Title: THE ROLE OF MEDIA DEPENDENCY IN PREDICTING CONTINUANCE INTENTION TO USE UBIQUITOUS MEDIA SYSTEMS

Author: Kevin Carillo Eusebio Scornavacca Stefano Za

PII: S0378-7206(16)30107-0
DOI: http://dx.doi.org/doi:10.1016/j.im.2016.09.002
Reference: INFMAN 2936

To appear in: *INFMAN*

Received date: 7-9-2015
Revised date: 18-7-2016
Accepted date: 2-9-2016

Please cite this article as: Kevin Carillo, Eusebio Scornavacca, Stefano Za, THE ROLE OF MEDIA DEPENDENCY IN PREDICTING CONTINUANCE INTENTION TO USE UBIQUITOUS MEDIA SYSTEMS, Information and Management http://dx.doi.org/10.1016/j.im.2016.09.002

THE ROLE OF MEDIA DEPENDENCY IN PREDICTING CONTINUANCE INTENTION TO USE UBIQUITOUS MEDIA SYSTEMS

Corresponding author

Kevin Carillo

The University of Toulouse, Toulouse Business School

20 Boulevard Lascrosses

31068 Toulouse

France

Tel.: +33 5 61 29 47 74

E-mail: k.carillo@tbs-education.fr

Eusebio Scornavacca

Merrick School of Business

University of Baltimore

1420 N. Charles St.

Baltimore

MD 21201

USA

Tel.: +1 (410) 837 6624

E-mail: escornavacca@ubalt.edu

Stefano Za

eCampus University

Novedrate (CO)

Italy

E-mail: stefano.za@uniecampus.it

Abstract

The emergence of new integrated forms of ubiquitous computing devices, allied with the proliferation of fluid multidevice platforms, has blurred the traditional boundaries between stationary and mobile information systems. This significant technological evolution has emerged in the form of ubiquitous media systems (UMSs) – a new and complex form of connected information technology (IT) artifact that encapsulates various functions and provides access to fluid information across a variety of channels, enabling users to accomplish a multitude of tasks and interact fluidly in a ubiquitous ecosystem. Such transformation has engendered an urgent need to revisit our understanding of technology usage through the lens of theories that encompass the multifaceted nature of ubiquitous systems. Relying on a media system perspective, this study investigates the role of individual media dependency in predicting continuance intention to use UMSs. The data collected from 150 UMS users were used to test the developed conceptual model. These results confirmed the overall effect of UMSs dependency on individuals' reasoned continuance usage decision. The findings suggest that the level of dependency toward a UMS raises the perceived positive attributes about the system: perceived usefulness and perceived ease of use; as well as the cognitive appraisal about the discrepancies between initial expectations and postuse performance. Theoretical and practical implications developed from these findings are then discussed.

Keywords: media system dependency theory, user behavior, continuance usage, mobile technologies.

Introduction

As of 2014, the total number of all the types of mobile-connected devices has exceeded the world's population and is forecasted to reach 1.5 devices per human being in 2019 [1]. The pace of the emergence and mainstream adoption of new forms of ubiquitous computing devices such as smartphones, tablets, "phablets," smart TVs, and smartwatches has not ceased gaining momentum – marking an evolutionary step in the *ubiquitous computing* trend [2]. The extinction of traditional mobile phones and the proliferation of fluid multidevice platforms such as iOS, Android, and Windows 10 have blurred the traditional boundaries between stationary and mobile information systems (ISs) – creating highly competitive and complex digital ecosystems composed of network operators and device manufacturers, as well as software, content, and service providers [3–11].

This dissolution of the traditional segmentation of computing contexts represents a remarkable shift in the fundamental temporospatial nature of information technology (IT) artifacts [12,13]. Indeed, individuals are gradually unable to perceive their mobile and nonmobile devices as single independent entities, but rather as an evolving collection of interconnected devices that are progressively playing a major role in their daily lives [14,15]. This significant technological evolution has given birth to a new and complex form of connected IT artifact, ubiquitous media systems (UMSs), that encapsulates multiple functions and provides information access across a variety of channels; allowing users to accomplish a multitude of tasks and interact fluidly in a ubiquitous ecosystem [4,16,17].

The emergence of fluid and evolving technoecosystems poses important challenges and opportunities for IS theory and practice. By gradually blurring physical, social, and temporal boundaries, *UMSs* allow the delivery of new as well as existing online products and services through a multitude of interconnected channels, in addition to radically novel and unthought-of opportunities for digital business [18–20].

As information access becomes fully ubiquitous and the utilitarian as well as the hedonic functionalities of those devices increase, users become more dependent on the affordances provided by these fluid technoecosystems [7,21]. As a result, there is a need to understand the role that dependency plays on user behavior in ubiquitous ecosystems [11,21].

Media system dependency (MSD) theory offers an untrodden path to explore user dependency in the specific context of UMSs [22–24]. Specifically, the microlevel of MSD theory, known as individual media dependency (IMD) theory provides a robust foundation to assess an individual's dependency relations with regard to a specific media [25,26]. Although MSD theory is quite diffused in the field of mass communication research [23,25,27], it has attracted quite limited attention from the IS discipline [11,28].

During the past two decades, the growing number of cases of Internet and video-game-related behavioral disorders has made scientists aware of the negative facet of technology dependency: IT addiction. Recent research shows that this is a primary psychopathology that should be recognized as a clinical disorder [29]. Early research efforts, particularly in the field of cyberpsychology, have shed some light on the specifics of technology dependency [30–32]. Only recently it has been shown, however, that technology dependency has raised the curiosity of IS scholars who have focused primarily on IT addiction. IS research has explored technology dependency in a variety of contexts such as online auctions [21], online games [33], social networking sites [34], or smartphones [35]. More specifically, the literature has provided some indication that technology dependency can influence an individual's reasoned IT usage decisions by distorting various systems' perceptions [7,21]. As a result, in a world where >80% of the population uses a mobile device [10] and where smartphone usage has been increasingly permeating the daily life of human beings [15], the IT dependency phenomenon appears to be particularly salient in the mobile device context [35]. This research study builds on the stream of IS research that has investigated the role played by IT dependency in influencing individuals' reasoned IT usage decisions [7,21].

However, in line with the core assumptions of MSD theory, this research argues that technology dependency has an unexplored facet that is utilitarian in nature. Although addiction explains individuals' "psychological dependency" on media, which is irrational and compulsive, this work aims to explain "utilitarian dependency" on media (media dependency), which is a rational and goal-directed phenomenon. Moreover, this paper adopts an alternative research focus by emphasizing the fact that dependency is a mental state that builds and evolves over time and through prolonged usage. Given this, and the fact that the study of technology dependency appears to be particularly pertinent in postadoption and prolonged usage settings [11,21], this research paper uses an IS continuance theoretical lens [36]. Based on a utilitarian view of dependency, and considering the dual nature that characterizes multimedia devices (IT artifacts and multimedia systems), incorporating an IMD perspective [25,26] within the IS continuance model [36] can provide a more encompassing approach to investigate continuance usage intention in the UMS context. This paper aims to shed light onto the role of IMD in predicting continuance intention (CI) to use UMSs.

In order to achieve such a goal, this research paper develops and validates a research model that combines MSD theory [23,24,37] with the IS continuance model [36]. In the next section, the theoretical foundations are described. This is followed by the introduction of the conceptual model and the development of the associated hypotheses. Then, research methodology, data analysis, and results are presented. The paper wraps up with a conclusion and recommendations for future research.

Literature review and theoretical background

This section aims to provide a theoretical background on the key bodies of the literature in which this research was anchored: the development of ubiquitous computing, MSD, and expectation–confirmation theories (ECTs).

Temporospatial Expansion of IS and Media Convergence

The temporospatial expansion of IS is deemed to be a product of the developments in wireless data access and technology portability [13,38]. Figure 1 represents graphically the expansion of temporospatial availability of ISs: the two perpendicular axes represent time and space, while the sinuous line represents the movement of an individual in the temporospatial continuum. The light gray areas represent locations in time and space where IS support is not available, while the dark gray areas represent places where IS support is available. The area bounded by large dashed lines represents physical boundaries (in this example “home,” “work,” and “Internet kiosk” are used), while the dotted line around the dark gray area represents a virtual boundary – delimitating areas where information can be accessed and IS-assisted tasks can be accomplished. Finally, the white elliptical areas represent instances when and where tasks supported by IS are performed – checking e-mail is used as an example in the figure for illustrative purposes, but the same rationale could be applied to an array of hedonic and utilitarian IS-supported tasks such as web browsing, chatting, or posting and exchanging pictures or video content.

In order to illustrate the evolution of IS, Figure 1 also shows three distinct stages: Figure 1 (A) represents a “stationary stage” where individuals can only access their e-mail within the boundaries of the workplace. Figure 1 (B) represents the introduction of wired "network" capabilities and the creation of a virtual boundary that merges with the existent physical boundaries, allowing the user to access their e-mail from "work," "home," or an "Internet kiosk," Finally, Figure 1 (C) represents the introduction of the "ubiquitous" stage that substantially increases the accessibility of information in the temporospatial continuum.

In each evolutionary stage, there is an increment of temporospatial availability of IS support – showing the increment of the dark gray area (Figure 1). In the "stationary" stage, the ability to have the support of IS to undertake tasks was quite limited and confined to the boundaries of the workplace. On the other hand, in the "networked" stage, users had to search for some physical location (in this example represented by the Internet kiosk) where network access was available beyond the physical boundaries of the workplace. In the "ubiquitous" stage, information access is continuous other than a few areas (represented in light gray) where connected IS support is not available (e.g., no network coverage in a building basement). Perhaps the few light gray areas remaining in Figure 1 (C) should be colored in black and called as "black holes" to better illustrate the absence of the ability to access information.

As shown in the example, the development of wireless data access and technology portability made possible the emergence of a ubiquitous environment that enables continuous connected IS support to individuals [39,40]. Although this new reality broke the traditional boundaries of stationary ISs, it initially created a partition between stationary and mobile systems. As a result, for more than a decade, mobile and nonmobile devices, software, and applications have evolved as

Only recently, the extinction of the traditional mobile phone and emergence of new integrated forms of ubiquitous computing devices (e.g., smartphones, tablets, "phablets," smart TVs, and smartwatches), alongside advances in cloud computing and the proliferation of fluid multidevice platforms (e.g., iOS, Android, and Windows 10) have blurred the preexisting boundaries between stationary and mobile ISs [7,10,11].

This combination of media convergence and ubiquitous environments not only facilitated the rise of a highly complex digital ecosystems but also engendered a remarkable shift in the fundamental nature of IT artifacts – from stand-alone independent devices to UMSs [4,7,10,11]. UMS can be defined as *a complex form of multipurpose, multicontext, connected IT artifact that uses an evolving collection of interconnected devices and encapsulates various functions, providing access to fluid information across a variety of channels and allowing users to accomplish a multitude of tasks and interact fluidly in a ubiquitous digital ecosystem* [4,15–17].

Although the increasing ubiquity and the utilitarian and hedonic functionalities of UMS devices provide incredible value to its users, they also engender a degree of technological dependency on the affordances provided by these fluid media systems [7,21]. As a result, it seems sensible to explore the notion of UMS dependency from a media system perspective. The following section presents MSD theory.

Media System Dependency

In the past, MSD theory has been used to investigate dependency relationships through mass communication channels such as television [25,41,42], radio, and newspapers [26,43]. During the past 10 years, some studies have revisited MSD in relation to the use of the Internet [44–47]. More recently, it has been used to investigate dependency relationships with IT health-care services [48], mobile technology [11], and IS work performance [49]. MSD theory defines dependency as a “relation between individuals’ goals and the extent to which these goals are contingent upon the resources of the media system [in which] those resources have the capacities to create and gather, process and disseminate information.” [23] Hence, dependency relations are goal oriented and the scope and intensity of the goals directly influence the strength of the dependency relationships between the user and the media [24,50].

IMD theory derives from MSD theory and provides concrete means to assess individual-level dependency relations with regard to a specific media [25,26]. In line with use and gratification research [51], IMD theory assumes that the extent to which a media is capable of fulfilling a person's needs and expectations, will stimulate dependency relations with the media per se which, in turn, influence usage patterns and media selection [25,26]. This research relies on the same assumption with regard to *UMSs* – a dependency relation between a person and a UMS develops proportionally to the extent it is able to fulfill this person's needs and expectations; in turn, the level of dependency influences the extent to which this individual will use such technology. In line with IMD theory, this research defines UMS dependency as *the extent to which an individual's capacity to reach his or her objectives depends on the use of his/her UMS* [23,25,52].

According to IMD theory, there are six levels of dependency relations between an individual and a media system [23,25,27]. As shown in Table 1, these levels can be represented as the product of three distinct goals: *understanding*, *orientation*, and *play*; and two different goal targets: *personal* and *social*. *Understanding* refers to the need of individuals to gain a basic understanding of themselves and to understand their social environment (including the perception of everyone's role in society). *Orientation* relates to the need one has to make behavioral decisions and to have guidance for interacting well with other people. *Play* pertains to the capacity of the media to provide an individual the mechanisms for relaxing and releasing stress when he or she is alone or accompanied by others.

A stream of research has used the term “technological addiction” referring to particular psychological states that cause behaviors such as obsessive–compulsive use of technology [53–55]. Turel et al. [21] defines it as a psychological state of maladaptive dependency on the use of a technology engendering typical behavioral addiction symptoms such as salience, withdrawal, and conflict. For instance, some research has demonstrated the mediating role of addiction in explaining the influence of cognitive absorption on usage continuance and spending intentions in the context of goal-oriented virtual worlds [56]. In the online auction context, Turel et al. [21] showed that a user’s level of addiction influences the reasoned IT usage decisions of this individual by “distorting various systems’ perceptions” (p. 1044). This research argues that psychological dependency, often referred to as “addiction” in IS research, is only one side of the coin: the MSD stream of research has demonstrated that dependency also has a utilitarian and goal-oriented facet. Although the two concepts may be structurally or causally related (a research issue that is worth investigating but that goes beyond the scope of this research paper), utilitarian dependency and psychological dependency are distinct concepts, thus potentially producing different effects on human beings. Although addiction explains individuals’ “psychological dependency” on media, media dependency explains “utilitarian dependency” on media. Table 2 highlights the differences that exist in the conceptual definitions of the two notions but also in terms of their impact on individuals. As a consequence, this research paper’s viewpoint is that they may influence individuals’ reasoned IT usage decisions in unique ways.

Because of its utilitarian nature, dependency tends to focus on the more positive consequences of the use of technology. However, because of its obsessive–compulsive nature, addiction focuses on the more negative effects. In addition, it is important to notice that, while possible in extreme cases, addiction is not necessarily a consequence of dependency [63]. Unfortunately, this utilitarian facet of the dependency phenomenon is still unexplored in IS research. It is only through the understanding of both dependency types, and also of their interplay and interaction, that researchers will develop an encompassing understanding of how technology dependency relations develop and influence human behavior. The next section provides a succinct background on IS continuance research.

IS Continuance Research

Understanding individuals' intention to continued usage of IT after its initial adoption has been an area of high interest for the IS research community [64]. An in-depth analysis of articles published in the AIS basket of eight journals[1] in the past 20 years revealed that the most widely acknowledged and empirically validated depiction of the IS continuance phenomenon is Bhattacherjee's conceptual model [36]. According to the IS continuance model, the congruence between initial expectations and actual performance (confirmation) affects both perceived usefulness (PU, embodying expectations) and user satisfaction. In addition, PU influences satisfaction, which in turn determines CI (see Figure 2).

The theoretical foundations of the IS continuance model are grounded in ECTs. In the marketing literature, ECT is also called "disconfirmation of expectations" theory and the confirmation construct can also be labeled "disconfirmation." [36,65,66] The key difference is that confirmation is positively related to satisfaction because it implies realization of the

[1] http://aisnet.org/?page=SeniorScholarBasket

expected benefits of use, while disconfirmation (perceived performance lagging expectation) denotes failure to achieve expectation [36].

A review of the existent body of the literature revealed the existence of three broad categories of papers that used the IS continuance model. The first group consists of studies whose main focus is on “CI” as the dependent variable and that aimed at extending the full model or a subset of it (e.g., [67–70]). This research paper falls within this category. The second group of studies adopted some of the constructs defined in Bhattacherjee’s model when investigating a phenomenon, that is, different from IS continuance: in short, the dependent variable was not “CI” (e.g., [71–74]). Finally, the third cluster of studies (e.g., [75–78]) used general findings/implications from Bhattacherjee [36] to support certain assertions in their theoretical development – for example, to highlight the importance played by “satisfaction” to determine future usage of a service, to confirm that affective factors (such as attitude) influence continuance decisions, or merely to state that the continued use of a system determines its long-term viability and success.

Research Model and Hypotheses

Figure 3 presents the conceptual model. It aims at explaining how dependency affects UMS continuance usage intentions by hypothesizing that the level of dependency toward a UMS raises the perception of positive attributes (PU and perceived ease of use (PEOU)) as well as the cognitive appraisal about the discrepancies between initial expectations and postuse performance (confirmation) [11,21,23,36].

Theoretical boundaries

Each time a theoretical model is developed, it is essential to precisely delineate its bounding assumptions as it directly determines the application domain of the model [79]. In this paper, the novelty of the conceptual boundaries of the IT artifact rendered this step even more critical. As a result, caution was taken to define the boundary conditions of the conceptual model. UMS is conceptualized as a cluster of connected devices that individuals interact with for the purpose of accomplishing an array of IS-supported tasks in their daily life. The pertinence of defining such a new and complex form of IT artifact is justified by the gradual perceptional shift among users that tasks and services are no longer performed by a set of independent IT artifacts, but rather by an evolving cluster of interconnected devices that provide fluid access to information. More precisely, this research paper focuses on the interactions between individuals and the nodes that characterize UMSs. In other words, the developed research model is intended to be valid in the context of UMS devices.

Model development

The theoretical logic of the conceptual model, grounded in both the IS continuance model and IMD theory, relies on the assertion that the preacceptance phase of a UMS – characterized by initial expectations (t1) and perceived performance (t2) – is followed by a cognitive appraisal of the expectation performance discrepancy (confirmation). Both confirmation and dependency are hypothesized to have an influence on usage-related behaviors.

In line with Bhattacherjee's [36] argument, it is posed that the preacceptance variables are embedded within the confirmation and satisfaction constructs. In addition, the IS continuance model captures expectations through the notion of PU [80] relying on the assumption that it is the sole belief that affects user intention at various temporal stages of IS use [36]. As a result, the constructs from the IS continuance model and their associated hypotheses (H_1, H_2, H_3, H_4, and H_5) are preserved from the original model.

H_1: The level of confirmation resulting from usage experiences with a UMS has a positive effect on the level of PU.

H_2: The level of confirmation resulting from usage experiences with a UMS has a positive effect on the level of satisfaction.

H_3: The level of usefulness perceived from usage experiences with a UMS has a positive effect on the level of satisfaction.

H_4: The level of usefulness perceived from usage experiences with a UMS has a positive effect on CI.

H_5: The level of satisfaction resulting from usage experiences with a UMS has a positive effect on CI.

The notion of integrating PEOU within the IS continuance model has been recently promoted as a way of tapping into another important facet of users' expectations toward IT artifacts. Empirical evidence has emerged from the literature about the positive effect exerted by confirmation on PEOU [81–85]. As a consequence, the hypothesis that follows was derived:

H_6: The level of confirmation resulting from usage experiences with a UMS has a positive effect on the level of PEOU.

The literature has also provided indications about the existence of a positive link between PEOU and satisfaction [81,83,84,86–88]. The following hypothesis is posed:

H_7: The level of ease of use perceived from usage experiences with a UMS has a positive effect on the level of satisfaction.

Earlier studies on IS research [89,90] stressed the need for identifying important predictors of the two proximal beliefs, PEOU and PU, from the technology acceptance model (TAM) [91]. A range of construct types was then examined in the literature. This includes system characteristics [92,93], task-technology fit, [94] emotional states [95], cognitive factors such as trust, [96] and cognitive absorption,[97,98] as well as individual differences such as computer anxiety [99] and computer self-efficacy [100]. Within the IT dependency stream of

IS research, the psychological facet of dependency, that is, IT addiction, has been shown to influence reasoned IT usage decisions by altering the users' belief systems embodied in the constructs of PU and PEOU [21]. The authors argue that technology dependency, perceived as a form of addiction, has a distorting effect on the expectancy-value formulation developed by individuals when making decisions [101]. In short, the underlying logic is that IT dependency plays the role of a magnifying glass through which one looks at a system (to which he or she is addicted) that magnifies the positive attributes of the system (usefulness and ease of use). The rationale behind such line of thought is that emotions have a particularly strong influence in the formation of perceptions for addicted individuals [102]. This emotional bias has a tendency to irrationally minimize the negative facets that characterize a system while maximizing its positive aspects. Research has extended the validity of this phenomenon to the IT addiction context. Specifically, in the context of online games, addicted individuals were found to have more positive perceptions in terms of convenience and interest [103]. In addition, in the context of online auctions, addiction was found to augment user perceptions of usefulness and ease of use [21].

This research sheds some light on the utilitarian facet of the IT dependency phenomenon, which is rational and goal oriented in nature. Although the role played by substance-, behavior-, and IT-based psychological dependency in the formation of individual perceptions has been widely explored in research, [21] little attention has been, however, paid on the role of its counterpart: utilitarian dependency. It seems reasonable to argue that the utilitarian and goal-oriented facet of dependency may also have a distorting effect on an individual's perceptions about a system he or she is highly dependent on. Consequently, the following hypotheses were derived:

H$_8$: The level of dependency resulting from usage experiences with a UMS has a positive direct effect on PU.

H$_9$: The level of dependency resulting from usage experiences with a UMS has a positive direct effect on PEOU.

The underlying assumption of MSD theory is that an individual's dependency on a media is directly related to the ability of the media in fulfilling his or her informational needs [23]. Furthermore, MSD theory assumes that when realizing the effectiveness of a media (in achieving one's personal goals), an individual will then tend to explore further benefits from the media in order to better attain his or her goals [23,25,52]. In other words, the theory assumes that the initial usage phase of a given media leads to a cognitive appraisal (a confirmation mechanism) of the congruence between one's play-, orientation-, and interaction-related goals and the capacity of the media to fulfill them. As a consequence, it can be argued that a high level of dependency toward a UMS may lead to a confirmation bias, [104] a term used in the psychology literature to refer to the erroneous seeking or interpreting of evidence in a way that confirms ones given beliefs or expectations [105,106]. In the case of a confirmation bias, only confirming evidence may be retained (while disconfirming evidence is omitted) when mentally assessing the extent to which a device has allowed an individual to successfully fulfill their goals (play, orientation, and understanding).

Besides, the "IT addiction" stream of research has demonstrated the positive (distorting) effect of IT addiction on the notion of perceived enjoyment [21], defined as the mental state reflecting the extent to which the use of IT is "perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated."[107] Such relationship implies that the psychological state associated with one's addiction influences the emotional confirmation of the intrinsic utility of the IT being used [21]. Keeping in mind the main argument of this research paper that asserts that dependency also has a utilitarian and goal-oriented facet, it can be argued that the above psychological mechanism may have its rational counterpart: a high sense of dependency toward a given UMS may have a distorting effect on the cognitive appraisal that consists of mentally assessing the extent to which the system has satisfied one's goal-oriented expectations (the utility perceived from the media resources). High dependency may thus lead to maximizing positive experiences and minimizing (or omitting) negative ones. As a result, the following has been hypothesized:

H_{10}: The level of dependency resulting from usage experiences with a UMS has a positive direct effect on the level of confirmation.

Research Methodology

This research adopts a positivist epistemology because it assumes an objective reality, examines causal relationships, and attempts to test theory with the purpose of increasing the predictive understanding of phenomena [108,109].

While reflecting on the most legitimate UMS device types that shall be considered to test the conceptual model, it appeared crucial to select devices that had already reached a certain maturity level in terms of societal acceptance and adoption. Indeed, the investigation of the concept of dependency is not pertinent with devices that are too "young" from the market's perspective. After careful consideration, it was decided to collect empirical data for the specific instance of UMS devices: smartphones. The media system perspective, developed in this research, allows concentrating on the core functional aspects of smartphones (conceptualized as UMS nodes), thus ignoring the technical specificities of such devices. Moreover, the adopted approach allows the replication of this study for all other UMS device types, a subset of devices, and overall UMS IT artifacts. The following subsections present the steps taken in operationalizing the model.

Operationalization of the constructs

The components of the IS continuance model were measured using scales provided by Bhattacherjee, [36] while PEOU was measured through a scale adapted from Davis [91]. UMS dependency was measured through the most commonly used dependency scale [26,43,110,111]. The set of items were adapted to the context of the research. Table 3 presents the items used in the survey.

As the data were collected in Italy, the items had to be translated from English into Italian. Double back translation was performed by two bilingual specialists [112]. Finally, an online questionnaire was created using the Google Forms tool and a pretest was performed to ensure clarity [113].

Data collection

Data collection was conducted in November 2012 among visitors of the Zoological Gardens in Rome. The zoo was a convenient location, which provided an interesting array of individuals using UMSs. Generally in that period of the year, as a public space, the zoo is visited by the general population (this is confirmed by the demographic information shown in Table 4).

Two researchers equipped with tablets randomly asked visitors if they were smartphone users, and if so, invited them to take the survey. A total of 345 interview requests were made and 150 complete questionnaires were collected. Although the majority (48%) of the respondents were 20–29 years, 33% were 30–39 years of age. The gender distribution of the sample was properly balanced. In regard to occupation, 59% of the respondents were currently employed and 29% were students (the remaining 12% corresponding to pensioners, unemployed individuals, or “others”). Interestingly, 37% of the sample had their current smartphone for <1 year while 53% were between 1 and 2 years. On average, respondents indicated that they used their device for approximately 3.5 h per day. In addition, 64% used their device mainly for accomplishing personal rather than work purposes. Apple and Samsung were the two most common device brands (35% and 34%, respectively).

Instrument validation (validation of the measurement model)

A partial least square (PLS) approach was implemented (using SmartPLS 3.0) to analyze the data. The main objective of PLS analyses is to maximize the explained variance of a model's endogenous constructs [114]. PLS has gained increasing popularity in IS research for its ability to model complex latent constructs (with a high number of items or for second/third order constructs), with small sample sizes and under nonnormality conditions [115,116]. Because of the presence of a formative construct (UMS dependency) and to the nonnormality of some of the measures, PLS appeared as the most appropriate technique for conducting the analysis in this study.

In PLS, a structural equation model consists of two models [114,117]. The outer model (or measurement model) specifies the relationships between the constructs and their associated indicators. The inner model (or structural model) connects the various constructs together. In PLS, the evaluation of the outer model must be first performed before an inner model can be legitimately assessed [115,118].

Nature and dimensionality of the UMS dependency construct

As the original scale assessing MSD was developed to capture television dependency, it was important to investigate the extent to which the six initial dependency dimensions were relevant to this research context [43]. Moreover, the literature has provided conflicting positions toward both the dimensionality (unidimensional vs. bidimensional) and the nature (reflective vs. formative) of the media dependency construct.

The initial development of the scale resulted into a 12-item scale, each dependency component having two items [52]. The most common operationalization of the construct considered dependency as a formative first-order construct; its measure consisting of the sum of all the 12 items [25,42]. Nonetheless, the adopted nature of the construct was never discussed by the authors but simply inferred from the different scorings used to measure dependency. An alternative perspective was more recently suggested by Currás-Pérez et al. [119] who operationalized media dependency, after rounds of confirmatory factor analysis, as a reflective second-order construct consisting of three dimensions: understanding, guidance, and entertainment. With the intention of generalizing the usage of the scale to other types of media but also to provide an instrument with stronger psychometric properties, authors then provided further refinements leading to a well-acknowledged 18-item scale (three items per component). Opinions again diverged. Authors such as Loges [26] or Patwardhan and Yang [46] continued relying on the initial operationalization of the construct seeing it as a first-order formative construct. Others decided to specifically investigate the structure of the dependency construct and concluded about its second-order nature using various exploratory and confirmatory factor analysis techniques. Alcañiz et al. [27] used the scale to measure both television and teleshopping dependency. They questioned the dimensionality of the two constructs and concluded that television dependency consisted of three dimensions: self-understanding (SeU)/orientation (10 items), social understanding/individual entertainment (four items), and social entertainment (two items); while teleshopping dependency consisted of two dimensions: basic information aspects (three items) and further information aspects (nine items). Ruiz Mafé and Blas [120] used the same scale to assess Internet dependency found through rounds of exploratory factor analyses (EFAs) suggested that the construct consisted of four dimensions: entertainment and relaxation (six items), searching for guides to behavior and understanding (five items), searching for information to take decisions (three items), and searching for information to keep up to date and to use in communication (two items). In both cases, despite the clear lack of reflection about the nature of the relationship between the dependency construct and its measurement items [121], the adopted construct scorings indicated the authors' choice for considering dependency as a second-order formative construct. In order to investigate the dimensionality of the UMS dependency construct, EFA techniques (with varimax rotation) using SPSS version 20 were used with thresholds of 0.50 for factor loadings and 0.40 for cross-loadings, following recommendations from Straub [122] and Straub et al. [123]

The initial EFA simulation with all items resulted into a four-factor solution explaining 72.2% of the total variance (Kaiser–Meyer–Olkin measure (KMO) = 0.819/Bartlett's test of sphericity, $\chi^2 = 2168$, df = 153, $p = 0.000$). The measurement items related to the dimensions: social understanding, SeU, self-play, and interaction orientation cleanly loaded in separate dimensions with item loadings above the threshold of 0.5 and cross-loadings <0.4. Two action orientation items, AO1 and AO2, did not load above the thresholds of 0.5 while AO3 loaded with the solitary play (SolP) items but also cross-loaded (>0.4) with SeU. All the three items were dropped. The subsequent EFA simulation still led to a four-factor solution explaining 76.9% of the total variance (KMO = 0.816/Bartlett's test of sphericity, $\chi^2 = 2883$, df = 105, $p = 0.000$). Social play items, SocP1 and SocP2, loaded >0.5 with both the SeU and SolP items. They were dropped for cross-loading reasons. SocP3 loaded with the SeU items with no cross-loading problem.

The next EFA round provided a clean four-factor solution: social understanding, SolP, interaction orientation, and SeU added to one SocP item (SocP3), explaining 79.5% of the total variance (KMO = 0.819/Bartlett's test of sphericity, χ^2 = 1445, df = 78, p = 0.000). Various strategies and procedures were implemented in order to assess the stability of the factorial analysis results. This includes using an oblique rotation method (direct oblimin), dropping one or several items for each analysis iteration, as well as discarding SocP items before removing AO items. All the measurement items of the conceptual model were also tested. Each simulation run ended in a strictly identical factorial structure, providing extra confidence in the results.

A careful semantic analysis was performed to determine whether a common content domain covered the SeU items and SocP3. Four researchers external to the project were also consulted. After careful consideration, it was concluded that there was no obvious and reasonable semantic commonality; the item was then dropped to ensure that the associated factor corresponded to a proper dependency dimension. Besides, SocP3 had the lowest loading (0.614), whereas the remaining items had loadings of ≥0.8, providing extra confidence in the removal of the item. A final EFA simulation was performed resulting in the final factor structure presented in Table 5, explaining approximately 82% of the total variance. Based on the above findings, UMS dependency in the context of our study was found to behave as a second-order construct consisting of four dimensions: social understanding, SeU, SolP, and interaction orientation. After thoughtful consideration and a review of the literature regarding the nature of formative and reflective constructs, it was concluded that media dependency consisted of a composite of multiple measures [124]. Unlike reflective measures where changes in the construct influence the associated measures, changes in any of the dependency dimension measures were perceived as causing changes in the underlying media dependency construct [125]. Following recommendations by Petter et al.,[121] it was then decided to operationalize media dependency as a formative second-order construct.

Common method bias

While analyzing a dataset, researchers in social sciences need to be particularly wary with common method bias (CMB) issues [122,123]. CMB can raise the estimates of structural parameters in a model, and can potentially lead to erroneous conclusions [126]. When it is not possible to collect data using different methods or sources, Harman's one-factor (or single-factor) test is widely used to assess the existence of CMB in a dataset [127]. The test consists of loading all the measurement items in an EFA and examining the unrotated factor solution. The rationale behind the technique is that in the presence of CMB, the EFA would result in a single factor solution, which would account for a large proportion of the covariance among the measurement items [127].

In this study, the EFA with unrotated solution resulted in an eight-factor solution accounting for 80.7% of the total variance. Meanwhile, the covariance explained by a forced one-factor solution was found to be 29.92%. These results strongly argued in favor of the conclusion that CMB was not a threat to the validity of the findings [128].

Podsakoff et al.'s recommendations to investigate CMB through a common method factor approach [127] were also followed by using the procedure recommended by Liang et al. [128]. The detailed results are provided in the Appendix section. An extended PLS model was built by adding a common method factor. Afterward, all the indicators were converted into single-indicator constructs. As a result, all first-order constructs became second-order constructs while ubiquitous media dependency turned into a third-order construct. Finally, the common method factor was linked to all the single-indicator constructs. For each of the single-indicator constructs, the two path coefficients (the one coming from the corresponding substantive construct and the other from the method factor) were examined. As mentioned by Liang et al. [128], each provided coefficient is equivalent to the factor loading associated with the item (while the error term of the path coefficient represents the measurement error of the factor loading). The squared loadings of the method factor (the path coefficients associated with the single-item constructs) can be interpreted as the amount of indicator variance explained by the method, while the squared values of the substantive constructs' loadings represent the amount of indicator variance explained by the substantive constructs.

Evidence of CMB can be provided by jointly examining the statistical significance of the factor loadings associated with the method factor, as well as by comparing the variances (the squares of the provided path coefficients) of each indicator explained by the method and its substantive construct.

The results were conclusive as the average indicator variance caused by the substantive constructs was 0.79, while the average method-based variance was found to be <0.01 – providing a ratio of substantive versus method-based variance >80:1 [128]. Furthermore, a large majority of method factor loadings (provided through the associated PLS structural model analysis) were not significant. Considering the low magnitude and absence of significance of the method variance, we could confidently conclude that CMB was not a concern in this study.

Validation of the measurement scales

Internal consistency was assessed through both Cronbach's alpha and composite reliability coefficients using a threshold of 0.70 [115,129]. Individual item reliability was evaluated by examining the loadings of the measurement items (using a bootstrap procedure with 5000 resamples) with their respective construct [114,130]. A common rule of thumb is to retain the items, which loadings are >0.707 [123,131]. Construct convergent validity was evaluated for each construct by looking at the average variance extracted (AVE), with a threshold value of 0.50 [115,117]. Construct discriminant validity was evaluated by using the Fornell–Larcker criterion [132] and item cross-loadings [114,130]. In addition, as ubiquitous media dependency was operationalized as a formative construct, it was important to ensure that there were no multicollinearity issues with the dependency measures [121]. The variance inflation factors (VIFs) were all below the recommended threshold of 3.3,[133] with dimension scores being 1.56, 1.45, 1.32, and 1.26 for SeU, interaction orientation, SolP, and social understanding, respectively (Table 5).

Tables 5–8 present the results of the outer model validation phase. All Cronbach's alpha and composite reliability coefficients were >0.7 (see Tables 5 and 6). Individual item reliability was satisfactory for all constructs as all item loadings were >0.707 with the exception of CI3, which had a loading slightly lower than the threshold value (0.68) but significant ($p < 0.001$). The item was eventually retained as its loading was very close to the threshold and because the composite reliability of the construct decreased when the item was omitted [114,115]. All constructs' AVE values were >0.5 indicating good levels of construct convergent validity. The assessment of construct discriminant validity did not raise any concerns because all the item loadings were higher in their respective construct than with any of the other constructs (see Table 7). Meanwhile, the square root of the AVE of each construct was found to be greater than the correlations of the construct with the other constructs (Table 8).

extracted values

Results

Once the measurement model was evaluated, the next step involved analyzing the structural portion of the research model [130,134]. This section first describes the various tests that were conducted to assess the overall quality of the model. This is followed by a more detailed analysis of the various paths of the theoretical model. Subsequently, the robustness of the results was evaluated through a round of subsequent tests.

Overall model assessment

The degree to which the variance explained in a PLS model is maximized, which is determined through the examination of the R^2 measures associated with all the dependent (or endogenous) constructs [114,115,130]. The model explained 25% of the variance of continuance usage intention of 49%, 16%, 14%, and 9% for satisfaction, PU, PEOU, and confirmation, respectively.

Recent reviews about the use of PLS analysis techniques in social sciences have strongly criticized the lack of assessment of a model's predictive relevance [114,116,118,130]. In the review performed by Ringle et al. [116], the authors expressed serious concern that none of the reviewed studies had assessed the predictive relevance of their structural models. Recently, researchers using PLS have been encouraged to assess model predictive relevance using Stone's [135] and Geisser's [136] cross-validated redundancy measure Q^2 [114,116,118,130]. Chin [137] (p. 320) earlier stated "the prediction of observables or potential observables is of much greater relevance than the estimator of what are often artificial construct-parameters."

Overall, positive Q^2 scores indicate that a model has predictive relevance whereas a negative Q^2 means a lack of predictive relevance [134,138,139]. Stone–Geisser's Q^2 test was performed in this study (skipping every *n* = seventh data point) for evaluating the predictive relevance of the structural model. The Q^2 scores of the endogenous constructs were all positive, that is, 0.06, 0.08, 0.09, 0.42, and 0.15 for confirmation, PU, PEOU, satisfaction, and CI to use, respectively.

Finally, researchers have recently encouraged the use of a global goodness-of-fit (GoF) criterion to evaluate the quality of a model in PLS [140]. The model was found to have a GoF score of 0.41, indicating a high-quality model. Indeed, Wetzels et al. (2009) recommend to use GoF baseline values of $GoF_{small} = 0.1$, $GoF_{medium} = 0.25$, and $GoF_{large} = 0.36$.

Path analysis

The path coefficients generated by PLS are used to confirm or reject the hypotheses associated with the conceptual model [115,130]. Chin [115] argues that standardized paths should be at least 0.20 (and ideally >0.30) to be considered meaningful. In addition, recent reviews of PLS analyses in social sciences research [114,116] have criticized the lack of consideration of a model's predictive capability and the absence of assessment of the paths' effect size. In response to such criticism, both f^2 effect sizes and q^2 predictive relevance coefficients were calculated for each hypothesized path. Following recommendations from Cohen [141], baseline values of 0.02, 0.15, and 0.35 corresponding to *small*, *medium*, and *large* levels, respectively, shall be used to assess both effect size and predictive relevance [118].

Figure 4. PLS analysis of the structural model

Nine out of the 10 hypotheses were supported (see Figure 4; Tables 8 and 9) with seven path coefficients being >0.20 and the other two being close to this threshold. The results demonstrated the positive effect of UMS dependency on confirmation (path coefficient = 0.28, $p < 0.001$, $f^2 = 0.09$, $q^2 = 0.06$), PU (path coefficient = 0.27, $p < 0.001$, $f^2 = 0.09$, $q^2 =$

0.05), and PEOU (path coefficient = 0.18, $p < 0.05$, $f^2 = 0.05$, $q^2 = 0.02$). These findings provide strong evidence about the overall influence of dependency on the reasoned usage decisions through the distortion of beliefs and perceptions.

Confirming the original IS continuance model and its more recent additions, confirmation was found to be positively associated with satisfaction (path coefficient = 0.44, $p < 0.001$, $f^2 = 0.35$, $q^2 = 0.25$), PU (path coefficient = 0.21, $p < 0.01$, $f^2 = 0.07$, $q^2 = 0.03$), and PEOU (path coefficient = 0.26, $p < 0.01$, $f^2 = 0.09$, $q^2 = 0.03$). As expected, satisfaction was found to be strongly influencing continuance usage intention (path coefficient = 0.48, $p < 0.001$, $f^2 = 0.29$, $q^2 = 0.16$). PEOU (path coefficient = 0.33, $p < 0.001$, $f^2 = 0.21$, $q^2 = 0.14$) and PU to a lesser extent (path coefficient = 0.16, $p < 0.05$, $f^2 = 0.07$, $q^2 = 0.03$) were found to affect satisfaction. However, the results did not confirm the existence of a positive effect of PU on CI to use. Cohen's f^2 effect size coefficients can be used to compare the explanatory power of each hypothesized path. Considering Cohen's effect size corresponds to the ratio of explained over unexplained variance for a given effect, the associated proportion of variance can be obtained by looking at $f^2/(1 + f^2)$ [141]. A *small* effect accounts for 2% of the variance in the criterion variable while *medium* and *large* effects account for 13% and 26%, respectively, of the variance. Six hypotheses (H_1, H_3, H_6, H_8, H_9, and H_{10}) were found to correspond to *small* effects, that is, to say that the associated paths explained between 2% and 13% of the variance of the related endogenous variable. Two hypotheses (H_5 and H_7) had a *medium* effect size (between 13% and 26% of the variance). Finally, hypothesis H_2 was characterized by a *large* effect size (>26% of the variance being explained).

The Stone–Geisser criterion ($Q^2 > 0$) postulates that a model shall be able to predict the endogenous latent variable's indicators [118] – the higher is Q^2, the higher is the predictive ability of the model. As a consequence, the relative impact of the predictive relevance for each exogenous–endogenous hypothesized relationship can be compared by means of the q^2 effect size. H_2 and H_5 were found to have *medium* predictive relevance whereas the remaining paths (with the exception of H_4 that was not supported) had *small* predictive relevance.

Robustness of the results

The data are further analyzed in order to assess the robustness of the results. This appeared as an important matter to tackle as this study was among one the first attempts to use media dependency theory in IS research but also within the boundaries of a newly defined and complex IT artifact: UMS.

UMS dependency estimation: Repeated items versus Two-Step

In this research, Lohmöller's [142] "Hierarchical Component Model Repeated Indicators Approach" was used to compute the UMS dependency scores (conceptualized as a second-order construct). The approach consists of repeating the manifest indicators of the associated lower-order constructs (the four dependency dimensions) in the second-order construct [117,140].

An alternative "two-step" approach has been introduced by some researchers to estimate second-order constructs in PLS (e.g., Agarwal and Karahanna [97], Bock et al.,[143] and Croteau and Bergeron [144]). The procedure consists of initially estimating the latent variable scores in a model without the second-order constructs. Subsequently, the provided latent variable scores are subsequently used as indicators in a model that includes the second-order constructs. The first-order latent variable scores can be computed by either averaging the manifest variable scores of each latent variable [144] or by directly using the latent variable scores provided during the first step of the PLS analysis without the second-order constructs [97,143]. This procedure has the advantage, contrary to the repeated indicators method, of being able to estimate higher-order models with formative indicators [145]. The data are analyzed in a subsequent PLS analysis using the two-step approach to assess UMS dependency and to verify the stability and consistency of the final results. In both cases, the generated R^2 coefficients for each of the endogenous variables were very close to the ones found when using a repeated-items approach. In addition, the path coefficients and significance levels were almost identical to the results provided when using the repeated indicators strategy (see Tables 9 and 10). Finally, it was concluded with confidence that the strategy used to measure UMS dependency had no effect on the results, providing confidence in their stability.

Full mediation versus partial mediation

This research introduced the notion of UMS dependency and hypothesized its effect on satisfaction through the mediation of confirmation, PU, and PEOU. Similarly, UMS dependency was also hypothesized to affect the dependent variable, CI to use UMSs through the mediation of confirmation, PU, and PEOU. Because of the novelty of the approach by borrowing the dependency construct from Individuals' MSD theory and testing its impact on both satisfaction and CI to use, supplemental analyses were then run to determine whether the data supported the two posited full mediations [97,117,146]. Consequently, two additional models including all direct and indirect paths were tested. The model referred as Model 2 in Tables 9 and 10 consisted of the main conceptual model to which a direct link between dependency and satisfaction was added. In a similar way, Model 3 hypothesized a direct influence on CI to use.

Overall, the evaluation of Models 2 and 3 allowed to conclude in the existence of full mediations between UMS dependency and satisfaction/CI to use. The quality of all the three models was found to be strictly identical in terms of GoF as well as R^2 scores. With the exception of the PU → ST path that dropped from 0.16 to 0.13 and became nonsignificant ($t = 1.73$, suggesting only partial support of the related hypothesis), all other path coefficients and significance levels were nearly not affected. The direct path between MSD and satisfaction was not significant while the mediating relationships between the two constructs remained high (>0.20) and significant. Similarly, no direct relationship was found between UMS dependency and CI whereas the mediating effects were all significant with all path coefficients >0.20. In conclusion, an additional layer of confidence was provided in the structural portion of the model, leading to important theoretical implications that are discussed in the next section. The final results of this study are compiled in Table 11.

Discussion and Conclusion

This section presents a discussion of the findings alongside to its limitations and contributions to theory and practice.

Summary of findings

The IT market is undoubtedly witnessing the surge of a number of smart interconnected products – ranging from smart led light bulbs, fitness wristbands to smartwatches, tablets, PCs, TVs, and WiFi-enabled cars. In addition, digital ecosystems leaders such as Microsoft, Apple, and Google have taken key strategic directions that are steadily redefining and blurring the boundaries between mobile and stationary systems [7,10,11]. As a result, individuals are gradually migrating from a device-centric relationship with IT to perceiving their interactions with IT as a unique interconnected “media-system” composed of interchangeable, multicontext, and multifunction devices. This paper's intent is to provide a stepping-stone that may trigger future research efforts and shed some light on the theoretical specificities of UMS.

By combining MSD theory [24] with the IS continuance model [36], this paper investigated the role of IMD in predicting CI to use UMS. A research model was developed and validated, shading some new light on the investigation of usage-related phenomena in the context of UMSs. The model explained 25% of the variance of continuance usage intention of 49%, 16%, 14%, and 9% for satisfaction, PU, PEOU, and confirmation, respectively. The GoF score of 0.42 provided extra confidence in the overall quality of the model.

The results confirmed the overall effect of UMS dependency on individuals' reasoned continuance usage decisions. The findings suggest that the level of dependency toward a UMS device raises the perceived positive attributes about the device, as well as the cognitive appraisal about the discrepancies between initial expectations and postuse performance. Furthermore, with regard to the valuation of the device's attributes, the level of dependency has an equivalent influence on both PEOU and PU. This result yields that the functional characteristics of the UMS device (e.g., enabling use without effort) as well as its affordances (e.g., allowing an improvement of user performance or effectiveness) are equally affected by dependency. This insight could perhaps instigate a theme for future research.

Counter-intuitive results were found in regard to the absence of effect between PU and CI to use. A possible explanation resides in the nature of the mediating effect of satisfaction between PU and CI to use. The results may suggest the existence of a full mediation (as opposed to partial mediation). Some further investigation would be needed before confidently asserting such a strong conclusion. Another possible reason, concurring with Zhang [147], would be that affective variables may play a more important role than cognitive factors in the case of UMSs.

This research conveys important messages to the actors of the digital ecosystem. First, by introducing the UMS concept and highlighting its pertinence in the current technological context, this research heralds a critical mindset shift in which researchers and practitioners shall engage – replacing the conventional device-centric with a more encompassing media system-oriented view (UMS). Second, this paper sheds some light on the existence of two distinct facets of technology dependency – utilitarian (goal oriented) versus psychological (emotional) dependency. Unlike technology addiction, utilitarian dependency is a conscious process based on “initial evaluations of technological efficacy in problem solving, and again at the point that the absence of the ability to solve a given problem forces conscious recognition of the dependency state.”[11] Such a distinction highlights the fact that the two types of dependency build and evolve in distinct ways but also affect human behavior differently. Although they appear to be interrelated, at a subtle level, they could potentially influence each other. The concentration of the attention and efforts by both practitioners and researchers on the irrational side of dependency could be one of the reasons explaining the overall lack of uniformity on the understanding of the technology dependency phenomenon [148].

Limitations

This study has some obvious limitations. Even though extra caution was taken to adopt a media-centric approach that would equally apply to all types of UMS devices, it is important to acknowledge that this study focused on a single type of UMS device (smartphones). Investigating the stability of the results with a variety of UMS devices such as tablets, laptops, phablets, or smartwatches would help to assess the extent to which the results can be generalized. Moreover, to fully confirm the soundness of this approach, it is crucial to further investigate the link between UMS device dependency and overall UMS dependency.

The four-dimension structure of MSD found in this study also deserves further attention. It would be worthwhile to evaluate whether the current dimensional structure holds for various types of ubiquitous system device as well as the overall IT artifact: UMS.

This research assesses dependency in terms of the capacity of a UMS to reach different individual goal categories (e.g., social understanding, SolP, and so on). It could be argued that the 'extent of dependency' can be captured by the number of hours of smartphone usage. This could potentially be an important variable to provide complementary insights regarding the relationship between media dependency and usage. The rationale behind such reasoning is that the more an individual uses a UMS, the larger shall be the extent of dependency. As the survey instrument captured smartphone usage (in terms of the number of hours per day), we investigated the potential moderating effect of 'usage extent' on the relationships between dependency and PU/PEOU/confirmation. An array of analysis strategies (e.g., operationalizing usage extent as a numerical and a categorical variable, normalization) led to inconclusive results. A closer look at the corresponding Italian version of the questionnaire revealed presence of a potential clarity issue. Indeed, one could potentially either understand that it referred to "active daily usage" or to "the amount of time during the day which the smartphone is on and with the respondent" (although most of the time idle). As a result, the investigation could not be performed further; future research efforts about the potential influence of usage extent on UMS dependency shall be envisaged.

Other limitations pertain to the nature of survey research. For instance, the results provide a snapshot picture of the influence of dependency on continuance usage intention. It is likely that the relationship between the two notions evolves over time. It could be argued that longer initial usage would engender a higher level of dependency toward a UMS. However, the causality between the various constructs of the model was only inferred. One could, for example, argue that the direction of the link between dependency and confirmation could be reverse: the congruence between initial expectations and actual performance (confirmation) affects the level of dependency toward a given system. Longitudinal studies would help in performing this investigation.

Implications for theory and research

This study strives to raise awareness on UMSs as a nascent but important stream of IS research. Because of the inherent complexity and fluid form of UMS, it raises questions of the extent to which a large bulk of IS research on use and adoption of technology (developed in a stationary, device-centric context) could be applicable to this new reality. For example, theories that have been largely used in IS research (such as the TAM) focus on the technical specificities of IT devices as individual IT artifacts. In the context of UMS, assessing the PU (or PEOU) associated with a given UMS consisting of five different devices, may not correspond exactly to compounding the five levels of associated PU. For instance, it is very likely that the quality and degree of integration among the nodes (in other words, the devices) of a UMS would have some synergistic effect on the overall PU and ease of use toward this UMS. The existing body of the IS literature as well as the wide array of theories that have been used in ISs are vast sources of high-quality insights. As a result, revisiting the applicability of the IS body of knowledge in the UMS context could be of great help in unveiling the inner workings of UMS. More specifically, it would be interesting to distinguish the results on IT usage and adoption that still hold in the UMS context, from those that do not. This paper also contributes to the IS body of knowledge by furthering the application of MSD theory [24] in the context of the IS discipline [11]. IS researchers have dedicated substantial research efforts to investigate the antecedents and consequences of psychological dependency (often referred to as 'addiction' in IS research) on individual behavior. This research demonstrates that the notion of dependency is complex and has a more utilitarian and goal-oriented facet, which is equally important but largely unexplored in IS research. By extending the application of MSD theory to the IS field, this paper provides a theoretical lens that can help shed some light on this other form of dependency. This paper also contributes to developing a more encompassing understanding of how technology dependency relations develop and how they affect human behavior.

In terms of future research, there are several possible avenues for a logical continuation of this line of inquiry. First, it would be desirable to replicate this study and link the notion of dependency across various UMS components. Second, it will be essential to further investigate the link between UMS dependency and the various characteristics of UMS (such as cluster size, level of connectedness, heterogeneity, system fluidity, and so on). Third, this research approach introduces an alternative view to study the use of cross-platform, multidevice applications such as collaboration tools for instance, by conceptualizing it as a UMS subdomain. Fourth, considering this project has shown that high dependency leads to a higher chance of engendering prolonged usage, investigating the factors that generate such strong relationships/dependencies with ubiquitous technologies would complement the understanding of UMS usage. Indeed, gaining insights on how to effectively generate such a high sense of UMS dependency would be very insightful for researchers, users, and practitioners. Finally, dependency is inherently related to the notion of time. It would also be insightful to understand the evolution of UMS dependency when adding or removing certain devices – studying the evolution of UMS dependency through time could be equally interesting.

Implications for practice

In terms of contribution to practice, the results and recommendations of this research encourage device manufactures to strive to fulfill users' needs by rather focusing on providing a more fluid, integrated, and multidevice UMS user experience [149] instead of improving the functionalities of each newly designed device [150]. Similarly, software, content, and service providers should dedicate substantial efforts to develop services that are as multisystem and multiplatform as possible in order to create a true UMS environment [151]. A simple illustration of this is that nearly all websites have a mobile and nonmobile version that are automatically loaded depending on the type of device that is being used. A large number of software applications also have a desktop and a 'mobile app' version both providing equivalent functionalities. Finally, mobile app developers need to pay attention on the fact that users select apps more on the basis of functionality than the "users' taste."[152] Considering the abovementioned points, the understanding of how UMS dependency forms and develops is a crucial step that will allow companies to gain a significant competitive advantage in an area where the battle among competitors is fierce.

Another practical contribution of this paper is to allow users to become more aware about UMS and the dual nature of dependency. On the basis of our findings, users should be able to reflect on the motivations (psychological or utilitarian) behind UMS devices continuing usage. Indeed, this research provides an evaluation tool that can help users to appraise their perceptions and usage of UMS devices. The use of UMS devices is taking an ever-larger place in people's daily life. The developed goal-oriented dependency measure could be used as a diagnosis tool to assess the extent to which one really requires the use of a UMS. Continuing this line of thought, the awareness and assessment of both types of dependency can help users distinguish the behaviors that have a positive influence from those that have a negative influence on their productivity and well-being. For instance, if an individual realizes that the affordances of her/his smartphone or tablet is associated with a high level of psychological dependency and a low level of goal-oriented dependency, it would then signify that the devices could potentially have an overall negative effect on this person's life. However, a low sense of addiction and a high sense of rational dependency toward a given device could indicate a positive effect on this person's life. These examples illustrate our emphasis on the need to adopt an encompassing understanding of dependency that includes both facets.

It is believed that the advances made in this paper will stimulate further reflection about how the gradual emergence of UMSs are questioning and modifying the existing theoretical boundaries used in IS when studying the interaction between human beings and IT.

References

[1] Cisco, Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update 2014–2019, 2015. http://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white_paper_c11-520862.html.

[2] K. Lyytinen, Y. Yoo, U. Varshney, M. Ackerman, G. Davis, M. Avital, et al., Surfing the next wave: design and implementation challenges of ubiquitous computing, Commun. Assoc. Inf. Syst. 13 (2004) 697–716.

[3] S. Vodanovich, D. Sundaram, M. Myers, Research Commentary —Digital Natives and Ubiquitous Information Systems, Inf. Syst. Res. 21 (2010) 711–723.

[4] K. Carillo, E. Scornavacca, S. Za, An investigation of the role of dependency in predicting continuance intention to use ubiquitous media systems: combining a media sytem

perspective with expectation-confirmation theories, in: Twenty Second Eur. Conf. Inf. Syst., Tel Aviv, Israel, 2014: pp. 1–17.

[5] E. Scornavacca, S.J. Barnes, S.L. Huff, Mobile Business Research Published in 2000-2004 : Emergence , Current Status , and Future Opportunities, Commun. Assoc. Inf. Syst. 17 (2006) 635–646.

[6] Y. Yuan, N. Archer, C.E. Connelly, W. Zheng, Identifying the ideal fit between mobile work and mobile work support, Inf. Manag. 47 (2010) 125–137.

[7] C. Sorensen, Enterprise mobility: tiny technology with global impact on work, Palgrave Macmillan, 2011.

[8] L. Chen, T.O. Meservy, M. Gillenson, Understanding Information Systems Continuance for Information-Oriented Mobile Applications, Commun. Assoc. Inf. Syst. 30 (2012) 127–146.

[9] N. Mallat, M. Rossi, V.K. Tuunainen, A. Öörni, The impact of use context on mobile services acceptance: The case of mobile ticketing, Inf. Manag. 46 (2009) 190–195.

[10] Nielsen, The Mobile Consumer: A Global Snapshot, 2013. http://www.nielsen.com/content/dam/corporate/uk/en/documents/Mobile-Consumer-Report-2013.pdf.

[11] T.F. Stafford, M. Belton, T. Nelson, A. Peevyhouse, Exploring Dimensions of Mobile Information Technology Dependence, in: ICIS 2010 Proc., 2010.

[12] M.H. Jackson, Fluidity, Promiscuity, and Mash-Ups: New Concepts for the Study of Mobility and Communication, Commun. Monogr. 74 (2007) 408–413.

[13] E. Scornavacca, Incorporating System Portablity into Technology Acceptance Models, in: Int. Conf. Mob. Bus., London, UK, 2014.

[14] C. Sørensen, D. Gibson, Ubiquitous visions and opaque realities: professionals talking about mobile technologies, Info. 6 (2004) 188–196.

[15] R. Scheepers, C. Middleton, Personal ICT Ensembles and Ubiquitous Information Systems Environments: Key Issues and Research Implications, Commun. Assoc. Inf. Syst. 33 (2013) 381–392.

[16] J. Lin, H. Chan, L. Xu, A Tale of Four Functions in a Multifunctional Device: Extending Implementation Intention Theory, Prof. Commun. IEEE Trans. 55 (2012) 36–54.

[17] S.A. Matei, A. Faiola, D.J. Wheatley, T. Altom, The Role of Physical Affordances in Multifunctional Mobile Device Design, Int. J. Inf. Technol. Web Eng. 5 (2010) 40–57.

[18] K. Lyytinen, Y. Yoo, Research Commentary: The Next Ware of Nomadic Computing, Inf. Syst. Res. 13 (2002) 377–388.

[19] O. Henfridsson, R. Lindgren, Multi-contextuality in ubiquitous computing: Investigating the car case through action research, Inf. Organ. 15 (2005) 95–124.

[20] R. Lindgren, M. Andersson, O. Henfridsson, Multi-contextuality in boundary-spanning practices, Inf. Syst. J. 18 (2008) 641–661.

[21] O. Turel, A. Serenko, P. Giles, Integrating technology addiction and use: An empirical investigation of online auction users, MIS Q. 35 (2011) 1043–1061.

[22] S.J. Ball-Rokeach, M.L. DeFleur, A Dependency Model of Mass-Media Effects, Communic. Res. 3 (1976) 3–21.

[23] S.J. Ball-Rokeach, The origins of individual media-system dependency: A Sociological Framework, Communic. Res. 12 (1985) 485–510.

[24] S.J. Ball-Rokeach, A Theory of Media Power and a Theory of Media Use : Different Stories , Questions , and Ways of Thinking, Mass Commun. Soc. 1 (1998) 5–40.

[25] a. E. Grant, K.K. Guthrie, S.J. Ball-Rokeach, Television Shopping: A Media System Dependency Perspective, Communic. Res. 18 (1991) 773–798.

[26] W.E. Loges, Canaries in the Coal Mine: Perceptions of Threat and Media System Dependency Relations, Communic. Res. 21 (1994) 5–23.

[27] E.B. Alcañiz, S.S. Blas, F.T. Torres, Dependency in consumer media relations: an application to the case of teleshopping, J. Consum. Behav. 5 (2006) 397–410.

[28] N. Park, Y.C. Kim, H.Y. Shon, H. Shim, Factors influencing smartphone use and dependency in South Korea, Comput. Human Behav. 29 (2013) 1763–1770. doi:10.1016/j.chb.2013.02.008.

[29] D.L. King, P.H. Delfabbro, M.D. Griffiths, Clinical Interventions for Technology-Based Problems: Excessive Internet and Video Game Use, J. Cogn. Psychother. 26 (2012) 43–56. doi:10.1891/0889-8391.26.1.43.

[30] K.W. Beard, E.M. Wolf, Modification in the proposed diagnostic criteria for Internet addiction., Cyberpsychology Behav. 4 (2001) 377–383. doi:10.1089/109493101300210286.

[31] B.D. Ng, P. Wiemer-Hastings, Addiction to the internet and online gaming., Cyberpsychology Behav. 8 (2005) 110–113. doi:10.1089/cpb.2005.8.110.

[32] L.S.-M. Whang, S. Lee, G. Chang, Internet over-users' psychological profiles: a behavior sampling analysis on internet addiction., CyberPsychology Behav. 6 (2003) 143–50. doi:10.1089/109493103321640338.

[33] Z. Xu, O. Turel, Y. Yuan, Online game addiction among adolescents: motivation and prevention factors, Eur. J. Inf. Syst. 21 (2012) 321–340. doi:10.1057/ejis.2011.56.

[34] O. Turel, A. Serenko, The benefits and dangers of enjoyment with social networking websites, Eur. J. Inf. Syst. 21 (2012) 512–528. doi:10.1057/ejis.2012.1.

[35] L. Lapointe, C. Boudreau-Pinsonneault, I. Vaghefi, Is smartphone usage truly smart? A qualitative investigation of IT addictive behaviors, in: Proc. Annu. Hawaii Int. Conf. Syst. Sci., 2013: pp. 1063–1072. doi:10.1109/HICSS.2013.367.

[36] A. Bhattacherjee, Understanding information systems continuance: an expectation-confirmation model, MIS Q. 25 (2001) 351–370.

[37] M. DeFleur, S.J. Ball-Rokeach, Theories of Mass Communication, Longman, New York, 1989.

[38] R. Kalakota, M. Robinson, M-Business: The Race to Mobility, McGraw-Hill, New York, NY, USA, 2002.

[39] R. Basole, Transforming enterprises through mobile applications: a multi-phase framework, in: Proc. Am. Conf. Inf. Syst., 2005: pp. 1935–1939.

[40] W. Zheng, Y. Yuan, Identifying the differences between stationary office support and mobile work support: a conceptual framework, Int. J. Mob. Commun. 5 (2007) 107–122.

[41] H. Nossek, H. Adoni, The social implications of cable television: Restructuring connections with self and social groups, Int. J. Public Opin. Res. 8 (1996) 51–69.

[42] S. Skumanich, D. Kintsfather, Individual Media Dependency Relations Within Television Shopping Programming A Causal Model Reviewed and Revised, Communic. Res. 25 (1998) 200–219.

[43] W.E. Loges, S.J. Ball-Rokeach, Dependency Relations and Newspaper Readership, Journal. Mass Commun. Q. 70 (1993) 602–614.

[44] J.-Y. Jung, J.L. Qiu, Y.-C. Kim, Internet Connectedness and Inequality: Beyond the “Divide,” Communic. Res. 28 (2001) 507–535.

[45] L. Leung, Effects of Internet Connectedness and Information Literacy on Quality of Life, Soc. Indic. Res. 98 (2009) 273–290.

[46] P. Patwardhan, J. Yang, Internet dependency relations and online consumer behavior: a media system dependency theory perspective on why people shop, chat, and read news online, J. Interact. Advert. 3 (2003) 57–69.

[47] J.C. Lyu, How young Chinese depend on the media during public health crises? A comparative perspective, Public Relat. Rev. 38 (2012) 799–806.

[48] K.B. Lakshmi, M. Rajaram, Impact of information technology reliance and innovativeness on rural healthcare services: study of dindigul district in Tamilnadu, India., Telemed. E-HEALTH. 18 (2012) 360–370.

[49] Y. Deng, K.T.T. Chang, Task-Technology Fit for Low-Literate Consumers: Implications for IS Innovations in the Developing Regions, in: Thirty Fourth Int. Conf. Inf. Syst., Milan, Italy, 2013: pp. 1–11.

[50] J.-Y. Jung, W.-Y. Lin, Y.-C. Kim, The dynamic relationship between East Asian adolescents' use of the internet and their use of other media, New Media Soc. 14 (2012) 969–986.

[51] E. Katz, J. Blumler, M. Gurevitch, Uses and gratifications research, Public Opin. Q. 37 (1973) 509–523.

[52] S. Ball-Rokeach, M. Rokeach, J.W. Grube, The great American values test: Influencing behavior and belief through television, Free Press, 1984.

[53] A. Bianchi, J.G. Phillips, Psychological predictors of problem mobile phone use, CyberPsychology Behav. 8 (2005) 39–51.

[54] J.J. Block, Issues for DSM-V: internet addiction., Am. J. Psychiatry. 165 (2008) 306–307.

[55] S. Byun, C. Ruffini, J.E. Mills, A.C. Douglas, M. Niang, S. Stepchenkova, et al., Internet addiction: metasynthesis of 1996-2006 quantitative research., CyberPsychology Behav. 12 (2009) 203–207.

[56] S.J. Barnes, A.D. Pressey, Caught in the Web? Addictive behavior in cyberspace and the role of goal-orientation, Technol. Forecast. Soc. Change. 86 (2014) 93–109.

[57] T.E. Robinson, K.C. Berridge, Addiction, Annu. Rev. Psychol. 54 (2003) 25–53. doi:10.1146/annurev.psych.54.101601.145237.

[58] G. Ferraro, B. Caci, A. D'Amico, M. Di Blasi, Internet addiction disorder: an Italian study, Cyberpsychology Behav. 10 (2007) 170–175. doi:10.1089/cpb.2006.9972.

[59] J. Morahan-Martin, P. Schumacher, Incidence and correlates of pathological internet use among college students, Comput. Human Behav. 16 (2000) 13–29. doi:10.1016/S0747-5632(99)00049-7.

[60] P.M. Yellowlees, S. Marks, Problematic Internet use or Internet addiction?, Comput. Human Behav. 23 (2007) 1447–1453. doi:10.1016/j.chb.2005.05.004.

[61] N. Kakabadse, G. Porter, D. Vance, Addicted to technology, Bus. Strateg. Rev. 18 (2007) 81–85.

[62] K. Scheibenberger, I. Pansa, Modelling dependencies of IT infrastructure elements, in: 3rd IEEE/IFIP Int. Work. Business-Driven IT Manag. BDIM 2008, Salvador, Brazil, 2008: pp. 112–113. doi:10.1109/BDIM.2008.4540083.

[63] J. D'Arcy, A. Gupta, M. Tarafdar, O. Turel, Reflecting on the "Dark Side" of Information Technology Use, Commun. Assoc. Inf. Syst. 35 (2014) 109–118.

[64] F.F. Bagayogo, L. Lapointe, G. Bassellier, Enhanced Use of IT : A New Perspective on Post-Adoption, J. Assoc. Inf. Syst. 15 (2014) 361–387.

[65] R.L. Oliver, A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions, J. Mark. Res. 17 (1980) 460–469.

[66] R. Oliver, Cognitive, affective, and attribute bases of the satisfaction response, J. Consum. Res. 20 (1993) 418–430.

[67] A. Benlian, M. Koufaris, T. Hess, Service Quality in Software-as-a-Service: Developing the SaaS-Qual Measure and Examining Its Role in Usage Continuance, J. Manag. Inf. Syst. 28 (2011) 85–126.

[68] L. Deng, D.E. Turner, R. Gehling, B. Prince, User experience, satisfaction, and continual usage intention of IT, Eur. J. Inf. Syst. 19 (2010) 60–75.

[69] Z. Zhou, Y. Fang, D.R. Vogel, X.-L. Jin, X. Zhang, Attracted to or Locked In? Predicting Continuance Intention in Social Virtual World Services, J. Manag. Inf. Syst. 29 (2012) 273–306.

[70] A. Schwarz, C. Schwarz, Y. Jung, B. Pérez, S. Wiley-Patton, Towards an understanding of assimilation in virtual worlds: the 3C approach, Eur. J. Inf. Syst. 21 (2011) 303–320.

[71] D.J. Kim, D.L. Ferrin, H.R. Rao, Trust and Satisfaction, Two Stepping Stones for Successful E-Commerce Relationships: A Longitudinal Exploration, Inf. Syst. Res. 20 (2009) 237–257.

[72] S.Y. Ho, D. Bodoff, K.Y. Tam, Timing of Adaptive Web Personalization and Its Effects on Online Consumer Behavior, Inf. Syst. Res. 22 (2011) 660–679.

[73] Y. Dang, Y. Zhang, H. Chen, S. a. Brown, P.J.-H. Hu, J.F. Nunamaker, Theory-Informed Design and Evaluation of an Advanced Search and Knowledge Mapping System in Nanotechnology, J. Manag. Inf. Syst. 28 (2012) 99–128.

[74] J. Hsieh, A. Rai, S. Petter, T. Zhang, Impact of User Satisfaction with Mandated CRM Use on Employee Service Quality, MIS Q. 36 (2012) 1065–1080.

[75] R. Briggs, B. Reinig, G. de Vreede, The yield shift theory of satisfaction and its application to the IS/IT domain, J. Assoc. Inf. Syst. 9 (2008) 267–293.

[76] D.R. Compeau, D.B. Meister, C.A. Higgins, From Prediction to Explanation: Reconceptualizing and Extending the Perceived Characteristics of Innovating, J. Assoc. Inf. Syst. 8 (2007) 409–439.

[77] R.D. Ruth, Conversation as a source of satisfaction and continuance in a question-and-answer site, Eur. J. Inf. Syst. 21 (2011) 427–437.

[78] C. Van Slyke, V. Ilie, H. Lou, T.F. Stafford, Perceived critical mass and the adoption of a communication technology, Eur. J. Inf. Syst. 16 (2007) 270–283.

[79] R. Dubin, Theory building, Free Press, 1969.

[80] F.D. Davis, R.P. Bagozzi, P.R. Warshaw, User acceptance of computer technology: a comparison of two theoretical models, Manage. Sci. 35 (1989) 982–1003.

[81] C. Liao, J.L. Chen, D.C. Yen, Theory of planning behavior (TPB) and customer satisfaction in the continued use of e-service: An integrated model, Comput. Human Behav. 23 (2007) 2804–2822.

[82] Ø. Sørebø, T.R. Eikebrokk, Explaining IS continuance in environments where usage is mandatory, Comput. Human Behav. 24 (2008) 2357–2371.

[83] S. Hong, J.Y.L. Thong, K.Y. Tam, Understanding continued information technology usage behavior: A comparison of three models in the context of mobile internet, Decis. Support Syst. 42 (2006) 1819–1834.

[84] J.Y.L. Thong, S.J. Hong, K.Y. Tam, The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance, Int. J. Hum. Comput. Stud. 64 (2006) 799–810.

[85] J.C. Roca, M. Gagné, Understanding e-learning continuance intention in the workplace: A self-determination theory perspective, Comput. Human Behav. 24 (2008) 1585–1604.

[86] S.-C. Chen, H.-H. Chen, M.-F. Chen, Determinants of satisfaction and continuance intention towards self-service technologies, Ind. Manag. Data Syst. 109 (2009) 1248–1263.

[87] A.K.M.N. Islam, M. Mäntymäki, Continuance of Professional Social Networking Sites: A Decomposed Expectation-Confirmation Approach, in: Thirty Third Int. Conf. Inf. Syst., Orlando, 2012: pp. 1–18.

[88] J. Recker, Continued use of process modeling grammars: the impact of individual difference factors, Eur. J. Inf. Syst. 19 (2010) 76–92.

[89] I. Benbasat, R. Zmud, Empirical research in information systems: the practice of relevance, MIS Q. 23 (1999) 3–16.

[90] I. Benbasat, R.W. Zmud, The Identity Crisis Within The IS Discipline : Defining And Communicating The Discipline ' s Core Properties, MIS Q. 27 (2003) 183–194.

[91] F.D. Davis, Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, MIS Q. 13 (1989) 319–340. doi:10.2307/249008.

[92] T. Ahn, S. Ryu, I. Han, The impact of Web quality and playfulness on user acceptance of online retailing, Inf. Manag. 44 (2007) 263–275. doi:10.1016/j.im.2006.12.008.

[93] B. Adipat, D. Zhang, L. Zhou, The Effects of Tree-View Based Presentation Adaption on Mobile Web Browsing, MIS Q. 35 (2011) 99–122.

[94] M.T. Dishaw, D.M. Strong, Extending the technology acceptance model with task–technology fit constructs, Inf. Manag. 36 (1999) 9–21. doi:10.1016/S0378-7206(98)00101-3.

[95] N. Venkatesh, Determinants of perceived ease of use: integrating control, intrinsic motivation and emotion into the technology acceptance model, Inf. Syst. Res. 11 (2000) 342–365.

[96] D. Gefen, E. Karahanna, D.W. Straub, Trust and TAM in Online Shopping: An Integrated Model, MIS Q. 27 (2003) 51–90. doi:10.2307/30036519.

[97] R. Agarwal, E. Karahanna, Time flies when you’re having fun: Cognitive absorption and beliefs about information technology usage, MIS Q. 24 (2000) 665–694.

[98] R. Saadé, B. Bahli, The impact of cognitive absorption on perceived usefulness and perceived ease of use in on-line learning: An extension of the technology acceptance model, Inf. Manag. 42 (2005) 317–327.

[99] M. Igbaria, J. Iivari, The effects of self-efficacy on computer usage, Omega. 23 (1995) 587–605. doi:10.1016/0305-0483(95)00035-6.

[100] D.R. Compeau, C.A.. Higgins, Computer self-efficacy: Development of a measure and initial test., MIS Q. 19 (1995) 189–211.

[101] S. Sutton, Social-psychological Approaches to Understanding Addictive Behaviours: attitude-behaviour and decision-making models, Br. J. Addict. 82 (1987) 355–370.

[102] A.R. Damasio, Descartes’ Error: Emotion, Reason, and the Human Brain, Putnam Berkley Group, Inc, New York, 1995. doi:10.7202/051028ar.

[103] S. Huh, N. Bowman, Perception and Addiction of Online Games as a Function of Personality Traits, J. Media Psychol. 13 (2008) 1–31.

[104] R.S. Nickerson, Confirmation bias: A ubiquitous phenomenon in many guises., Rev. Gen. Psychol. 2 (1998) 175–220.

[105] J.S.B.T. Evans, Bias in human reasoning: Causes and consequences, Lawrence Erlbaum Associates, London, UK, 1989.

[106] P.C. Wason, The processing of positive and negative information, Q. J. Exp. Psychol. 11 (1959) 92–107.

[107] F.D. Davis, R.P. Bagozzi, P.R. Warshaw, Extrinsic and intrinsic motivation to use computers in the workplace, J. Appl. Soc. Psychol. 22 (1992) 1111–1132.

[108] E. Babbie, T.C. Wagenaar, Practicing Social Research, Wadsworth, CA, 1992.

[109] J. Mingers, The Paucity of Multimethod research: a review of the Information Systems literature, Inf. Syst. J. 13 (2003) 233–249.

[110] C.E. Aydin, R.E. Rice, Social worlds, individual differences, and implementation, Inf. Manag. 20 (1991) 119–136.

[111] R.M. Grant, Toward a knowledge-based theory of the firm, Strateg. Manag. J. 17 (1996) 109–122.

[112] R.W. Brislin, The wording and translation of research instruments, in: W.L. Lonner, J.W. Berry (Eds.), F. Methods Cross-Cultural Res., Sage, Newbury Park, CA, 1986: pp. 137–164.

[113] D.A. Dillman, Mail and internet surveys: The tailored design method, Wiley, New York, 2000.

[114] J.F. Hair, C.M. Ringle, M. Sarstedt, PLS-SEM: Indeed a Silver Bullet, J. Mark. Theory Pract. 19 (2011) 139–152.

[115] W.W. Chin, Issues and Opinion on Structural Equation Modeling., MIS Q. 22 (1998) vii–xvi.

[116] C.M. Ringle, M. Sarstedt, D.W. Straub, Editor’s Comments: A Critical Look at the Use of PLS-SEM in MIS Quarterly, MIS Q. 36 (2012) iii–xiv.

[117] M. Wetzels, G. Odekerken-Schröder, C. van Oppen, Using PLS path modeling for assessing hierarchical construct models: Guidelines and Empirical Illustration, MIS Q. 33 (2009) 177–195.

[118] J. Henseler, C.M. Ringle, R.R. Sinkovics, THE USE OF PARTIAL LEAST SQUARES PATH MODELING IN INTERNATIONAL MARKETING, Adv. Int. Mark. 20 (2009) 277–319.

[119] R. Currás-Pérez, C. Ruiz-Mafé, S. Sanz-Blas, Explaining consumer acceptance of mobile competitions and prize draws, Int. J. Internet Mark. Advert. 6 (2011) 315–332. doi:10.1504/IJIMA.2011.043654.

[120] C. Ruiz Mafé, S.S. Blas, Explaining Internet dependency: An exploratory study of future purchase intention of Spanish Internet users, Internet Res. 16 (2006) 380–397.

[121] R.A. Petter S, Straub D, Specifying formative constructs in information systems research, MIS Q. 31 (2007) 623–656. doi:10.2307/25148814.

[122] D. Straub, Validating instruments in MIS research, MIS Q. 13 (1989) 147–169.

[123] D. Straub, M.-C. Boudreau, D. Gefen, Validation Guidelines for IS Positivist Research, Commun. Assoc. Inf. Syst. 13 (2004) 380–427.

[124] R.C. MacCallum, M.W. Browne, The Use of Causal Indicators in Covariance Structure Models: Some Practical Issues, Psychol. Bull. 114 (1993) 533–541. doi:10.1037/0033-2909.114.3.533.

[125] C.B. Jarvis, S.B. MacKenzie, P.M. Podsakoff, A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research, J. Consum. Res. 30 (2003) 199–218. doi:10.1086/376806.

[126] D. Gefen, E.E. Rigdon, D. Straub, Editor’s comment: An Update and Extension to SEM Guidelines for Administrative and Social Science Research., MIS Q. 35 (2011) iii–A7.

[127] P.M. Podsakoff, S.B. MacKenzie, J.-Y. Lee, N.P. Podsakoff, Common method biases in behavioral research: a critical review of the literature and recommended remedies., J. Appl. Psychol. 88 (2003) 879–903.

[128] H. Liang, N. Saraf, Q. Hu, Y. Xue, Assimilation of Enterprise Systems: the Effect of Institutional Pressures and the Mediating Role of Top Management., MIS Q. 31 (2007) 59–87.

[129] J.C. Nunnally, Psychometric theory, McGraw Hilll, New York, 1978.

[130] J. Hulland, Use of partial least squares (PLS) in strategic management research: A review of four recent studies, Strateg. Manag. J. 20 (1999) 195–204.

[131] D. Gefen, D.W. Straub, A Practical Guide to Factorial Validity using PLS-GRAPH:Tutorial and Annotated Example, Commun. Assoc. Inf. Syst. 16 (2005) 91–109.

[132] C. Fornell, D.F. Larcker, Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics, J. Mark. Res. 18 (1981) 382–388.

[133] A. Diamantopoulos, J.A. Siguaw, Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration, Br. J. Manag. 17 (2006) 263–282. doi:10.1111/j.1467-8551.2006.00500.x.

[134] V.E. Vinzi, L. Trinchera, S. Amato, PLS Path Modeling: From Foundations to Recent Developments and Open Issues for Model Assessment and Improvement, in: V.E. Vinzi, W.W. Chin, J. Henseler, H. Wang (Eds.), Handb. Partial Least Squares, Springer Berlin Heidelberg, Berlin, Heidelberg, 2010: pp. 47–82.

[135] M. Stone, Cross-Validatory Choice and Assessment of Statistical Predictions, J. R. Stat. Soc. Ser. B. 36 (1974) 111–147.

[136] S. Geisser, A predictive approach to the random effect model, Biometrika. 61 (1974) 101–107.

[137] W.W. Chin, The Partial Least Squares Approach for Structural Equation Modeling, in: G. A. Marcoulides (Ed.), Mod. Methods Bus. Res., Lawrence Erlbaum Associates, Mahwah, NJ, 1998: pp. 295–336.

[138] W.W. Chin, How to Write Up and Report PLS Analyses, in: V.E. Vinzi, W.W. Chin, J. Henseler, H. Wang (Eds.), Handb. Partial Least Squares, Springer-Verlag, Berlin Heidelberg, 2010: pp. 665–690.

[139] C. Fornell, J. Cha, Partial least squares, in: R.P. Bagozzi (Ed.), Adv. Methods Mark. Res., Blackwell, Cambridge, 1994: pp. 52–78.

[140] M. Tenenhaus, V.E. Vinzi, Y.M. Chatelin, C. Lauro, PLS path modeling, Comput. Stat. Data Anal. 48 (2005) 159–205.

[141] J. Cohen, Statistical power analysis for the behavioral sciences, Associates, Lawrence Erlbaum, Hillsdale, NJ, 1988.

[142] J.-B. Lohmöller, Latent Variable Path Modeling with Partial Least Squares, Physica-Verlag, Heidelberg, 1989.

[143] G. Bock, R. Zmud, Y. Kim, J. Lee, Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological forces, and organizational climate, MIS Q. 29 (2005) 87–111.

[144] A.M. Croteau, F. Bergeron, An information technology trilogy: Business strategy, technological deployment and organizational performance, J. Strateg. Inf. Syst. 10 (2001) 77–99.

[145] W. Reinartz, M. Krafft, W.D. Hoyer, The customer relationship management process: Its measurement and impact on performance, J. Mark. Res. 41 (2004) 293–305.

[146] G.N. Holmbeck, Toward terminological, conceptual, and statistical clarity in the study of mediators and moderators: examples from the child-clinical and pediatric psychology literatures, J. Consult. Clin. Psychol. 65 (1997) 599–610.

[147] P. Zhang, The Affective Response Model: A Theoretical Framework of Affective Concepts and their Relationships in the ICT Context, MIS Q. 37 (2013) 247–274.

[148] R.A. Davis, G.L. Flett, A. Besser, Validation of a New Scale for Measuring Problematic Internet Use: Implications for Pre-employment Screening, CyberPsychology Behav. 5 (2002) 331–345. doi:10.1089/109493102760275581.

[149] S. Robinson, G. Marsden, M. Jones, There's Not an App for That, Elsevier Inc., 2015.

[150] N. McNamara, J. Kirakowski, Functionality, usability, and user experience: three areas of concern, Interactions. 13 (2006) 26–28. doi:10.1145/1167948.1167972.

[151] A. Charland, B. Leroux, Mobile application Development : Web vs . native, Commun. ACM. 54 (2011) 49–53. doi:10.1145/1941487.

[152] X. Xu, K. Dutta, A. Datta, Functionality-Based Mobile App Recommendation by Identifying Aspects from User Reviews, in: ICIS 2014 Proc., Auckland, NZ, 2014: pp. 1–10. http://aisel.aisnet.org/icis2014/proceedings/DecisionAnalytics/12.

independent ecosystems [5,6].

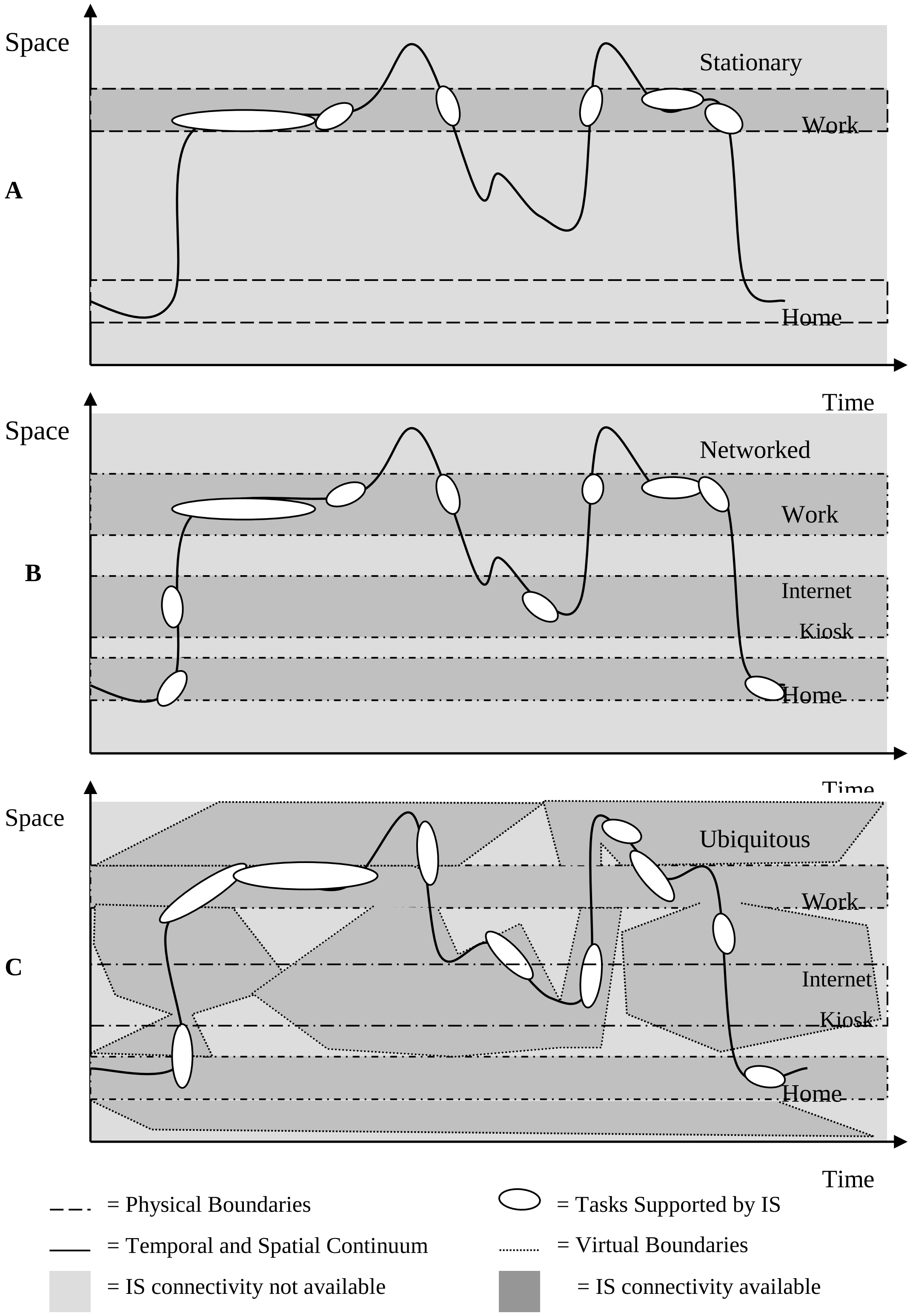
Space
Stationary
Work
A
Home
Time
Space
Networked
Work
B
Internet
Kiosk
Home
Time
Space
Ubiquitous
Work
C
Internet
Kiosk
Home
Time
= Physical Boundaries
= Tasks Supported by IS
= Temporal and Spatial Continuum
= Virtual Boundaries
= IS connectivity not available
= IS connectivity available

Fig 1

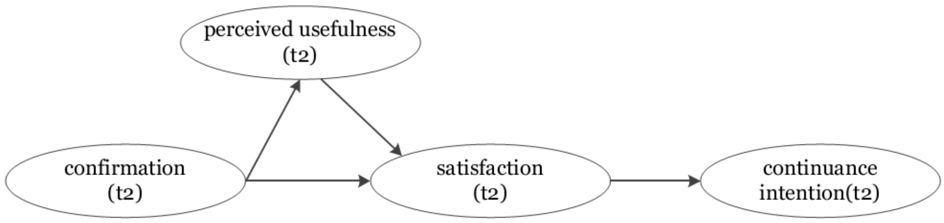
perceived usefulness (t2)
confirmation (t2)
satisfaction (t2)
continuance intention(t2)

Fig 2

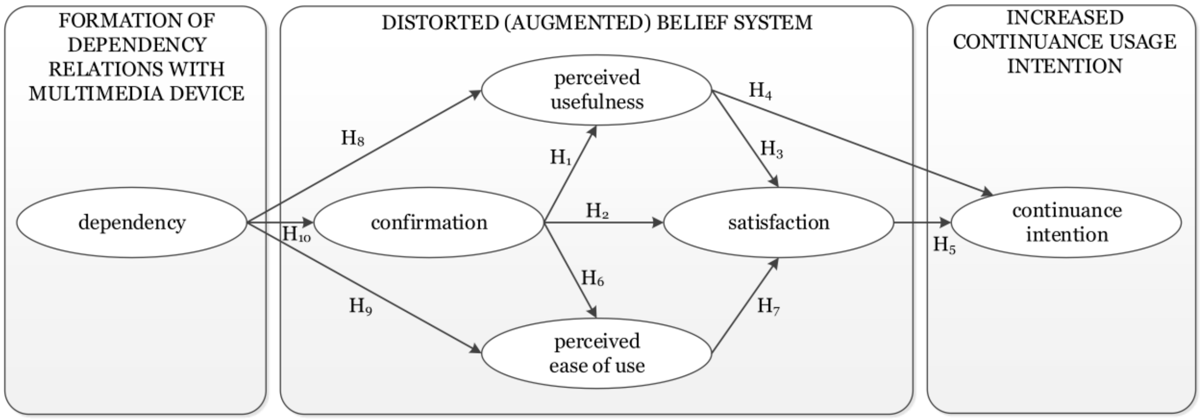
FORMATION OF DEPENDENCY RELATIONS WITH MULTIMEDIA DEVICE
DISTORTED (AUGMENTED) BELIEF SYSTEM
INCREASED CONTINUANCE USAGE INTENTION
dependency
confirmation
perceived usefulness
satisfaction
perceived ease of use
continuance intention
H_8
H_{10}
H_9
H_1
H_2
H_6
H_3
H_4
H_7
H_5

Fig 3

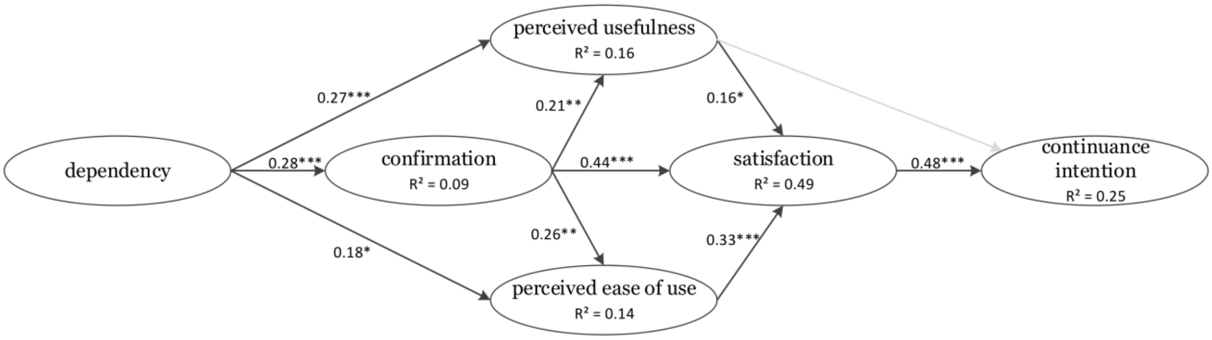
perceived usefulness
R² = 0.16
0.27***
0.21**
0.16*
dependency
0.28***
confirmation
R² = 0.09
0.44***
satisfaction
R² = 0.49
0.48***
continuance intention
R² = 0.25
0.26**
0.33***
0.18*
perceived ease of use
R² = 0.14

Fig 4

Table 1. Typology of Individuals' Media System Dependencies (adapted from [23])

	Understanding	**Orientation**	**Play**
Personal	*Self-understanding:* basic understanding of themselves	*Interaction orientation:* to make a behavioral decision	*Solitary play:* for relaxing and releasing stress when individuals are alone
Social	*Social understanding:* understanding of social environment	*Action orientation:* to have a guidance for interacting correctly with other people	*Social play:* for relaxing and releasing stress together with other people

Table 2. Psychological Dependency versus Utilitarian Dependency

Psychological Dependency	**Utilitarian Dependency**
Definition	*Definition*
Psychological state of maladaptive dependency on the use of a technology to such a degree that the following typical behavioral addiction symptoms arise: (1) salience – the technology dominates a user's thoughts and behaviors; (2) withdrawal – negative emotions arise if a person cannot use the technology; (3) conflict – the use of the technology conflicts with other tasks, which impairs normal functioning; (4) relapse and reinstatement – a user is unable to voluntarily reduce the use of the technology; (5) tolerance – a person has to use the technology to a greater extent to produce thrill; and (6) mood modification – using the technology offers thrill and relief, and results in mood changes. [21]	The extent to which an individual's capacity to reach his or her objectives depends on the use of specific technology [23,25,52].
Effects	*Effects*
Technology addiction is further exhibited through an obsessive pattern of IT-seeking	The intensity of media dependency relations depends on the perceived helpfulness of the

and IT-use behaviors that take place at the expense of other important activities [57]	media in meeting goals [26]
Technology addiction may compromise the user's social life; disrupt emotional functioning; interfere with school, family, and work; and negatively affect others in the user's social circle [54,58,59]	Individuals have to rely on media information resources in order to attain their various goals [46]
Technology addiction may have personal, social, and workplace-related implications, such as substantial productivity losses [60], severe health problems [54], and organizational liability [61]	The dependencies of the underlying ICT infrastructure elements have to be considered in order to run interorganizational processes properly [62].
A system to which a person is addicted is viewed through a misrepresenting lens that augments the positive attributes of the system (e.g., ease of use) and the abilities attributed to the system to cater to one's intrinsic (as captured by enjoyment) and extrinsic (as captured by usefulness) needs [21]	Both intensity and goal scope may be determined by how exclusive media resources are perceived to be in attaining these goals. [22–24,37]

Table 3. Construct definitions and measurement items

Construct	Measurement items
Ubiquitous media system dependency [23,25,52] *the extent to which an individual's capacity to reach his or her objectives depends on the use of his/her multimedia device*	In your daily life, how useful/helpful is your smartphone to: *Self-understanding* *SeU1*: Gain insight into why you do some of the things you do *SeU2*: Imagine what you will be like when you grow older *SeU3*: Observe how others cope with problems or situations like yours *Social understanding* *SoU1*: Stay on top of what is happening in the community *SoU2*: Find out how the country is doing *SoU3*: Keep up with world events *Interaction orientation* *IO1*: Discover better ways to communicate with others *IO2*: Think about how to act with friends, relatives, or people you work with *IO3*: Get ideas about how to approach others in important or difficult situations *Action orientation* *AO1*: Decide where to go for services such as health, financial, or household *AO2*: Figure out what to buy *AO3*: Plan where to go for evening and weekend activities

	Solitary play *SolP1*: Unwind after a hard day or week *SolP2*: Relax when you are by yourself *SolP3*: Have something to do when nobody else is around *Social play* *SocP1*: Give you something to do with your friends *SocP2*: Have fun with family or friends *SocP3*: Be a part of events you enjoy without having to be there
Confirmation [36] *Users' perception of the congruence between expectation toward the use of a multimedia device and the actual performance derived from the use.*	*CF1*: My experience with using my smartphone was better than what I expected. *CF2*: The capabilities/functionalities provided by my smartphone were better than what I expected. *CF3*: Overall, most of my expectations from using my smartphone were confirmed.
Perceived usefulness [36] *A user's perception of the expected benefits of using his/her*	Using my smartphone in my daily life…. *PU1*: improves my overall performance *PU2*: increases my overall productivity. *PU3*: enhances my overall effectiveness. *PU4*: is useful.

multimedia device.	
Perceived ease of use [91] *The degree to which a person believes that using a particular smartphone is free from effort.*	Overall, I feel that my smartphone is: *PEOU1*: Easy to Learn/Difficult to Learn. *PEOU2*: Easy to manipulate/Difficult to manipulate. *PEOU3*: Clear to interact with/Obscure to interact with. *PEOU4*: Flexible to interact with/Rigid to interact with. *PEOU5*: Easy to master/Difficult to master. *PEOU6*: Very usable/Very cumbersome.
Satisfaction [36] *A user's experience with (feelings about) previous use of his/her multimedia device.*	How do you feel about your overall experience using your smartphone: *ST1*: Very dissatisfied/Very satisfied. *ST2*: Very displeased/Very pleased. *ST3*: Very frustrated/Very contented. *ST4*: Absolutely terrible/Absolutely delighted.
Continuance intention [36] *A user's intention to continue using his/her multimedia device.*	*CI1:* I intend to continue using my smartphone rather than discontinue using it. *CI2:* My intentions are to continue using my smartphone than to use any alternative devices. *CI3:* If I could, I would like to discontinue using my smartphone.

Table 4. *Demographic profiles of the respondents*

Demographic profiles	**Category**	**Subjects**	
		Frequency	*Percentage*
Gender	Male	73	49
	Female	77	51
	Total	150	100
Age	<20 years	9	6
	between 20 and 24 years	32	21
	between 25 and 29 years	40	27
	between 30 and 39 years	50	33
	between 40 and 49 years	8	5
	>50 years	11	7
Employment	Student	44	29
	Worker	89	59
	Pensioner	4	3
	Other	4	3
	Unemployed	9	6
Device Brand	Apple	52	35
	Samsung	51	34
	Nokia	22	15
	Blackberry	9	6
	HTC	5	3

	Sony Ericsson Others	5 6	3 4
Length of ownership of current device	<6 months between 6 and 12 months between 12 and 24 months >2 years	42 14 79 15	28 9 53 10
Experience using mobile devices in general	<6 months between 6 and 12 months between 12 and 24 months >2 years	29 10 72 39	19 7 48 26
Daily mobile device usage	not >1 h between 1 and 3 h between 3 and 10 h >10 h	38 69 34 9	25 46 23 6
Usage Purpose	Mainly for work activities 75% for work, 25% for personal tasks 50% for work, 50% for personal tasks 25% for work, 75% for personal tasks Mainly for personal tasks	3 14 37 44 52	2 9 25 29 35

Table 5. Dependency–Exploratory factor analysis and scale validation results

Item	Final EFA				Outer model evaluation tests				
	Factor 1	*Factor 2*	*Factor 3*	*Factor 4*	*Mean*	*Std*	*Loading*	*Reliability*	*AVE*
SoU1				**0.541**	3.23	1.44	0.75^{***}	α = 0.83	
SoU2				**0.947**	3.13	1.47	0.92^{***}	CR = 0.90	0.75
SoU3				**0.955**	3.10	1.48	0.92^{***}	VIF = 1.26	
IO1			**0.866**		2.68	1.56	0.87^{***}	α = 0.86	
IO2			**0.881**		2.11	1.40	0.91^{***}	CR = 0.92	0.78
IO3			**0.738**		2.12	1.42	0.87^{***}	VIF = 1.45	
SolP1		**0.910**			3.00	1.39	0.95^{***}	α = 0.93	
SolP2		**0.910**			2.99	1.42	0.95^{***}	CR = 0.96	0.88
SolP3		**0.888**			3.27	1.42	0.92^{***}	VIF = 1.32	
SeU1	**0.790**				1.53	1.08	0.88^{***}	α = 0.93	
SeU2	**0.876**				1.38	0.90	0.90^{***}	CR = 0.92	0.78
SeU3	**0.797**				1.71	1.14	0.88^{***}	VIF = 1.55	
Kaiser–Meyer–Olkin measure of sampling adequacy = 0.796/Bartlett's test of sphericity, χ^2= 1352, df = 66, p = 0.000					*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$				

Table 6. Measurement scale validation results

Construct	**Item**	**Mean**	**Std.**	**Loading**	**Reliability**	**AVE**
Confirmation	CF1	3.65	1.1	0.92^{***}	α = 0.89 CR = 0.93	0.82
	CF2	3.64	1.07	0.94^{***}		
	CF3	3.67	1.10	0.85^{***}		
Perceived Ease of Use	PEOU 1	4.47	0.94	0.87^{***}	α = 0.92 CR = 0.94	0.72
	PEOU 2	4.27	1.10	0.82^{***}		
	PEOU 3	4.43	0.92	0.85^{***}		
	PEOU 4	4.07	1.14	0.83^{***}		
	PEOU 5	4.40	0.91	0.91^{***}		
	PEOU 6	4.38	0.89	0.81^{***}		
Perceived Usefulness	PU1	4.35	1.06	0.91^{***}	α = 0.89 CR = 0.93	0.76
	PU2	4.04	1.33	0.91^{***}		
	PU3	4.34	1.056	0.92^{***}		
	PU4	4.01	1.21	0.73^{***}		
Satisfaction	ST1	4.00	0.92	0.94^{***}	α = 0.96 CR = 0.97	0.89
	ST2	3.91	0.94	0.96^{***}		
	ST3	3.89	0.98	0.93^{***}		
	ST4	3.97	0.91	0.94^{***}		
Continuance Intention	CI1	4.48	0.86	0.91^{***}	α = 0.79 CR = 0.88	0.71
	CI2	4.17	1.08	0.91^{***}		
	CI3	3.37	1.16	0.68^{***}		

Table 7. Item cross-loadings

Item/Construct	SoU	IO	SolP	SeU	CF	PEOU	PU	ST	CI
SoU1	**0.75**	0.39	0.39	0.31	0.21	0.27	0.28	0.20	0.08
SoU2	**0.92**	0.31	0.21	0.33	0.20	0.14	0.25	0.30	0.05
SoU3	**0.92**	0.27	0.22	0.31	0.22	0.14	0.27	0.30	0.07
IO1	0.32	**0.87**	0.34	0.37	0.26	0.19	0.19	0.27	0.06
IO2	0.33	**0.91**	0.29	0.45	0.25	0.20	0.28	0.32	0.14
IO3	0.35	**0.87**	0.33	0.52	0.23	0.16	0.29	0.27	0.10
SolP1	0.32	0.36	**0.95**	0.41	0.12	0.29	0.19	0.23	0.11
SolP2	0.33	0.34	**0.95**	0.40	0.19	0.24	0.22	0.24	0.11
SolP3	0.25	0.32	**0.92**	0.44	0.19	0.19	0.05	0.20	0.11
SeU1	0.34	0.50	0.37	**0.88**	0.12	0.10	0.16	0.15	0.01
SeU2	0.24	0.46	0.34	**0.90**	0.15	0.06	0.16	0.14	0.00
SeU3	0.40	0.39	0.48	**0.88**	0.10	0.00	0.28	0.12	−0.04
CF1	0.26	0.27	0.19	0.18	**0.92**	0.25	0.24	0.51	0.35
CF2	0.24	0.28	0.21	0.16	**0.94**	0.37	0.30	0.59	0.39
CF3	0.14	0.19	0.06	0.01	**0.86**	0.19	0.24	0.46	0.32
PEOU1	0.17	0.12	0.21	0.00	0.24	**0.87**	0.26	0.39	0.21
PEOU2	0.27	0.26	0.26	0.13	0.22	**0.81**	0.30	0.43	0.20
PEOU3	0.15	0.10	0.13	−0.02	0.32	**0.85**	0.21	0.47	0.22
PEOU4	0.15	0.24	0.26	0.08	0.28	**0.83**	0.28	0.46	0.30
PEOU5	0.21	0.13	0.23	0.01	0.31	**0.91**	0.30	0.44	0.30
PEOU6	0.15	0.18	0.21	0.09	0.18	**0.82**	0.12	0.39	0.24

PU1	0.27	0.23	0.12	0.21	0.23	0.19	**0.91**	0.26	0.17
PU2	0.28	0.25	0.10	0.23	0.21	0.17	**0.91**	0.29	0.12
PU3	0.26	0.24	0.12	0.23	0.24	0.21	**0.93**	0.32	0.20
PU4	0.26	0.27	0.22	0.13	0.30	0.40	**0.73**	0.41	0.18
ST1	0.31	0.30	0.18	0.12	0.57	0.49	0.38	**0.94**	0.42
ST2	0.28	0.28	0.23	0.11	0.58	0.49	0.37	**0.96**	0.48
ST3	0.23	0.29	0.26	0.15	0.53	0.45	0.33	**0.93**	0.46
ST4	0.35	0.35	0.23	0.21	0.51	0.48	0.36	**0.94**	0.47
CI1	0.11	0.10	0.10	0.06	0.39	0.23	0.18	0.48	**0.91**
CI2	0.03	0.14	0.15	0.01	0.37	0.34	0.20	0.43	**0.91**
CI3	0.06	0.01	0.01	−0.17	0.19	0.13	0.09	0.27	**0.68**

Table 8. Correlation among variables/square root of average variance extracted values

Construct	SoU	IO	SolP	SeU	CF	PEOU	PU	ST	CI
Social Understanding	**0.87**								
Interaction Orientation	0.38	**0.89**							
Solitary Play	0.32	0.36	**0.94**						
Self-Understanding	0.37	0.51	0.45	**0.89**					
Confirmation	0.24	0.28	0.18	0.14	**0.90**				
Perceived Ease of Use	0.22	0.21	0.26	0.06	0.31	**0.85**			
Perceived Usefulness	0.31	0.29	0.17	0.23	0.29	0.29	**0.87**		
Satisfaction	0.31	0.32	0.24	0.16	0.58	0.51	0.38	**0.94**	
Continuance Intention	0.08	0.11	0.12	−0.01	0.39	0.29	0.20	0.48	**0.84**

Table 9. Path analysis and robustness assessments

Hypothesis	**Main Model**				**Model 2** *Mediation DEP → ST*	**Model 3** *Mediation DEP → CI*
	Repeated items			**Two-Step**		
	Path coeff.	**f^2**	**q^2**	**Path coeff.**	**Path coeff.**	**Path coeff.**
H_1 CF → PU	**0.21****	0.07	0.03	**0.21****	**0.21***	**0.21****
H_2 CF → ST	**0.44*****	0.35	0.25	**0.43*****	**0.41*****	**0.43*****
H_3 PU → ST	**0.16***	0.07	0.03	**0.16***	*0.13 (t =*	**0.16***

					1.73)	
$\mathbf{H_4}$ PU → CI	0.02			0.02	0.02	0.04
$\mathbf{H_5}$ ST → CI	**0.48*** **	0.29	0.16	**0.48*** **	**0.48*** **	**0.50*** **
$\mathbf{H_6}$ CF → PEOU	**0.26** **	0.09	0.03	**0.26** **	**0.26** **	**0.26** **
$\mathbf{H_7}$ PEOU → ST	**0.33*** **	0.21	0.14	**0.33*** **	**0.31*** **	**0.33*** **
$\mathbf{H_8}$ DEP → PU	**0.27*** **	0.09	0.05	**0.27*** **	**0.28*** **	**0.27*** **
$\mathbf{H_9}$ DEP → PEOU	**0.18***	0.05	0.02	**0.18***	**0.18***	**0.19***
$\mathbf{H_{10}}$ DEP → CF	**0.28*** **	0.09	0.06	**0.28*** **	**0.29*** **	**0.29*** **
DEP → ST					*0.11 (t = 1.64)*	
DEP → CI						*−0.08 (t = 0.90)*
*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$						
DEP = dependency / CF= confirmation / PU = perceived usefulness / PEOU = perceived ease of use / ST = satisfaction / CI = continuance intention						

Table 10. Mediation analysis

Endogenous variables	**Main model** (GoF = 0.42)			**Model 2** DEP → ST (GoF = 0.42)	**Model 3** DEP → CI (GoF = 0.42)
	Repeated items		Two step		
	R^2	**Q^2**	**R^2**	**R^2**	**R^2**
confirmation	0.09	0.06	0.08	0.09	0.09
perceived usefulness	0.16	0.10	0.15	0.17	0.17
perceived ease of use	0.14	0.08	0.12	0.14	0.14
satisfaction	0.49	0.42	0.48	0.50	0.50
continuance intention	0.25	0.15	0.24	0.25	0.25

Table 11. Final Results

Hypothesis	**Model** *(high predictive quality, GoF = 0.41)*			
	Path coeff.	**Effect size f^2**	**Predictive relevance q^2**	**Result**
H_1 CF → PU	**0.21****	small	small	*supported*
H_2 CF → ST	**0.44*****	large	medium	*supported*
H_3 PU → ST	**0.16***	small	small	*partially supported*
H_4 PU → CI	0.02			*not supported*
H_5 ST → CI	**0.48*****	medium	medium	*supported*
H_6 CF → PEOU	**0.26****	small	small	*supported*
H_7 PEOU → ST	**0.33*****	medium	small	*supported*
H_8 DEP → PU	**0.27*****	small	small	*supported*
H_9 DEP → PEOU	**0.18***	small	small	*partially supported*
H_{10} DEP → CF	**0.28*****	small	small	*supported*

APPENDIX

Table 1A. Common Method Bias Analysis

Item/Construct	Substantive factor loading (R1)	R1²	Common method factor loading (R2)	R2²
SoU1	0.594***	0.353	0.167*	0.028
SoU2	0.983***	0.966	−0.065*	0.004
SoU3	0.980***	0.960	−0.060*	0.004
IO1	0.890***	0.792	−0.029	0.001
IO2	0.911***	0.830	0.013	0.000
IO3	0.853***	0.728	0.015	0.000
SolP1	0.939***	0.882	0.027	0.001
SolP2	0.936***	0.876	0.022	0.000
SolP3	0.943***	0.889	−0.051	0.003
SeU1	0.863***	0.745	0.029	0.001
SeU2	0.914***	0.835	−0.026	0.001
SeU3	0.878***	0.771	−0.002	0.000
CF1	0.917***	0.841	0.000	0.000
CF2	0.846***	0.716	0.126*	0.016
CF3	0.963***	0.927	−0.144*	0.021
PEOU1	0.938***	0.880	−0.089	0.008
PEOU2	0.740***	0.548	0.105	0.011

PEOU3	0.886***	0.785	−0.045	0.002
PEOU4	0.743***	0.552	0.110	0.012
PEOU5	0.904***	0.817	0.002	0.000
PEOU6	0.876***	0.767	−0.078	0.006
PU1	0.982***	0.964	−0.079**	0.006
PU2	0.986***	0.972	−0.086**	0.007
PU3	0.976***	0.953	−0.048	0.002
PU4	0.482***	0.232	0.293***	0.086
ST1	0.946***	0.895	−0.002	0.000
ST2	0.970***	0.941	−0.010	0.000
ST3	0.976***	0.953	−0.049	0.002
ST4	0.890***	0.792	0.060	0.004
CI1	0.855***	0.731	0.059	0.003
CI2	0.873***	0.762	0.066	0.004
CI3	0.808***	0.653	−0.157	0.025
Average	0.880	0.787	0.003	0.008