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IS Continuance in Experiential Computing Contexts: Linking Rational and Non-rational Behaviors through Technology Associability

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Research-in-Progress

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Abstract

The IS literature currently explains continuous-use of IT as a post-adoptive behavior driven by rational cognitive beliefs or non-rational affective/automatic responses. Yet the use contexts, IT artifact characteristics, and the notion of the IT user, underlying the current thinking have evolved. We are in a so-called experiential computing paradigm where computing capabilities have become so deeply embedded in everyday life experiences that IT artifacts have become an extension of the human self, closely tied to the personal behaviors and preferences of users. In this empirical context, new continuance behaviors are emerging for which the current literature falls short in explanation. We have just begun a program of study to address this issue. In the summer paper reported here, we build on previous work in IS and draw from theories of self-identity and stereotypes in social psychology to introduce the concept of IT Associability, and argue that it plays a central role in explaining and predicting continuous-use in experiential computing contexts. Our concept of IT associability taps the social and relational characteristics of an IT to theorize how user attachment to an IT they currently use may significantly influence their decisions concerning future versions of the IT. We attempt, through this perspective, to bridge the gap between rational and non-rational theories by offering a novel yet complementary lens for exploring other processes shaping continuous-use of everyday IT artifacts. We present preliminary validated items for measuring IT associability. Some implications for managing the blurring lines between organizational and personal IT use at the workplace are also discussed.

Keywords: Post adoption, Continuous use, Experiential computing, Self identity, Social actor, Inertia, Stereotypes

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Introduction

The topic of technology adoption is very central in IS research (Sidorova et al. 2008) and has clearly evolved in the last decade from predicting initial IT acceptance (Davis et al. 1989; Venkatraman et al. 2003) to explaining temporal changes in user beliefs and attitudes toward long-term IT usage intention and behavior (continuance) (Bhattacherjee 2001; Jasperson et al. 2005). Based on well-established adoption theories such as technology acceptance models, researchers have investigated post-adoption behaviors via new constructs such as user satisfaction (Bhattacherjee 2001; Bhattacherjee and Premkumar 2004; Kim et al. 2009) user habit (Limayem et al. 2007; Polites and Karahanna 2012), status quo bias (Kim and Kankanhalli 2009) and loyalty (Kim and Son 2009). Such post-adoption behaviors are mostly viewed as intentional and conscious decisions that can be explained from rational evaluations of user perceptions and beliefs (Ortiz de Guinea and Markus 2009). Yet, other research shows that intentional decisions may also be influenced by affective and emotional responses to technology use (Agarwal and Karahanna 2000; Kim et al. 2009; Zhang et al. 2006, Zhang 2013), which has opened up a growing stream of research on non-rational psychological factors driving post-adoption behavior, including emotions (Beaudry and Pinsonneault 2005; Ortiz de Guinea and Markus 2009; Ortiz de Ginea and Webster 2013), cognitive absorption (Agarwal and Karahanna 2000), and desirability (Cheikh-Ammar and Barki 2012).

Nonetheless, while these studies provide a much needed multifaceted explanation of post-adoptive behavior, the various perspectives still hinge on the instrumentality (or the lack thereof) of the IT artifact (Yoo, 2010). In effect, there is a seeming dichotomy between rational (e.g. utilitarian) and non-rational (e.g. affective) explanations which obscures understanding of behaviors that do not easily lend themselves to either ends. Yet the essential use contexts, characteristics of the IT artifact, and the notion of the IT user which drove prior theorizing have fast evolved (Yoo, 2010). In particular, the user has been reconceptualized as a social actor embedded in a network of relations, not merely an atomic individual who uses an IT to perform a task (Lamb and Kling 2003). Moreover, given how rapid development of digital technology continues to make computing a part of everyday experiences, the IS community has been strongly encouraged to expand its intellectual boundaries beyond organizational contexts to embrace the new paradigm of experiential computing (Yoo 2010). Experiential computing describes use contexts where users apply their natural human senses directly to observe data and information of interest related to particular events (Jain 2003) and involves digital mediation of everyday activities in the four dimensions of human experiences (time, space, actors, and artifacts) (Yoo 2010). As computing capabilities become ubiquitously distributed and embedded in everyday life experiences, IT artifacts have emerged as an extension of the human self, becoming closely tied to the personal behaviors and preferences of the people who own them (French et al 2014), and blurring lines between organizational and personal IT use. One implication of the user as a social actor in experiential computing context is that social and relational factors in the IT and user interaction, which the current post-adoption literature ignores, may play a key role in explaining emergent post-adoptive behaviors such as continuous use in experiential use contexts.

The current study aims to probe the relevance of social and relational characteristics of IT mainly driven by self-identity and social categorization in predicting individual post-adoption continuous use. Specifically, we investigate why users identify themselves with, and continue to use particular IT artifacts over others of comparable value. This phenomenon may be observed in experiential computing contexts such as the use of smartphones (e.g. iPhone vs Androids), social media (e.g. Facebook vs Twitter), personal computing (e.g. Mac vs PC), or online shopping websites (Amazon vs E-bay). Drawing on social identity (Tajfel et al. 1971) and self-categorization (Turner 1985) theories, our central premise is that individuals tend to associate certain IT artifacts with social categories (e.g. gender, age, personality types, social status etc.) and thus are likely to identify themselves with an IT when they perceive a fit between the technology and their social categorization. Our concept of IT associability has both practical and theoretical value. First, in organizational computing, user's continuous-use is thought to be strongly driven by inertia, defined as "user attachment to, and persistence in, using an incumbent system, even if there are better alternatives or incentives to change" (Polites and Karahanna 2012, p24). IT associability taps an IT artifact's social and relational characteristics that lead to the formation of inertia and explain how this may reinforce continuous use of future instantiations of an incumbent IT. Second, from a practical standpoint, there is currently a growing trend of bring-your own-device (BYOD) in the workplace (e.g. up to 67.8% of smartphone-owning employees use their devices for work and 36.3 % of them do so without the IT department's knowledge, Eddy 2013), IT associability potentially unravels how employees strongly/weakly self-identify with their devices and help managers develop BYOD policies that align with employee's IT use behaviors to promote their performance. The remainder of the paper is organized as follows. We first summarize the current literature on continuous-use of IS and highlight where it struggles to account for post-adopbtion behaviors in experiential use contexts. Next, we draw on relevant theoretical bases from IS and social psychology to conceptualize the construct of IT associability and develop a theoretical model of continuous-use in experiential computing contexts. Finally, we describe our methodology, present findings from our scale development effort conducted over the summer 2015, and discuss challenges for future research.

Literature Review: IS Continuance

Among the set of user behaviors thought to be important at later stages of the adoption process such as continued use (Bhattacherjee 2001), routinization (Jasperson et al. 2005; Saga and Zmud 1994) automatic use (Kim et al. 2005) and enhanced use (Bagayogo et al. 2014), continuous use has been emphasized as the most critical to determining the long-term viability and eventual success of an IS implementation (Bhattacherjee 2001; Limayem et al. 2007). IS continuance refers to the stage where the use of an IT goes beyond behavioral consciousness and becomes part of a routine (Bhattacherjee, 2001) and has been depicted as resulting from a series of repeated individual decisions to continue using a particular IT following initial adoption (Limayem et al., 2007), which stops following a discontinuance decision (Bhattacherjee, 2001). Based on this definition, past research has focused on two main theoretical angles: explaining continuous use from rational or utilitarian versus non-rational or affective perspectives in different (organizational versus experiential) use contexts. Rational perspectives mainly implicate conscious evaluations in individual decision making and have been investigated with TAM and expectation confirmation theory as the main theoretical foundations. In the organizational use context, users' conscious IS continuance decisions have been described via antecedents such as intention to continue usage (Hsieh et al., 2008), user satisfaction and attitude (Bhattacherjee 2001; Bhattacherjee and Premkumar 2004), and user engagements in periods of substantive use (Jasperson et al 2005). User satisfaction (Bhattacherjee and Premkumar 2004) and loyalty (Kim and Son 2009) have also been used to explain continuous use in experiential use contexts. In contrast, non-rational perspectives of continuous-use have been investigated with theories of automaticity, learned response, affect and emotions to describe user's subconscious IS continuance decisions via antecedents such as periods of habitual use (Jasperson et al 2005), past usage and habitual use (Limayem et al. 2007), inertia (Polites and Karahanna 2012), and incumbent system habits (Polites and Karahanna 2012; 2013) in organizational use contexts, whereas cognitive absorption (Agarwal and Karahanna 2004) and IT desirability (Cheikh-Ammar and Barki 2012) are posited to explain continuous use in experiential use contexts. Empirically, continuous-use has mostly been examined as the overall utilization of an IT and measured as a function of frequency and duration of use (e.g. "in the last seven days, how often/how many hours did you use XXX", Limayem et al 2007, p722). In general, the limitations of such lean conceptualizations of use have been noted in the IS literature (Burton-Jones and Grange 2013; Straub and Burton-Jones 2007; Jasperson et al. 2005; Barki et al. 2007;), but this approach is still relevant in the context examined here since our objective is to explain how user attachment to an incumbent IT influences their repeated decisions to continue using future instantiations of the IT. Consequently, we define continuous-use as the repeated decisions of users to maintain an association with future instantiations of an incumbent IT. This definition is broadly in line with IS continuance which is pictured as the result of a series of repeated individual decisions to continue using a particular IT following initial adoption (Limayem et al., 2007) and stops following a discontinuance decision (Bhattacherjee, 2001).

The notion of user attachment to IT brings to the fore some critical gaps related to the rational – non-rational theoretical perspectives of continuous use in experiential use contexts. IT desirability and IT loyalty are particularly salient constructs that offer some explanations for how users may bond with particular technologies as their affectively charged passionate-relationship with an IT drives their eagerness to acquire or engage with an IT (Cheikh-Ammar and Barki 2012). However, experiential computing is characterized by rapid obsolescence of IT artifacts with quick successions of instantiations (i.e. upgrades / versions) in relatively short lifespans and high user volition (Yoo 2010), hence the temporal effect of habits, emotions, desirability and loyalty developed by a user for in incumbent IT remains to be closely examined. On the one hand, rational or utilitarian perspectives such as IT loyalty do not sufficiently explain the fact that users choose to associate themselves with only one out of several competing artifacts that offer comparable satisfaction from achieving similar purposes. (For example, social networking sites such as Facebook, Twitter and MySpace offer similar social media utilities, yet adoption and continuous use of Facebook is far more widespread (at 1.15 billion monthly users) than Twitter (240 million users) or Myspace (30 million users) (Balvve, 2013). On the other hand, non-rational or affective perspectives such as IT desirability do not also sufficiently explain why some users maintain simultaneous association with competing artifacts and appear prepared to disassociate from one or all of them in favor of new ones at any time. (For example, an iPhone user may also own an Android phone and, even if they have strong desires towards one or both of them, may not hesitate to switch to the latest Blackberry). Thus, when presented with opportunities for IS continuance decisions in experiential contexts, there is a seeming paradox of rational and non-rational behaviors that the current literature falls short in explanation. We address this issue through the construct of IT associability below.

Theory and Research Model

Conceptualizing Technology Associability

A useful starting point for resolving the rational – non-rational continuous use paradox is to examine the social and relational characteristics of IT in experiential use contexts. To be more specific, the increased IT diffusion driving ubiquitous and experiential computing (Yoo, 2010) necessitates a reconceptualization of the IT user as a social actor (Nass and Moon 2000) instead of the traditional notion of the user as an organizational member (Lamb and Kling, 2003). As social actors, IT users do not treat certain technologies as mediums or tools of instrumental value, but rather undertake personal interactions with the IT even while acknowledging technology's inability to reciprocate human feelings and motivations (Nass and Moon 2000). Thus, the beliefs users form about IT artifacts go beyond a simple evaluation of their utility to include the artifact's social and relational characteristics, as well as the hedonic and social outcomes users experience from the artifacts' use (Al-Natour and Benbasat 2009). This could then lead people to develop and sustain relationships with these technologies (Cheikh-Ammar and Barki 2013; Huang and Lin 2011). In the context of experiential computing, an artifact's social and relational characteristics, termed associability, is proposed as one of the characteristics that need to be carefully theorized in order to be implemented in the digital artifact (Yoo, 2010). In particular, Yoo defines associability as the ability of a digitalized artifact to be related and identified with other entities (such as other artifacts, places, and people) based on certain commonly shared attributes. From this perspective, the structure and dynamics of the user as a social actor in a hybrid network of users and artifacts is likely to influence their decisions to maintain or break their associations with IT artifacts. For conceptual clarity, we adopt Yoo's definition of associability but limit its scope in the context of post-adoption continuous-use as follows:

> *IT Associability is the extent to which an IT artifact can be related to and identified with by a group of users who share certain common attributes.*

Defined this way, IT associability is essentially a decision-making characteristic that describes the perceptual state of a member of a group of users who adopt and continue to use a particular artifact in experiential (everyday) computing. The unique characteristic of the class of IT artifacts in this definition is the high level of planned obsolescence embedded in their features which drive frequent release of new instantiations. Yet, while other technologies (e.g. vehicles) may also share this characteristic, only IT can exhibit the associability envisioned in this context because it is has the unique ability to serve as an extension of the self (French et al 2014) in everyday social interactions. Given that social interactions invoke mutual assessment of the capabilities of individuals and perceptions about the social groups attributed to interacting parties (Fiske et al 2002) , we define IT associability as a reflective construct with two dimension (self-identification and social categorization or stereotypes) that together tap the social and relational characteristics of an IT to drive continuous use intentions. We further clarify these dimensions below.

In social psychology, social identity theory (Tajfel et al. 1971) and self-categorization theory (Turner 1985) suggest that individuals tend to be attracted to, and sustain relationships with similar others in order to reinforce their self-esteem and maintain balance in their self-identity, which makes their interactions much easier and less cognitively challenging. In the context of user-IT interaction, this suggests that people may be likely to associate certain IT artifacts with social categories (such as gender, age, personality type, race, income, social status etc.) and will identify themselves with an IT when they perceive a fit between the technology and their social categorization. Therefore, we define the first dimension of IT Associability, self-identification, as the degree to which an individual self-identifies him or herself as a regular user of an IT. Furthermore, we define the second dimension of IT Associability, stereotypicity, as an individual's level of agreement with stereotypes about an IT's user group. We have hypothesized a reflective structure for IT Associability because we expect self-identification to be strong correlate of the stereotypes about users of the IT as a distinct social category. Stereotypes are beliefs about the characteristics, attributes, and behaviors of members of certain groups, or theories about how and why certain attributes go together (Hilton and von Hippel, 1996). Stereotypes are not necessarily negative in nature, but as users coalesce around competing IT artifacts, out-group technologies are more likely to have negative connotations for in-group stereotype-users (Hilton and von Hippel, 1996). In this context, then, the social and relational characteristic of an IT refers to the degree to which an individual self-identifies as a user of an IT and agrees with stereotypes (other's beliefs) about the social characteristics of users of the IT. Our definition of stereotypicity connotes an element of social influence on individual decision making, but we must emphasize that the construct is conceptually distinct from subjective norms in the Theory of Planned Behavior (TPB) (Arjen, 1991). The reason is that unlike subjective norms, user's self-identification with an IT is a voluntary decision despite the beliefs held by others about the IT. Social psychologists have identified that subjective norms captures the mandatory aspect of social influence, while self-identity can capture the voluntary aspect of social influence (Charng et al. 1998). This is because self-identity is formed through an internalization process which compares other's expectations with an individual's value, beliefs, and previous experience and transforms expectations by others into the person's own self expectation. On the other hand, this internalization process is absent in subjective norms and thus only pressure from others directly affects a person's technology acceptance decision (Lee et al., 2006) which may not be congruent with the individual's values, beliefs or previous experience. Additionally, social psychologists also show that unlike subjective norms, the effect of self-identity does not diminish with repeated experience of performing a behavior (Sparks and Guthrie 1998; Terry et al. 1999). Similar findings have been reported in IS research, where the effect of subjective norms was only significant on technology acceptance under mandatory use (Venkatesh and Davis, 2000) and diminished as users gained more experience with the system (Hartwick and Barki, 1994). Thus, Stereotypicity as defined here and operating through voluntary internalization of social influence, will likely result in stronger user intentions to maintain their association with an IT than subjective norms.

Linking Technology Associability and Continuous Use

A number of models exist for explaining continuous use of IS, predominantly based on Bhattercherjee's (2001) expectation-confirmation model, but they rarely focus on situations where an incumbent IS has to compete for use continuance with another IS. A notable exception is Polites and Karahanna's (2012) model which posits inertia as a key driver of continuous use of an incumbent systems when a new system is introduced in organizations. Other IS research has shown that it is necessary to overcome organizational inertia oriented toward a current system when an upgrade or new enterprise system is implemented (Seddon et al 2010). These studies suggest that at the individual-use level, inertia plays a crucial intervening process for continuance use decisions regarding both incumbent and new systems. We therefore address our overall research model (Figure 1) to understanding how the social and relational characteristics of IT may lead to inertia formation and subsequently impact IS continuance in experiential use. In IS context, inertia has been defined as "user attachment to, and persistence in, using an incumbent system (i.e., the status quo), even if there are better alternatives or incentives to change." (Polites and Karahanna 2012, p.24). In this formulation, inertia is thought to form from two sources: when incumbent system habits become embedded in routines which are maintained as a status quo by users seeking to avoid stress; and when users perceive high switching costs due to their psychological commitment to the incumbent system (Polites and Karahanna 2012). We label this type of inertia as rational/cognition-based inertia due to the involvement of users' rational evaluations of the benefits of the status quo. However, in experiential computing, we propose a second type of inertia – emotional/affection-based inertia (defined below) – which ensue from non-rational evaluation or affective response to the hedonic experience (status quo) induced by features of the incumbent IT (Zhang 2013). In general, individuals in experiential contexts are thought to be likely to continue using a given IT, and not another, based on its desirability even if other IT exist with similar usefulness or usability levels (Cheick-Ammar and Barki 2012). Explanation for this observation are grounded in Zhang's (2013) affective response model, which theorizes different types of affective evaluations or appraisals that can emerge from the interaction between a user and an IT. The most entrenched level of affective evaluation, called learned affective dispositions, occurs when users' affective evaluations are based on prior experience, knowledge, inclinations, or predispositions toward an IT. This results in higher level reflections stored in memory and oriented toward future thinking, being, or action readiness regarding the IT or interactions with the IT. Such evaluations tend to be learned over time, stored in memory, long-lasting, and not so easy to change (Zhang, 2013). This process has also been described as affective commitment (Li et al. 2006), a situation in which a user demonstrates strong affective and emotional attachment to the relationship with a particular IT. Inspired by this reasoning, we define affection-based inertia as a user's affective attachment to, and persistence in, using an incumbent system (i.e., the status quo), even if there are better alternatives or incentives to change. Furthermore, it is important to clarify the conceptual distinction between the affect operating in this affection-based inertia and the affect described in the Attitude construct in the Theory of Planned Behavior (TPB) (Arjen, 1991). TPB's Attitude captures affect resulting from an individual's positive or negative evaluation of self-performance of a specified behavior, whereas affection-based inertia captures positive or negative affect elicited by a user's interaction with an IT which may be purely hedonic and non-goal directed (Cheick-Ammar and Barki 2012; Van der Heijden 2004). In the balance of this section, we analyze how cognition-based and affection-based inertia partially mediate the impact of social and relational characteristics of IT on continuous use behaviors in experiential use context.

Inertia and Continuous Use.

Polites and Karahanna (2012) proposed that cognition-based inertia is the mechanism by which incumbent system habit and perceived switching cost impacts behavioral beliefs and intentions toward continuous use. That is, incumbent system habits, perceived sunk costs, and perceived transition costs will have an impact on behavioral beliefs and intention only to the extent that they bias a user toward the status quo. In order to rationalize continuance of the status quo, individuals strive to maintain cognitive consistency by holding negative views of alternatives (Polites and Karahanna 2012), engaging in cognitive misperceptions of loss aversion, by which losses of changing from the current situation appear larger than the gains (Kim and Kankanhalli 2009), or basing decisions on uncertainty regarding the new system's relative advantage (Samuelson and Zeckhauser 1988). Thus, cognition-based inertia will manifest itself in lowered perceptions of new system benefits, leading to a "behavioral lock-in" and direct positive impact on intentions to continue using the incumbent system. This mechanism was empirical supported in organizational context (Polites and Karahanna), and we expect it to also hold true in experiential use context based on the replication of cognitive belief studies (e.g. TAM) across a wide variety of contexts in the technology adoption literature. Similarly, when affection-based inertia fully forms in experiential use context, non-rational affective commitment has been shown to strongly influence choices individuals make regarding their relationship with an IT (Li et al., 2006). Hedonic experiential technologies such as smart phones and certain social networking sites have been shown to impel in users feelings of expected pleasure and relief from discomfort (Patterson, 2012). Individual who adopt such "desirable IT" (Cheick-Ammar and Barki 2012) may have intruding thoughts about positively evaluated experience of the IT stored in their memory (Zhang 2013) and engage in compulsive usage behaviors even when there is no predetermined task in mind. While such affective and hedonic experiences may be evaluated differently by individuals, the more intense and the more frequent the experience is for individuals, the more likely they will develop long term memory of the experience and form stronger affective attachments to the incumbent IT. Strong affective commitment has also been shown in marketing not only to result in greater willingness to repurchase a future version of a product but also to pay a premium price for the pleasure involved (Chaudhuri and Holdbrook, 2001;). Thus, affection-based inertia will also manifest itself in stronger continuous use behaviors regarding the incumbent IT. The forgoing arguments formalize as such:

H1a: Cognition-based inertia is positively related to continuous use of an incumbent system.
H1b: Affection-based inertia is positively related to continuous use of an incumbent system

IT Associability and Inertia

We suggest that the formation of cognition-based and affection-based inertia are both likely to be reinforced by the social and relational characteristics of the IT. In social psychology, the stereotype content model (Fiske et al 2002) posits that when members from different social groups engage in interactions, there is mutual assessment of each other's apparent intent for good- or ill-will (i.e. the 'warmth' dimension of stereotypes), as well as their capability to execute such benign or ill intentions (i.e. the 'competence' dimension of stereotypes). Cooperative versus competitive relationships respectively predict warmth or its lack (Cuddy et al., 2008), whereas social perceptions of others' status strongly predict perceptions of their competence (Fiske 1992). When these findings are foregrounded in experiential computing context, in which IT serves as an extension of the self (French et al 2014) for various groups of users deeply embedded in webs of social networks (Lamb and Kling 2003; Yoo 2010), we begin to see how stereotypical perceptions of warmth and competence can be attributed to the IT that represents a user group. Users of an IT that is perceived to represent a high-status social group are also likely to be perceived as engaging in competitive or contentious relationships. In contrast, users of an IT that is perceived to represent a low-status social group are also likely to be perceived as building cooperative relationships. Thus, via this process, we expect the social and relational characteristics of IT to explain unique variance in both cognition-based inertia and affection-based inertia for the following reasons. Given that associability of an IT in experiential use contexts materializes after the initial adoption stage when users become sensitive and alert to various stereotypes about the IT, a user's level of agreement with these stereotypes will be influenced by their personal experience (i.e. internalization) of stereotypes attributed to the IT. An experience of a positive match between the individual's values and the associability stereotypes of the IT will reinforce the user's self-identification with the IT (Tafjel 1981), her agreement with the set of stereotypes attributed to users of that IT (Turner 1985), and any associated status quo biases, thereby strengthening both cognition-based and affection-based inertia. This expectation has some broad empirical support in the social psychology literature. Previous studies have found a significant positive relationship between self-identity and individual behavior (e.g. Granberg and Holmberg 1990), usage intention (e.g. Sparks et al. 1995), and attitudes (e.g. Charng et al. 1988). Lee et al. (2006) also found direct and indirect effects of self-identity on technology acceptance in a voluntary use context. Hence we formalize this argument as follows:

> H2a: IT Associability is positively related to cognition-based inertia toward incumbent system. H2b: IT Associability is positively related to affection-based inertia toward incumbent system.

IT Associability and Continuous Use

Our last proposition is that in experiential use context, IT associability will be a direct antecedent of continuous use. Based on social identity theory, Charng *et al.* (1988) reasoned and found empirical support that if a behavior has been performed repeatedly in the past, and thus under habitual control, decisions to engage in it in the future depend more on the importance of the behavior for the person's self-identity than on judgments (i.e. rational evaluations) and feelings (i.e. affective evaluations). Thus, over time, the role of cognitive and affective determinants of both intention and actual behavior should diminish and self-identity should strengthen. One later study providing further support found that cognitive and affective evaluations diminish because repeated performance of a behavior increases both the likelihood of the behavior becoming an important component of an individual's self-identity and the individual's motivation to validate his or her status as a role performer (Terry et al 1999). In experiential use contexts characterized by highly intensive user and IT interactions, repeated engagement with an IT will eventually strengthen the user's self-identification with the IT and increase her positive internalization of warmth and competence stereotypes about the IT's user group. When self-identification with the IT fully takes center stage, social and relational characteristics of the IT will be able to maintain an inertial association toward the incumbent IT that is neither cognitively nor affectively driven. This theoretical explanation is one preliminary resolution to the seeming paradox of inconsistent rational and non-rational behaviors in experiential use context earlier discussed. We formalize the argument here thus:

> H3: IT associability is positively related to continuous use of an incumbent IT.

Control variables

Finally, based on well-established findings from prior IS research, we include four control variables that might reasonably be expected to impact an IT user's persistence in using an incumbent system. First, we include *propensity to resist change* (Oreg 2003; Polites and Karahanna 2012) to control for individual difference on routine seeking, emotional reaction to imposed change, short-term thinking, and cognitive rigidity. It has been suggested that individuals with any of these characteristics would be more likely to develop inertia even in the absence of a habit (Oreg 2003). Second, we include *personal innovativeness with IT* (PIIT) (Agarwal and Prasad 1998), the willingness of an individual to try out any new information technology, which might make individuals less prone to develop inertia toward incumbent system use. Third, we include *computer self-efficacy* to control for (cognitive) ease of use beliefs about the incumbent system. Finally, we include *prior experience with the new system* as a control for experience with a competing IT that might lead to negative relative advantage evaluation of an incumbent IT.

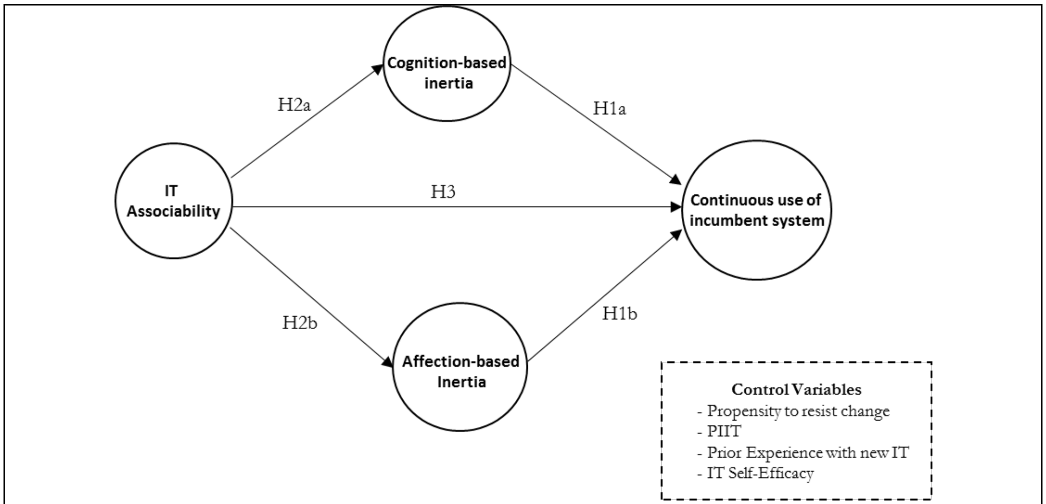


Figure 1: The effect of IT Associability on Continuous Use

Method

Research Design

In empirically assessing our model, there are a number of methodological issues noted in technology adoption in general and IS continuance research in particular that we seek to address. First, researchers have recently raised questions regarding the link between behavioral intention and actual usage of the system. For instance, habit has been found to limit the predictive power of intention on actual usage (Kim 2012; Limayem et al. 2007). Second, the use of self-reported measures for continuous use as DV has also been questioned. In one study, Wu and Du (2012) found that behavioral intention correlated much strongly with self-reported usage than it did with actual usage (an objective computer-recorded measure). These and other authors (e.g. Bagozzi 2007) have concluded that intention is not the most suitable predictor for actual behavior. To overcome some of these challenges, we are employing a mix of online and offline longitudinal survey and experimental design for a thorough study of our continuous-use model. The longitudinal design allows us to assess the impact of IT associability on both intention and actual continuous use behaviors over time (Bhattacherjee and Premkumar 2004). The experiential use contexts we are focusing on are smartphones (continuous use of iPhones versus continuous use of Androids); social networking sites (continuous use of Facebook vs continuous use of Twitter) and computers (continuous of Mac versus continuous use of PC). We intend to study these contexts over a 6 month to 1 year period, using major IT events (e.g. the release of the latest iPhone; a major update of Facebook functionality or privacy policy, etc.) as natural time demarcations in our longitudinal study. We envisage at least three measurement periods to allow us to assess the proposed changes in the effects of focal variables over time. We have structured our design into 2 studies; Study 1 involves surveys and study 2 will involve experiments. There are pre-validated scale items available in the literature for all constructs in our model except our newly proposed construct of IT Associability. Hence, we are currently developing a valid measure for IT we briefly summarize our method and preliminary findings below.

Measurement of IT Associability

We followed guidelines prescribed by Mackenzie et al. (2011) and Straub et al. (2004) in developing a measurement scale for IT Associability. For content validity, while some measures exist for self-identification from the social identity literature, measuring stereotypes present some difficulties. Stereotypes are known to be less stable over time and across contexts, but the stereotype content model (SCM) (Fiske et al 2002) is widely used to measure all types of stereotypes at the highest level of abstraction. Following the SCM approach, we coded IT stereotypes from online opinion polls along SCM's warmth and competence dimensions in 3 phases. In Phase 1, we asked respondents to identify different types of IT users North American society categorizes into groups. In Phase 2, we asked respondents to rank dominant IT user groups identified in Phase 1 on both positive and negative versions of IT stereotypes. In Phase 3, we combined dominant stereotypes from Phase 2 with self-identification items culled from the literature review into a full list of scale items for IT Associability. The full scale was assessed for validity through EFA and CFA in Phase 3. We pretested all three phases with volunteers from Desautels Faculty of Management graduate students at McGill University to refine item wordings before the main survey.

Participants and Procedure

We recruited participants using Amazon's Mechanical Turk (AMT) platform. Through this platform, we placed three HITs (human intelligence tasks) (one task per phase) to recruit workers (participants). We filtered out participants using AMT's participant qualification requirement, which prohibited users from participating if they had a HIT approval rate less than 95%. In HITs 1, we asked participants to identify between 8 and 16 different types of IT users who are categorized into groups in modern North American society. HITs 2 and 3 asked participants to rank IT user groups on stereotypes. Each hit (survey) was for a specific IT user group and no worker was allowed to complete more than one survey. Workers were paid $1.25 for the 15-minute survey. In recent times, using AMT as a data collection method is increasingly viewed as an acceptable – and perhaps even advantageous – method in comparison to traditional methods, and resulting data has generally been seen to be of high quality (Mason and Suri 2012; Buhrmester et al. 2011, Steelman et al.2014). Research using AMT for data collection are increasingly being published in top Management journals. Despite this, we were cautious to include in the survey five simple question with an unambiguous answer in order to ensure that workers were paying attention to the questions (e.g. "*I have never heard the name Obama*"), and also deleted responses complete far quicker than the average response time. The procedure for administering the survey was as follows: Potential participants on AMT were invited to complete an online survey on their impressions about users of various types of IT (e.g. iPhone, Androids, Mac, PC, Facebook, and Twitter). After agreeing to participate in the task, they were directed to the survey on Qualtrics. HIT1 asked workers to just name as many IT user group categories they can think of, but HITs 2 and 3 asked workers to choose an IT they currently use. HIT 3 respondents were randomly assigned to one of their regularly-used ITs, and subsequent questions asked about their self-identification with the IT and their level of agreement with specific stereotypes about users of that IT.

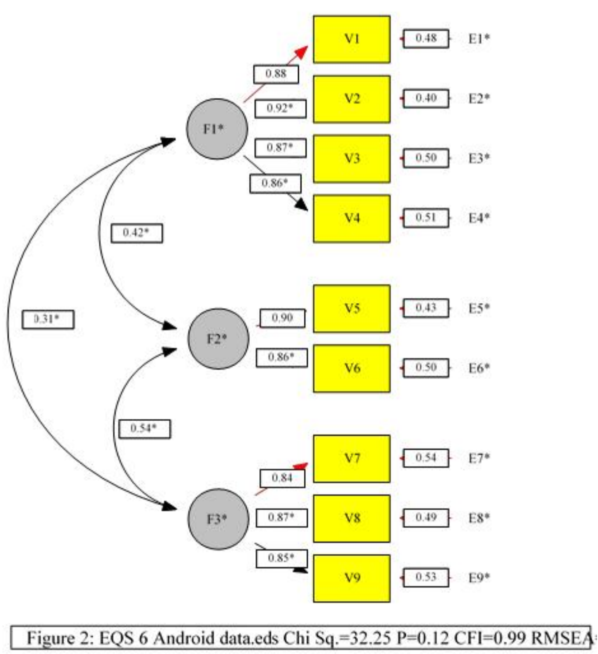
Data Analysis and Results

A total of N = 319 (N=46 phase 1, N=62 phase 2, N=189 phase 3) have provided data for analysis across the three phases, but we discuss phase 3 results here to be brief. Analysis for phases 1 and 2 are available on request. Respondents in Phase 3 were 60% male and 75% aged between 18 and 39 years old. 65% had at least a bachelor degree, 90% were currently working while only 4% were currently in school. The sample included N=95 iPhone users and N=96 Android users. Respondents answered the same set of questions but with dominant versions of stereotype items that emerged for their IT group in Phase 2. There were no significant differences between the two groups on any demographic variable. Descriptive statistics for both data sets are in Tables 1 and 2 in the Appendix. We performed an exploratory factor analysis (EFA) with data from iPhone users to test whether the underlying factor structure will be replicated through a confirmatory factor analysis (CFA) with the data from Android users. Results from the EFA appears below in Table 1. The best solution found was 3 factors with Oblimin rotation (allowing factors to correlate). Items for self-identification highly loaded on Factor 1. Factor 2 seemed to capture the warmth stereotype dimension while Factor 3 also captured the competence stereotype dimension. Next, we used a covariance based structural equational modeling software (EQS 6.0) for the CFA. We modeled a factor structure with the Android data similar to the solution obtained in the EFA with the iPhone data. Results of the fitted model is diagrammed in Figure 2 below. Overall, the output suggests a reasonably good fit of the model (Chi-square 32.25, p = 0.1209, d.f. = 24; all of the fit indices were in the highly recommended ranges, e.g. CFI = 0.988, Standardized RMR = 0.05, and RMSEA = 0.06). The standardized solution can thus be interpreted. The two scale reliability measures are above the conventional cut-off of 0.7 (Cronbach's alpha = 0.874, Reliability coefficient rho =0.948). The item reliabilities and factor composite reliabilities are also all above the recommended 0.7 cut off. Finally, there is medium but significant (at 95% confidence level) correlation among the factors, providing preliminary support for the reflective structure of IT Associability.

Table 1: Results of Exploratory Factor Analysis

Item	Item Wording	Factor 1	Factor 2	Factor 3
V1	Using the iPhone is an important part of who I am	**0.860**	0.025	-0.014
V2	I have a lot of pride in using the iPhone	**0.849**	-0.030	0.106
V3	I feel a strong attachment toward the iPhone	**0.768**	0.078	0.048
V4	I have a strong sense of being identified as an iPhone user	**0.823**	-0.116	0.045
V5	iPhone users are less self-organized	-0.200	**0.785**	0.054
V6	iPhone users are easily excited	0.363	**0.628**	-0.027
V7	iPhone users tend to hold highly prestigious jobs	-0.038	0.030	**0.893**
V8	iPhone users of tend to have high household incomes	0.002	-0.011	**0.902**
V9	iPhone users tend to be highly educated (i.e. college degree or higher)	0.096	-0.010	**0.847**

Figure 2: CFA Model Factor Structure



Discussion and Conclusion

The goal of the current research is to explore the role that an IT's social and relational characteristics play in driving continuous use behaviors in experiential computing contexts. One important question that extant IS continuance models struggle to explain is why users continue to use one out of many ITs offering similar utilities. We proposed that IT has some relational and social characteristics, captured through the construct IT Associability, which drive user association to particular ITs when they perceive a fit between the IT and their social categorization. While we plan to use a multi-method longitudinal design to test our theory, we are currently focused on developing valid measures for IT Associability to be enrolled later in our longitudinal studies. The progress we have made since our earlier submission to DIGIT has resulted in some preliminary measures with acceptable psychometric properties for assessing IT Associability. Due to peculiar constraints in measuring stereotypes, our construct validation approach was slightly modified from the conventional approach (e.g. using card sorting, Moore and Benbasat 1991). The major findings are that, first, the sample used in our study clearly categorized IT users groups on social and relational characteristics. From the social categorization (e.g. Turner 1985) and stereotype (e.g. Fiske et al 2002) literature, this is an important step in ensuring that such categories do not merely exist in the researcher's mind. Second, the items resulting from EFA and CFA analysis replicated to a great extent the hypothesized structure of IT associability across two different samples of IT user groups (iPhone vs Android). Thus, there is some preliminary evidence that the items can assess IT associability in other IT user groups. However two important challenges will need to be addressed regarding the future of the current scale. First, while we expected a number of stereotypes to be represented in the final scale (e.g. age, early/late adopter, and political orientation), they surprisingly did not emerge as dominant in Phase 2. It may be that while our sample generally mirrors the population in demographic distribution, most of them do not invest as much time in experiential computing as we have argued (for example, over 90% of respondents in Phase 2 were working adults against only 2% students). If these items ought to be part of the domain of stereotypes under study, we may have to focus exclusively on student samples and also in an off-line context to ascertain the validity of the current scale.

Nevertheless, the main contribution of our study at this stage remains our integrative model that accounts for rational and non-rational decision making in continuous use of experiential computing. Our model responds to calls for IS research to examine non-rational actions that influence "unplanned" and "unreasoned" IT use (Ortiz de Guinea and Markus 2009) and the need for new constructs and theories that adequately bridge the gap between utility and affect in explaining post-adoption behavior (Yoo, 2010). Relatedly, this study also introduces the construct of IT associability and a list of initial items for its assessment. Finally, our study potentially lays the ground work for future research into other emergent post-adoptive behaviors in experiential computing. There are immediate and long run practical implications of our study as well. With increased digitization and the growing trend of BYOD at the workplace, the time is particularly opportune to understand how employees strongly/weakly self-identify with their IT systems and devices. Unraveling this and other post-adoptive behaviors in experiential computing should be fruitful for system designers interested in embedding social and relational features into IT, while organizational IT managers can better align organizational use policies with employee behaviors to enhance employee productivity, efficiency, and effectiveness in the workplace.

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Appendix: Descriptive Statistics

Table 1. Descriptive Statistics for iPhone Data. N= 95

Item	Mean	St.Dev	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	1.70	4.62	1.00								
V2	1.66	4.84	0.84	1.00							
V3	1.39	5.54	0.63	0.76	1.00						
V4	1.77	4.50	0.71	0.77	0.64	1.00					
V5	1.23	2.45	-0.04	-0.07	0.04	-0.14	1.00				
V6	1.25	3.95	0.37	0.33	0.34	0.27	0.33	1.00			
V7	1.43	4.37	0.38	0.46	0.34	0.38	0.07	0.24	1.00		
V8	1.62	4.43	0.39	0.50	0.43	0.40	0.05	0.21	0.82	1.00	
V9	1.53	4.57	0.43	0.53	0.49	0.48	0.03	0.26	0.80	0.87	1.00

Table 2. Descriptive Statistics for Android Data. N= 96

Item	Mean	St.Dev	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	4.32	1.80	1.00								
V2	4.65	1.65	0.81	1.00							
V3	5.01	1.54	0.75	0.81	1.00						
V4	4.37	1.70	0.76	0.78	0.74	1.00					
V5	4.50	1.31	0.37	0.30	0.39	0.47	1.00				
V6	4.70	1.20	0.27	0.22	0.23	0.41	0.78	1.00			
V7	3.99	1.11	0.21	0.18	0.20	0.30	0.37	0.48	1.00		
V8	3.95	1.20	0.28	0.19	0.29	0.30	0.38	0.38	0.74	1.00	
V9	4.21	1.10	0.26	0.18	0.25	0.30	0.44	0.45	0.71	0.74	1.00