perceived Ubiquity is a multidimensional construct. Davis et al. (1992) created a scale consisting of three items for measuring Perceived Enjoyment in the context of computers which was used for this study. Self-Efficacy was measured with adapted three items from Venkatesh et al. (2003). One item ("I could complete a job or task using the system if I had just the built-in help facility for assistance" was dropped because it did not fit into the context of the study.

Habit was measured with three items which were adopted from Venkatesh et al. (2012). Personal innovativeness was measured with five items which were adopted from Ridgeway & Price (1983). Furthermore, four items were adopted from Bhattacherjee (2001) in order to measure continuance intention.

The wording of all scales was minorly adjusted to the context of the study in order to be clear and as short as possible. Two persons who have extensive knowledge and experience with the use of computer and smartphones were consulted and with their feedback, few scales were reformulated to guarantee the understanding of it. Ultimately, two supervisors of the study approved the scales for this study.

All items were measured with a seven-point Likert scale varying from "strongly disagree" to "strongly agree". Likert scales are attempting to measure attitudes and opinions which is the reason why it was used in this study (Hair et al., 2015). A seven-point Likert scale was applied because it is more precise than a five-point Likert scale (2015). However, it is hard to label individual numbers when the Likert scale is larger than seven (Hair et al., 2015). An option "I don't know" was not available in this questionnaire because the questions were related to the personal experiences of the participants.

All in all, the participants had to answer 62 questions. 60 items were relevant for the study, which means that two items were not analysed in the study. All questions were compulsory, and the survey items are provided in the appendix.

## 3.4 Data Analysis

The analysis of the data took several steps. First, the data was transferred from Webropol 3.0 to IBM SPSS Statistics 26. By doing so, the data sets were checked, and insufficient responses were deleted. In total, 30 responses were deleted. Second, the frequencies as well as other descriptive statistics were calculated.

In the next step, SmartPLS 3.3.3 (Ringle, Wende & Becker, 2015) was used to test the data and the hypotheses (Hair et al., 2017, 11). Partial least square structural equitation modeling (PLS-SEM) was executed for two reasons. Firstly, the goal of the study is to predict a key construct, which is continuance intention for computers and smartphones. Secondly, the sample size is small, and many variables were not distributed normally (Hair et al., 2017, 23).

A PLS-Path model consists of two elements: the structural model, so called inner model, and the measurement model, so called outer model (Hair et al., 2017, 12). The inner model includes the constructs and shows the relationships among them, while the outer model shows the relationships between constructs and their indicator variables (Hair et al., 2017, 12). The analysis of the measurement model was carried out first, and the analysis of the structural model followed. All results are shown in more detail in the following chapter.

## 3.5 Evaluation of the research

In the field of quantitative research, a quantitative study can be evaluated by measuring the reliability and validity, which includes construct validity and internal and external validity (Mertens, 2014, 399). Internal consistency is used to test the reliability using Cronbach's Alpha. The reliability of a quantitative study measures whether the constructs are functioning and if the results are repeatable. (Hair et al., 2015.). In chapter 4, Cronbach's Alphas for all constructs are discussed. Based on these results, the reliability of this research was confirmed.

Furthermore, construct validity assesses the correct operationalization of the constructs (Hair et al., 2015). In this study, all constructs and hypotheses were formed based on existing theory which supported similar hypotheses. Also, all measurement scales were adopted from previous studies. In order to assess construct validity, convergent validity as well as discriminant validity has to be checked. The extend of which the construct is positively correlating with other measures of the same construct is called convergent validity and is measured by average variance extracted (AVE). Discriminant validity was assessed with the help of the Fornell-Larcker criterion (Hair et al., 2011.). The results of the tests confirmed construct validity of this study.

Internal validity examines the causality of a dependent variable, which means that the independent variable truly effects the changes of the depend variable (Mertens 2014, 129.). This study used only relationships which were validated in similar previous studies, thus the causal assumptions between the dependent and the independent variables are justified.

Moreover, external validity describes the generalisation of the results, which means whether the results of the study can be generalised into other situations (Mertens, 2014, 133). This study used probability sampling, which means the sample was selected based on convenience. Hair et al. (2015) are stating that for these kind of samples, it is hard to ensure that they are representative and thus, the results cannot be generalised to the whole population. The distribution of the gender is not considered to be an issue in this study, because 50,4% were male and 49,6% female participants. However, the study was distributed in different countries which means that one cannot interpret the results for a specific country. Also, the vast majority of the participants were between 19 and 35 years old which means the results can hardly be generalised for other age groups.

# 4 RESULTS

This chapter focuses on the results of the study. First, demographic information on the participants is provided. Second, exploratory factor analysis is conducted before the measurement model as well as the structural model are assessed.

## 4.1 Demographic and background information

Male (50,4%) and female (49,6%) respondents were almost equally distributed in this survey. The majority of the participants are between 19 to 25 years old (58,7%). The second biggest age group was from 26 to 35 years old (31,4%). The detailed results are shown in table 3.

TABLE 3 Demographic factors of the respondents

| | N | % |
|---|---|---|
| **Gender** | | |
| Male | 61 | 50,4 |
| Female | 60 | 49,6 |
| Total | 121 | 100 |
| | | |
| **Age** | | |
| Under 18 | 1 | 0,8 |
| 19-25 | 71 | 58,7 |
| 26-35 | 38 | 31,4 |
| 36-45 | 4 | 3,3 |
| 46-55 | 4 | 3,3 |
| Over 55 | 3 | 2,5 |
| Total | 121 | 100 |

## 4.2 Exploratory factor analysis

In order to analyse the factors which were used for this study, exploratory factor analysis (EFA) was used in order to assess data patterns and identify factors for the study (Hair et al., 2015, 411). This pre-analysis method was used to detect unsuitable items and remove them if necessary. Before that, Kaiser-Meyer-Olkin's test (KMO) and Bartlett's test were executed to find out whether the variables are suitable for factorisation and if they are significantly different from each other (Karjaluoto, 2007, 44). The results of the test for both, the computer usage sample (KMO: 0.820, Bartlett's test: $p < 0.01$) and the smartphone usage sample (KMO: 0.823, Bartlett's test: $p < 0.01$), suggest that the preconditions of factor analysis are met (Karjaluoto, 2007, 44). Furthermore, the communalities of the variables were assessed in order to check if the variables are suitable for factor analysis. For the computer usage sample, two variables were below the suggested level of 0.3 (Karjaluoto, 2007, 48) therefore CON1, CON3 and INNO4 were removed. In the sample regarding the usage of smartphones, only one variable was below the suggested level, which is why HABIT2 was removed.

The EFA was executed using SPSS Statistics 26. Principal axis factoring as well as widely used varimax rotation was used (Hair et al, 2015). With this approach, the amount of variance of a particular factor is measured and factors with an eigenvalue of 1 or higher are retained (Hair et al., 2015).

The EFA of the computer sample extracted seven factors. Items relating to perceived enjoyment and perceived innovativeness as well as one item of searchability loaded to the first factor. The second factor included the items of portability, searchability, continuity, immediacy and one item of habit. Three items of continuance intention as well as two items of habit and one item of self-efficacy loaded to the third factor. The fourth factor included two items of innovativeness and one item of self-efficacy. The fifth factor included two items of perceived self-efficacy while the sixth factor only included one item of perceived enjoyment. Also, the seventh factor only included one item of searchability. The primary factor loadings were 0.321 or stronger.

Nevertheless, many cross-loadings were present that exceeded 0.300. The first factor explained 12,6% of the variance. 12,3% are explained with the second factor, 11,4% with the third factor, 8,4% with the fourth factor, 4,7% with the fifth factor, 4,1% with the sixth factor, and 3,6% with the seventh factor. Cumulatively, the five factors are explaining 57,1% of the total variance. Based on the EFA, HABIT 2 and SELF3 were excluded from the studies because they loaded to different factors than other similar items. The detailed results are provided in the appendix.

On the other side, the EFA of the smartphone sample extracted seven factors as well. All items of perceived enjoyment and three items of innovativeness as well as two items of continuance intention, and one item of continuity loaded to the first factor. The second factor included immediacy and one item of both, habit and portability. Furthermore, two items of continuance intention and one item of portability loaded to the third factor. The fourth factor included one item of each, searchability, portability, and continuity. The items of self-efficacy as well as one item of continuity loaded to the fifth factor. Also, the sixth factor included one item of innovativeness, and two items of searchability. Finally, the seventh factor includes one item of innovativeness. All primary factor loadings were .383 or stronger.

Similarly to the sample of the computer usage, many cross-loadings were present that exceeded 0.300. In total, 56,3% of the total variance are explained with these seven factors. Based on the results of EFA, CON2 was removed from the study because it is clearly loading to another factor than similar items. All results are shown in greater detailed in the appendix.

## 4.3 Measurement model

This study assesses the model within two different scenarios which means that all test and analyses were carried out for the data regarding the user's computer usage as well as their smartphone usage.

### 4.3.1 Assessment of Computer Usage sample

In order to measure the internal consistency of the measurement scales, Cronbach Alpha's as well as composite reliability were assessed. Composite reliability is similar but more accurate than Cronbach Alpha's (Hair et al., 2015, p. 255). According to the literature, Cronbach Alpha's ranging from 0.7 to 0.9 are considered to have a good association (Hair et al., 2015, p. 255). All values regarding the data of the usage of the computer are exceeding 0.7 except Habit and IT Self-Efficacy, which are just below 0.7 but both constructs are having each a considerably good composite reliability value.

The suggested level of Standardized loadings of each measurement scale is at least 0.7 (Hair et al., 2015, p. 447). Therefore, several items (IMM3, PORT2, PORT3, SEARCH2, SEARCH3, INN2) in the measurement model regarding the usage of a computer had to be removed.

The remaining indicators are loading to the latent factors well and are therefore considered to be reliable measurement indicators. Table 4 shows the values in greater detail.

TABLE 4 Factor loadings, Cronbach's alphas, and composite reliability

| Factor | Cronbach's Alpha | Composite Reliability | Item | Standardized Loading |
|---|---|---|---|---|
| **Continuity** | 1.000 | 1.000 | CON2 | 1.000 |
| **Immediacy** | .649 | .851 | IMM1 | .867 |
| | | | IMM2 | .853 |
| **Portability** | 1.000 | 1.000 | PORT1 | 1.000 |
| **Searchability** | 1.000 | 1.000 | SEARCH1 | 1.000 |
| **Ubiquity** | .864 | .902 | CON2 | .761 |
| | | | IMM1 | .786 |
| | | | IMM2 | .752 |
| | | | PORT1 | .856 |
| | | | SEARCH1 | .865 |
| **Perceived Enjoyment** | .780 | .870 | ENJOY1 | .853 |
| | | | ENJOY2 | .867 |
| | | | ENJOY3 | .772 |
| **Habit** | .667 | .857 | HABIT1 | .852 |
| | | | HABIT3 | .880 |
| **Innovativeness** | .754 | .854 | INNO1 | .799 |
| | | | INNO3 | .827 |
| | | | INNO5 | .814 |
| **Self-Efficacy** | .670 | .858 | SELF1 | .879 |

(continues)

TABLE 4 continued

| | | | | |
|---|---|---|---|---|
| | | | SELF2 | .854 |
| **Continuance Intention** | .814 | .890 | CONTIN1 | .910 |
| | | | CONTIN2 | .832 |
| | | | CONTIN4 | .817 |

Average variance extracted values (AVE) were used to assess the convergent validity of the measurement model. It tests how measures correlate with other measures of the same construct (Hair et al., 2015, p. 258). All of the values were above the suggested value of 0.5.

Furthermore, Discriminant Validity was examined using the Fornell-Larcker criterion. It compares the square root of AVE in each latent variable with other constructs and should exceed the square of its correlations with any other constructs (Hair et al., 2015, p. 448). Table 5 shows that in all cases the square root of AVE was greater than the construct correlations.

TABLE 5 Discriminant Validity, Means, and Standard Deviations for Computer Usage

| | AVE | CONTIN | ENJOY | HABIT | INNO | SELF | UBI |
|---|---|---|---|---|---|---|---|
| CONTIN | .730 | **.854** | | | | | |
| ENJOY | .692 | .606 | **.832** | | | | |
| HABIT | .750 | .556 | .400 | **.866** | | | |
| INNO | .662 | .425 | .569 | .196 | **.813** | | |
| SELF | .751 | .447 | .406 | .413 | .260 | **.867** | |
| UBI | .649 | .301 | .292 | .052 | .376 | .002 | **.806** |
| Mean | | 5.47 | 5.30 | 6.08 | 4.65 | 5.92 | 4.45 |
| S.D. | | 1.45 | 1.20 | 1.12 | 1.67 | 1.17 | 1.81 |

### 4.3.2 Assessment of Smartphone sample

In line with the analysis of the other sample, Cronbach Alpha's as well as Composite Reliability were assessed for the same constructs regarding the data of the participants use of their smartphone (Hair et al., 2015, p. 255). All Cronbach Alpha values are exceeding the suggested level of 0.7 or are just below the cut-off criterion. One exception is "Habit" with a Cronbach Alpha value of only 0.559. It was decided to keep it included in the model because it has a considerably good composite reliability value.

Furthermore, the factor loadings of each measure were evaluated and all items which loaded less than 0.7 (Hair et al., 2015, p. 447) were deleted (CON3, IMM3, PORT3, SEARCH2, SEARCH3, SELF1, INNO2, INNO4, CONTIN3). Table 5 shows the results more detailed.

TABLE 6 Factor loadings, Cronbach's alphas and composite reliability for Smartphone

| Factor | Cronbach's Alpha | Composite Reliability | Item | Standardized Loading |
|---|---|---|---|---|
| Continuity | 1.000 | 1.000 | CON1 | 1.000 |
| Immediacy | .641 | .848 | IMM1 | .848 |
| | | | IMM2 | .867 |
| Portability | .691 | .866 | PORT1 | .878 |
| | | | PORT2 | .870 |
| Searchability | 1.000 | 1.000 | SEARCH1 | 1.000 |
| Ubiquity | .871 | .903 | CON1 | .770 |
| | | | IMM1 | .726 |
| | | | IMM2 | .770 |
| | | | PORT1 | .797 |
| | | | PORT2 | .776 |
| | | | SEARCH1 | .836 |
| Perceived Enjoyment | .873 | .922 | ENJOY1 | .902 |
| | | | ENJOY2 | .912 |
| | | | ENJOY3 | .863 |
| Habit | .559 | .815 | HABIT1 | .765 |
| | | | HABIT3 | .891 |
| Innovativeness | .733 | .849 | INNO1 | .891 |
| | | | INNO3 | .772 |
| | | | INNO5 | .756 |
| Self-Efficacy | .646 | .849 | SELF2 | .874 |
| | | | SELF3 | .844 |
| Continuance Intention | .807 | .912 | CONTIN1 | .925 |
| | | | CONTIN2 | .906 |

In order to test the Convergent Validity of the measurement model, AVE values were assessed. All of the values were above the suggested value of 0.5.

Furthermore, the Fornell-Larcker-criterion used again to assess the Discriminant Validity. Table 7 shows that in all cases the square root of AVE was greater than the construct correlations.

TABLE 7 Discriminant Validity, Means, and Standard Deviations for smartphone sample

| | AVE | CONTIN | ENJOY | HABIT | INNO | SELF | UBI |
|---|---|---|---|---|---|---|---|
| CON-TIN | .838 | **.915** | | | | | |
| ENJOY | .797 | .636 | **.893** | | | | |
| HABIT | .689 | .494 | .494 | **.830** | | | |
| INNO | .654 | .389 | .601 | .205 | **.808** | | |
| SELF | .738 | .430 | .435 | .446 | .560 | **.859** | |
| UBI | .608 | .455 | .334 | .662 | -.31 | .193 | **.780** |
| Mean | | 5.75 | 5.50 | 6.40 | 4.76 | 5.38 | 6.43 |
| S.D. | | 1.37 | 1.32 | .940 | 1.59 | 1.38 | 0.92 |

## 4.4 Structural model

Structural path modelling was used to test the hypotheses. The direct affects in the structural model were tested using bootstrapping with 5000 samples (Hair et al., 2011). A bootstrap sample in PLS is created by nonparametric bootstrapping, "which involves repeated random sampling with replacement from the original sample to create a bootstrap sample, to obtain standard errors for hypothesis testing" (Hair et al., 2011, 148).

The models' predictive relevance was assessed by using the Stone-Geisser criterion ($Q^2$). The value for Continuance Intention regarding the use of a computer was 0.359 and the value for the use of a smartphone was 0.357 which is well above zero. This indicates the models' predictive relevance (Henseler, Ringle, & Sinkovics, 2009).

Furthermore, there are two indicators which are used to evaluate the structural model. The $R^2$ measures is assessed in combination with the path coefficient (Hair et al., 2011). In these models, $R^2$ values explain how much the target construct is explained by the endogenous latent variables. That is why the value of $R^2$ should be high. In consumer behaviour, a $R^2$ value of 0.2 is considered to be high (Hair et al., 2011). The individual path coefficients (ß) are showing whether the hypothesized relationships between two constructs are significant (Hair et al, 2011).

Based on the path coefficients, the strongest predictors for continuance intention of a personal computer are habit ($\beta$=0.342, p<0.01) and perceived enjoyment ($\beta$=0.314, p<0.01). Therefore, H2 and H5 are supported. Perceived ubiquity, personal innovativeness and IT self-efficacy had so significant effect on continuance intention of a personal computer. Thus, H1, H3 and H4 are not supported. Furthermore, regarding the predictors of continuance intention for the use of a smartphone, perceived enjoyment ($\beta$=0.448, p<0.01) and perceived ubiquity (ß=0.262, p<0.01) are the strongest predictors. H6 and H7 are therefore supported. Personal innovativeness, IT self-efficacy and habit had no significant effect on continuance intention which is the reason why H8, H9 and H10 are not supported.

The control variables age and gender did not yield any significant effect which is the reason why they were excluded from the model.

Figure 7 shows the structural model with path coefficients and the coefficients of determination for both the use of a personal computer and the use of a smartphone in parentheses.

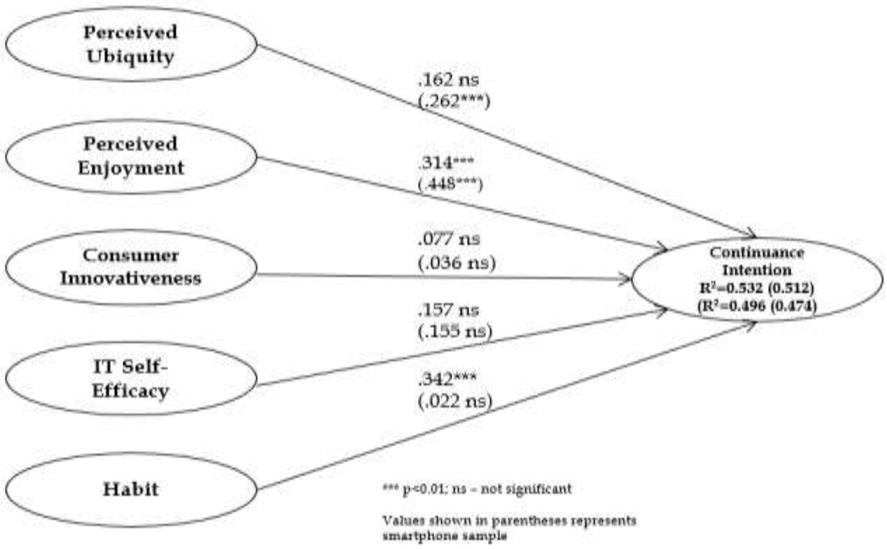


FIGURE 7 Structural Model

# 5 DISCUSSION

This chapter discusses the empirical findings of the study in connection with previous studies. Thus, the research questions asked in previous chapters are answered. Moreover, theoretical contributions as well as managerial implications are discussed and proposed. In addition, an evaluation of the study is presented, limitations of it are explained and suggestions for future research are given.

## 5.1 Theoretical contributions

This study aimed to gain a better understanding of factors which are highly relevant for users of different connected devices, especially for the use of computer and smartphone. More specifically, this study wanted to examine factors which are less studied compared to establish models in the field of technology acceptance and continuance intention, such as UTAUT (Venkatesh et. al, 2012) or TAM (Davis et. al., 1989). Also, the special part of this study is the focus on specific technologies, namely personal computer, and smartphone, instead of technology in a broad sense. Therefore, following research questions were applied in the beginning of the study:

- What factors motivate the usage behaviour of consumers when accessing and using smart devices and personal computers?
- How vary these factors between these two devices?

This research showed that perceived enjoyment, perceived ubiquity, and habit are the best predictors for continuance intention of specific technologies, depending on whether it is about a computer or a smartphone. However, perceived enjoyment predicted the continuance intention for both information technology systems very well. This result is consistent with previous studies which identified perceived enjoyment as one of the most important predictors for the use of information technology (Davis et al., 1992; Park et al., 2014; Teo et al., 1999; Ha et al., 2007).

Nevertheless, studies about other connected devices, such as smartwatches (Nascimento et al., 2018) and ebooks (Joo et al., 2017), showed that there is no significant effect of perceived enjoyment on continuance intention. Consistent with the results of this study, it indicates that predictors of continuance intention must be evaluated for each technology and cannot be generalised for all information technology.

Habit was the strongest predictor of continuance intention for the use of a computer, which is consistent with the findings of Lafley & Martin (2017), who suggested that consumers are preferring the path of least effort. Furthermore, the concept of technology inertia states that consumers continue to use an incumbent system, because it is too stressful to change, even if there is a superior one (Amoroso & Lim, 2017). However, habit did not significantly affect continuance intention of a smartphone which suggests that users are not unconsciously using it after they adapted to it and that habit is not surpassing other factors, such as perceived enjoyment or perceived ubiquity.

On the other hand, perceived ubiquity is a strong predictor of continuance intention of users' smartphone. This finding supports other studies, which stated that the 'anytime, anywhere' ubiquity of smartphones is highly important to users (Kleijnen et al., 2007; Nysveen et al, 2005; Okazaki et al., 2009) and that it is disrupting the field of marketing due to the ubiquitous nature of the technology (Shankar & Balasubramanian, 2009). In contrary, perceived ubiquity is not significantly affecting continuance intention of a computer. The reason for this may lies in the nature of a computer, which has not the same level of ubiquity than a smartphone or other technologies.

Surprisingly, IT self-efficacy does not have a significant influence on continuance intention of both technologies. It indicates that IT self-efficacy may be important in technology adoption models (Bandura, 2011; Compeau & Higgins, 1995; Alqurashi, 2016) or as a mediator predicting behavioural intention in mobile technology acceptance studies (Gan and Balakrishan, 2017) but does not directly affect continuance intention of an information technology.

Furthermore, there was no significant effect of personal innovativeness on continuance intention. As discussed in chapter 2, there is little research about personal innovativeness in a post-adoption context. Hong, Lin and Hsieh (2016) as well as Lu (2014) showed that personal innovativeness is an important determinant for continuance intention of smartwatches, but, however, there is no empirical support for this hypothesis regarding the continuance intention of computers or smartphones.

## 5.2 Managerial implications

This study yields different theoretical findings which can serve as a basis for further research in cross-device and cross-channel marketing. However, there are also results which decision makers in the marketing industry should consider with regard to cross-device marketing.

In the 21st century, many people are using different devices whereby smartphones and computers are the most used device at the moment. However, the use of other connected devices such as tablets, smartwatches and others are increasing, and new technologies will be developed in the future. That is why it is important for managers to understand the media fragmentation and increasing number of devices, more specifically, the reasons for 'why' and 'when' users are using a device. By knowing this, marketing strategies, especially cross-channel and cross-device marketing, can be carried out more effectively.

This study showed that different connected devices are used for different reasons. By understanding this, managers can better predict the device the user is using and increase the user experience as well as their marketing efforts. This study validated that perceived ubiquity is the most important predictor for the use of smartphones, which implies that users are using smartphones especially when they are not at home. This finding does not seem to be surprising, but however, there is little research empirically validating this. It also implicates that users want to be connected at all times and therefore they are receptive for mobile advertising.

Moreover, perceived enjoyment was a strong predictor of continuance for both devices, which suggests that hedonic motivations to use a device are not only important for technology adoption but also for the continued use. It implicates, that users are enjoying using a device and therefore they are more likely to be in a positive mood which can affect marketing efforts positively (Bakamitsos & Siomkos, 2004).

Habit was found to be the strongest predictor for the continuance intention of computers, which implies that users are going to continue using it even when there are new technologies arising. In a fast-developing environment, managers can consider computers as a device which will be used by many users in the future and is likely to stay as the most used device besides smartphones. This means that marketing managers should continue to increase marketing efforts tailored for computers, whereas devices such as different mobile devices could be replaced by superior technology in the near future.

## 5.3 Limitations of the study and future research

This chapter discusses the limitations that this study may has and how researchers can address these limitations in future studies.

First of all, this study took place during a worldwide pandemic. In their weekly epidemiological update, the world health organization (WHO) published the cumulative number of 93 million reported Covid-19 cases with more than 2 million deaths globally since the start of this pandemic (WHO, 2020). In the near future, tens of thousands of people will still be infected, and a significant number of those will still die (Dwivedi et al., 2020).

This pandemic affected many different aspects of the daily life where governments needed to reduce the personal contacts in almost all forms outside of a person's family. This is impacting in an unmatching way people's lives in a context of mental health (Singh et al., 2020), but also organisations which are trying to maintain their operations during these times (Dwivedi et al., 2020). This situation created a fast and radical transformation of how people interact and operate within their workplace. Due to social distancing altered work patterns needed to be established (Richter, 2020), such as remote working using new digital communication systems or rethinking the whole business model to adapt to the new situation (Carroll & Conboy, 2020).

Pandey and Pal (2020) are stating that due to the lockdowns across many countries the use of information systems and networks has risen, and the usage behaviour and patterns have changed drastically. Employees are adjusting to the "new normal", for instance meetings are held completely online, office work is shifting to work from home (WFH), and new work patterns are emerging. In fact, video – and audio-conferencing tools are increasingly used, and organisations are trying to develop their technology infrastructure, such as network equipment, software, and cloud services (Paned & Pal, 2020).

One sector which must undergo a drastically digital transformation is the global higher education sector (Dwivedi et al., 2020). Universities as well as schools are closed and due to social distancing, teaching materials and sessions must change into a format suitable for the online environment. Because of that, many academics learned new teaching techniques, which includes teachers and lecturers as well as post- and undergraduate students (Dwivedi et al., 2020). This is especially important for this study, because most of the participants were between 19 and 35 years old, which means that many of them are most likely be students.

Because of the transition to WFH and the fact that many people must stay at home due to the lockdowns, consumer behaviour to digital technologies has changed. An increasing number of consumers are more comfortable with using digital platforms and digital commerce (Dwivedi et al., 2020) as well as information technology in general which may affected different factors for this study as well.

With regard to the study itself, convenience sampling was used which means that the respondents might not represents the opinions of all computer or smartphone users. In order to get more generalizable results, a normal distribution of computer and smartphone users would have been required, e.g. the respondents were from different countries and not well distributed in age. Furthermore, the sample size of 126 respondents were evaluated as sufficient, but because of the not normal distribution of demographical variables, a bigger sample size would have showed even better results. However, the questionnaire should have been available for more participants for more weeks, but it was not possible due to time constraints.

The survey was carried out in the English language, which means that the original items were used. However, there is the risk that participants misinterpreted or misunderstood certain questions since most of the participants were from countries which does not have English as an official language in the country. Additionally, it was assumed that the participants were concentrated while filling the survey and that they were reading the description texts and questions carefully. Nevertheless, there cannot be certainty that if the respondents answered all questions carefully and honestly.

Moreover, based on the results of the full collinearity test, it was assessed that common method bias is not a problem in this study, but it cannot be completely ruled out even with all the efforts that were made.

This study was focused on factors which might influence continuance intention of personal computers and smartphones. However, important factors which are proofed to be highly relevant for the continuance intention of information technology, such as hedonic motivation or social influence (Venkatesh et. al, 2012), were not taken into account.

Nevertheless, the perceived ubiquity of mobile devices, as a relatively new construct in IS research, is highly relevant for smartphones. Therefore, it can be concluded, that constructs which were introduced in another technological environment are not covering functions that new technologies offer to users. Consistent with Yan et al. (2021), future studies should investigate specific functions of technologies and how it affects the continuance intention. Following the call of Okazaki and Mendez (2013), this research shed light on the importance of perceived ubiquity for mobile devices. Therefore, according to them, future studies about mobile services and devices should include the concept of perceived ubiquity and test the concept in different contexts to better understand which devices and services are enriching our future lives. Nevertheless, it is important to notice the restrictions in terms of data privacy, such das GDPR, which devices are subject to. Future studies need to include these fundamental regularities and how they affect the usage of connected devices.

Also, it would be interesting to research the role of advanced technology, such as artificial intelligence (AI) and how device usage is affected by it. Researchers could find out how users perceive the capabilities of AI and whether they prefer using AI based systems or if they have more trust in the human capabilities. Additionally, aligned with the research prioritization of the MSI, studies regarding the exposure time of different devices would give valuable insights of consumer behaviour as well (MSI Research Priorities 2020-2022)

Therefore, future studies should expand and alter this research model by incorporating new variables and review existing variables if they still cover all relevant aspects of current technologies. Also, it would be interesting to conduct this study in different countries, e.g. countries where information technology adoption is not as advanced as in Finland or in emerging markets, in which mobile devices and information technologies are quickly emerging.

Furthermore, future studies in this field should use bigger sample sizes as well as another sampling method. There are also possible future research directions which are worth exploring in the future. First, consistent with Kannan and Li (2017), it would be important for companies to find out in which situation devices are used over another one. Consequently, moderating variables could be examined when different devices are used simultaneously or complementary.

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# APPENDICES

## Appendix 1: List of survey items

**Perceived Ubiquity** (Okazaki & Mendez, 2013)

**Continuity**

[CON1] Using a personal computer/smartphone keeps me well informed at all times.

[CON2] With a personal computer/smartphone, I can always keep up with the world.

[CON3] When I use a personal computer/smartphone, I don't have to interrupt my current task.

**Immediacy**

[IMM1] Using a personal computer/smartphone allows me to access information at the best moment for me.

[IMM2] When I cannot wait and I need a certain type of information immediately, I will use a personal computer/smartphone

[IMM3] When I need to receive an urgent response, I will use a personal computer/smartphone.

**Portability**

[PORT1] A personal computer/smartphone is practical because I can use it without difficulty wherever I am.

[PORT2] Using a personal computer/smartphone outside my home or my workplace is not a problem for me.

[PORT3] I find it convenient to use a personal computer/smartphone because they don't make me dependent on any fixed installation.

**Searchability**

[SEARCH1] With a personal computer/smartphone, I can check out new things regardless of where I am.

[SEARCH2] Using a personal computer/smartphone helps me to reach my target information regardless of where it comes from.

**Perceived Enjoyment** (Davis et al., 1992)

[ENJOY1] Using a personal computer/smartphone is enjoyable.

[ENJOY2] Using a personal computer/smartphone is pleasurable.

[ENJOY3] I find using a personal computer/smartphone to be interesting.

**Personal innovativeness** (Ridgeway & Price, 1983)

[INNO1] I am creative with a personal computer/smartphone.

[INNO2] I am very curious about how computer/smartphone work.

[INNO3] I am comfortable working on computer/smartphone projects that are different from what I am used to.

[INNO4] I often try to do projects on my computer/smartphone without exact direction.

**Perceived self-efficacy** (Venkatesh et al., 2003)

[SELF] I can perform a task using * even if there is no one around to help me.

[SELF2] I can complete a task using a computer/smartphone if I have adequate time to complete it.

[SELF3] I am confident in my ability to perform a task using a computer/smartphone.

**Habit** (Venkatesh et al., 2012)

[HABIT1] The use of a personal computer/smartphone has become a habit for me.

[HABIT2] I am addicted using a computer/smartphone

[HABIT3] Using a computer/smartphone has become natural to me.

**Continuance Intention** (Bhattacherjee 2001)

[CONTIN1] I intend to continue using a computer/smartphone rather than discontinue its use.

[CONTIN2] My intentions are to continue using a computer/smartphone than use any alternative means.

[CONTIN3] I intend to use increase my use of a computer/smartphone in the future.

[CONTIN4] I will keep using a computer/smartphone as regularly as I do now.

## Appendix 2: Results of the exploratory factor analysis (computer usage sample)

| | | | | FACTOR | | | | |
|---|---|---|---|---|---|---|---|---|
| ITEM | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Commu-nality |
| CONTIN1 | **.846** | | | | .324 | | | .876 |
| CONTIN4 | **.673** | | | | | | | .578 |
| CONTIN2 | **.666** | | | | | | | .620 |
| HABIT3 | **.592** | | | | | | | .484 |
| ENJOY2 | **.532** | .331 | | | | .306 | | .541 |
| HABIT1 | **.475** | | | .301 | .463 | | | .541 |
| SEARCH3 | **.434** | | | | | | | .330 |
| SELF3*** | | **.712** | | | | | | .601 |
| INNO1 | | **.711** | | | | | | .573 |
| INNO3 | | **.594** | | | | | | .500 |
| INNO5 | | **.587** | | | | | | .491 |
| INNO2 | | **.561** | | | | | | .494 |
| ENJOY3 | | **.557** | | | | | | .524 |
| CONTIN3 | | **.441** | | | | | -.303 | .538 |
| PORT1 | | | **.906** | | | | | .897 |
| SEARCH1 | | | **.769** | .394 | | | | .805 |
| IMM1 | | | **.553** | .319 | | | | .477 |
| PORT2 | | | **.517** | | | | | .323 |
| PORT3 | | | **.451** | | | | | .321 |
| IMM2 | | | .321 | **.711** | | | | .680 |
| IMM3 | | | | **.592** | | | | .403 |
| HABIT2*** | | .368 | | **.553** | | | | .486 |
| CON2 | | | .400 | **.487** | | | .420 | .603 |
| SELF1 | | | | | **.719** | | | .635 |
| SELF2 | | | | | **.488** | | .348 | .589 |
| ENJOY1 | .373 | .405 | | | | .821 | | .999 |
| SEARCH2 | | | | | | | **.572** | .501 |

***=item removed based on the results of the EFA. All loadings .300 or stronger presented. Principal axis factoring and varimax rotation were applied.

# Appendix 3: Results of the exploratory factor analysis (smartphone usage sample)

| | FACTOR | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ITEM | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Commu-nality |
| ENJOY3 | **.727** | | | | .324 | | | .726 |
| INNO2 | **.686** | | | | | | | .524 |
| CONTIN3 | **.604** | | | | | | | .531 |
| ENJOY2 | **.583** | | .466 | | | | .508 | .881 |
| INNO1 | **.575** | | | | | .306 | | .516 |
| ENJOY1 | **.517** | | .396 | | | | .352 | .674 |
| INNO5 | **.508** | | | | | | | .381 |
| CONTIN4 | **.383** | | .356 | .302 | | | | .435 |
| CON3 | **.377** | | .345 | | | | | .322 |
| IMM2 | | **.901** | | | | | | .867 |
| PORT2 | | **.680** | | | | | | .605 |
| HABIT1 | | **.613** | | | | | | .500 |
| IMM3 | | **.539** | | | | | | .344 |
| IMM1 | | **.456** | | .376 | | | -.303 | .442 |
| CONTIN1 | | | **.731** | | | | | .754 |
| CONTIN2 | | | **.657** | | | | | .614 |
| PORT3 | | .342 | **.433** | | | | | .410 |
| SEARCH1 | | .413 | | **.842** | | | | .917 |
| PORT1 | | .441 | | **.608** | | | | .641 |
| CON1 | | .460 | | **.513** | | | | .546 |
| SELF1 | | | | | **.705** | | | .544 |
| SELF2 | | | | | **.598** | .417 | | .611 |
| SELF3 | | | | | **.556** | | | .479 |
| HABIT3 | | **.396** | | | **.396** | | .338 | .535 |
| CON2*** | | | | .314 | **.356** | | | .399 |
| INNO3 | .381 | | | | .402 | **.611** | | .739 |
| SEARCH3 | .350 | | .307 | | | **.513** | | .490 |
| SEARCH2 | | | | .323 | | **.476** | | .421 |
| INNO4 | | | | | | | **.643** | .461 |

***=item removed based on the results of the EFA. All loadings .300 or stronger presented. Principal axis factoring and varimax rotation were applied.