Mobile ICT use in early adopter vs. late majority countries

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Abstract

The rapid global diffusion of smartphones has not been uniform. This study uses Triandis' theory of interpersonal behaviour to investigate what drives smartphone use in early adopter (USA) versus late majority (Slovakia) countries. By surveying both current and potential owners, we also revisit Karahanna et al.'s question: Do potential adopters and users of IT hold the same behavioural and normative beliefs? PLS analysis finds that habit, affect, and perceived social norms explain 65% of the intention to buy a smartphone. Surprisingly, perceived consequences (i.e. perceived usefulness) and whether people live in an early adopter versus late majority country, are not significant. Comparing users and non-users finds

that they differ in almost every attribute measured in the study, and that users intend to continue using a smartphone whereas non-users have more ambivalent intentions.

Keywords: *Smartphone, mobile computing, ubiquitous computing, wireless, technology acceptance, technology use, theory of interpersonal behaviour, normative beliefs, diffusion of innovations, early adopter, late majority, cross-country comparison, users versus nonusers, partial least squares*

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1 Introduction

Much research investigates the adoption of new technology – ICT that is introduced for the first time or ICT that may have been introduced elsewhere but is available for the first time in a given setting. Little research has been conducted about the adoption of mobile technology after it has gone mainstream. While fashion waves may drive scholars to focus on novel technologies (Baskerville and Myers 2009), we still have much to learn about pervasive and mundane technologies (Dourish et al. 2010). Mobile ICT has been

the fastest diffusing technology in history, but acceptance of wireless innovations has varied among countries.

The smartphone has been available since the 1990s, but it reached an inflection point in 2008 as 3G networks reached a critical mass and Apple introduced the iPhone, spurring consumer interest in smartphones. The rate of smartphone acceptance has not been uniform across different groups of users. According to Rogers (2003), potential adopters can be categorised by their innovativeness and when they embrace a new innovation relative to other users. Like individuals, some countries rapidly accept a new technology while others are much slower to adopt an innovation. For example, the United States could be considered an ***early adopter*** of smartphones. In 2009, smartphone penetration in the USA was in the top three countries globally (Nielsen 2009). Within a few years, smartphones had become mainstream information and communication technology. In Western countries like Norway, the United Kingdom, and the United States, most of the population own smartphones (Google 2014). In countries such as these, smartphones have become the norm and are neither novel nor uncommon. To better understand the rapid acceptance of smartphones is early adopter countries, we seek to answer to the following research question:

RQ1: *What drives the use of smartphones in early adopter countries?*

Despite the rapid global diffusion of smartphones, some countries have experienced a much slower uptake of the technology. Rogers (2003) identifies those who begin using a new technology only after at least half of the people are already using it as ***late majority*** adopters. Slovakia, a Western nation belonging to the Eurozone, has experienced a slow uptake of the smartphone. By 2012 smartphones represented 58% of mobile phones sold globally (BBC 2014), but in 2012, only 14% of people living in Slovakia owned a smartphone (Google 2014). The slow smartphone adoption rate in some countries leads us to ask our second research question:

RQ2: *What drives the use of smartphone in late majority countries?*

ICT research generally focuses on novel technology. At the same time, much can be learned by studying the use of technology that has become mainstream, even mundane (Dourish et al. 2010). Research has shown that different values drive technology adoption among early adopters and those who embrace a technology later in its lifecycle (Kang et al. 2014, Chen et al. 2016). This paper investigates the adoption and use of smartphone technology in both early and late stages of diffusion by surveying people in both an early adopter and a late majority country. This paper reports findings from a field study conducted in early 2009 in the United States and in late 2012 in Slovakia. Little research has been conducted on late majority countries within the Western world and fewer have compared technology acceptance drivers between early

adopter and late majority countries. Therefore, this paper uses data collected in two countries at two different times to answer the research question:

RQ3: *What are the similarities and differences in the drivers of smartphone use in early versus late adopter countries?*

While the United States and Slovakia provide settings for exploring the drivers of smartphone use, Karahanna et al. (1999) call for researchers to explore what differentiates the drivers of initial adoption from those influencing continued use. Similarly, Blechar et al. (2006) stress the need to study the underlying motives for adoption and use of mobile technology. This leads us to revisit Karahanna et al.'s inquiry into whether potential adopters and current users of ICT are driven by the same beliefs. Therefore, this study aims to answer our fourth research question:

RQ4: *Do potential adopters and users of smartphones hold the same behavioural and normative beliefs?*

Traditional studies of information and communication technology (ICT) often use theories such as Theory of Reasoned Action (Fishbein and Ajzen 1975), Theory of Planned Behaviour (Ajzen 1985), the Technology Acceptance Model (Davis 1989), and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003). While these theories have made significant contributions, researching other theories can also enhance the understanding of new technology usage (Benbasat and Barki 2007, Venkatesh et al. 2007). To answer the calls for alternative theoretical perspectives, this paper employs the Theory of Interpersonal Behaviour (TIB) (Triandis 1980) to investigate the use of a mobile technology. According to the TIB, attitudinal, normative, and identity beliefs form behavioural intention.

This paper makes three contributions to the understanding of mobile adoption and use. First, it elucidates the commonalities and differences in what drives the acceptance of wireless technology in early adopter versus late majority countries. Second, it provides insight into the different drivers that motivate initial adoption versus continued use of smartphones. Third, this paper proposes a streamlined version of the theory of interpersonal behaviour for studying the adoption and use of wireless ICT.

This paper proceeds as follows. The next section provides an overview of theories used in extant literature and elaborates on the choice of TIB as our theoretical lens. The third section provides an overview to TIB and proposes six hypotheses. The fourth section details the method used for data collection and analysis. The fifth section presents the results, discusses the findings, and investigates the differences between smartphone users and non-users. Section 6 discusses the implications of the findings, suggests areas for future research, and brings the paper to a close.

2 Theoretical Background

The Diffusion of Innovations theory (DOI) (Rogers 1962, 2003) argues that individuals do not all adopt an innovation at the same time, but instead fall into time-based sequential categories that reflect their innovativeness. The users' degree of innovativeness, coupled with the preceived attributes of the innovation, drive the acceptance of new ideas and technologies. "Early adopters" accept technology shortly before it becomes mainstream. "Late majority" adopters, on the other hand, embrace a technology only after it has been accepted by a majority of the population.

While DOI focuses on the user's innovativeness and the attributes of the technology, other theories focus on the process by which someone makes the decision to use (or not use) a technology. Much of the literature regarding technology acceptance follows the Theory of Reasoned Action (TRA) tradition. TRA (Fishbein and Ajzen 1975) uses two primary constructs to predict behaviour: a person's attitude toward the behaviour and the subjective norm, which is the person's perception about whether or not the behaviour will meet with the approval of others. The Technology Acceptance Model (Davis 1989), which is the most widely used theory in IS research, argues that TRA's reliance on indirect influence of attitudes should be replaced by two more specific constructs: perceived usefulness and perceived ease-of-use. The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003) propose four criteria to predict technology adoption: performance expectancy, or the degree a potential adopter believes a technology will improve job performance; effort expectancy, which is the perceived ease-of-use; social influence, which is the perception that "important others" want the decision-maker to use the technology; and facilitating conditions, which represent a person's belief that the organization will support his or her use of the new technology.

Over the past decade, information systems researchers have expanded acceptance research to include the phenomenon of post-adoption technology acceptance. This research has placed a strong focus on what drives the continued use of a technology. While the volume of literature on the subject is relatively small, one of the most influential theories is Bhattacherjee's (2001) Information Technology Continuance (ITC) model. Based on Oliver's (1980) expectation-confirmation theory, ITC explains the intention to continue using a technology based on the user's satisfaction with the system. Satisfaction is determined by whether the user experience exceeds, meets, or falls short of pre-adoption expectations (Bhattacherjee 2001). While research into information technology continuance has provided new insights into technology acceptance, it assumes that the drivers of initial use are the same as those that drive subsequent use (Ortiz de Guinea and Markus 2009) and overemphasises utilitarian motivation (Ng and Kwahk 2010). Users, however, can develop complex and paradoxical relationships with technology (Mick and Fournier 1998, Jarvenpaa and

Lang 2005). For example, users who begin using a mobile device to gain freedom from their desk often find that with physical freedom comes a new obligation to be available irrespective of time and place (Jarvenpaa and Lang 2005). Often to confront these paradoxes, people change their attitudes and their behaviour in ways that may not have been anticipated prior to using a new technology (Mick and Fournier 1998). As a result, people may stop using technology even when it satisfies their initial goals (Hung et al. 2007).

Mobile technology is always with the user and plays an increasingly large part in everyday life; therefore, it is increasingly more personal and is often viewed as an extension of the user. The intimate relationship between users and technology also suggests that a new technology age has dawned, one that requires us to search for new insights and different ways to understand it. The majority of technology acceptance research focuses on instrumental beliefs to the exclusion of personal determinants and social influences (Lu et al. 2005). Consequently, many scholars have called for different insights into consumer ICT because use may be an end to itself (Bagozzi 2007) and to investigate the role that non-utilitarian factors play in the decision to use information and communication technology (Venkatesh and Brown 2001, Van der Heijden 2004, Magni et al. 2010).

Bagozzi (2007) encourages scholars to employ new theoretical perspectives that help fill gaps in our understanding while bringing together many elements already used in existing research. H.C. Triandis' theory of interpersonal behaviour (TIB) (Triandis 1980) offers such a unifying approach. The theory encompasses many of the factors that influence behaviour found in models such as the technology acceptance model, theory of reasoned action, theory of planned behaviour, and UTAUT. At the same time, TIB considers extensive social, cultural, and personal factors, answering the calls for different insights into ICT research by providing a more encompassing understanding of what motivates behaviour (Facione 1993, Gagnon et al. 2003). Table 1 compares TIB with other popular theories.

Table 1. Comparison of Theories

	TRA	TAM	UTAUT	TIB
Attitude	✓			✓
Subjective Norms	✓			✓
Usefulness		✓	✓	✓
Ease-of-Use		✓	✓	
Social Influence			✓	✓
Facilitating Conditions			✓	✓
Habit				✓

3 Theory of Interpersonal Behaviour

Inspired by Hofstede's work on culture, Triandis distinguishes between cultural (i.e. social) and individual influences (Triandis 2004). Triandis' theory of interpersonal behaviour (TIB) encompasses many of the factors that influence behaviour that are found in models such as the technology acceptance model, theory of reasoned action, and theory of planned behaviour; however, TIB considers social, cultural, and moral factors that are not addressed in more widely used theories (Facione 1993, Gagnon et al. 2003). Triandis argues for expanding the understanding of Fishbein and Ajzen's (1975) "attitude" construct. As an alternative, Triandis argues that intention is formed by attitudinal, normative, and self-identity beliefs (Triandis 1980).

While much of the technology research employing TIB has studied personal computer use (McQuarrie and Langmeyer 1987, Thompson and Higgins 1991, Thompson et al. 1994, Al-Khaldi and Wallace 1999, Pee et al. 2008), the theory has also provided insights into the use of executive information systems (Bergeron et al. 1995), student use of collaborative systems (Limayem and Hirt 2003), web surfing while at work (Chang and Cheung 2001), physician acceptance of telemedicine (Gagnon et al. 2003), and the adoption of mobile data services (Bina et al. 2007).

According to the TIB, prior experience with a situation-behaviour sequence influences a person's decisions. *Habit* represents a routinization of behaviour that comes from frequent occurrence. The more common a behaviour, the less deliberation one makes about whether to perform the action (Triandis 1980). Researchers have found habit to have a significant direct effect on the use of information technologies (McQuarrie and Langmeyer 1987, Thompson et al. 1994, Limayem and Hirt 2003, Pee et al. 2008). Research has also found that habit has an indirect effect on a person's decision because habit also influences a person's affect toward an action (Bagozzi 1981, Bergeron et al. 1995, Gagnon et al. 2003). The role habit has on behavioural intention and affect lead us to the following hypothesis:

H1A: Habit is a predictor of intention to use smartphones.

H1B: Habit has a moderating influence on a person's affect about using smartphones.

Triandis argues that *affect*, or the direct emotional response to the thought of a given behaviour, brings about psychological arousal. Affect is the emotional driver of behaviour that can be hard to explain rationally. Unlike other theories, such as the TRA, Triandis specifically separates affect from cognitive drivers of behaviour. Positive affect motivates behaviour (Triandis 1980). Prior research has found a strong

relationship between affect and technology use (Bergeron et al. 1995, Al-Khaldi and Wallace 1999, Pee et al. 2008); therefore, we propose the following hypothesis:

H2: Affect is a predictor of intention to use smartphones.

Perceived consequences represent a cognitive evaluation of the likely consequences of a given behaviour. People are motivated by their desire to experience an expected outcome. The underlying premise that people evaluate potential behaviour in terms of potential rewards and take actions that are likely to bring desirable outcomes (Triandis 1980). Triandis' concept of perceived consequences is analogous to TAM's perceived usefulness concept (Gagnon et al. 2003). Prior research has shown that perceived consequences have a significant effect on behavioural intention (Thompson and Higgins 1991, Bergeron et al. 1995, Limayem and Hirt 2003, Pee et al. 2008). The role that perceived consequences is expected to play in decisions leads us to propose the following hypothesis:

H3: Perceived consequences are predictors of intention to use smartphones.

Triandis argues that people internalize implicit social contracts they have with others along with the subjective culture of their reference groups. Accordingly, people should act certain ways in certain situations (Triandis 2004). Prior research employing the TIB has found that social factors play a significant role in determining behaviour (Thompson et al. 1994, Limayem and Hirt 2003). Triandis incorporates two dimensions of social factors: social norms and personal norms. Prior Triandis-based research has shown that norms play a key role in shaping the use of technology (Thompson et al. 1994, Gagnon et al. 2003, Pee et al. 2008).

Social norms are the internalisation by a person of other people's opinions about a given behaviour and role beliefs. They are commonly held beliefs about how a certain type of person "should" behave. When the behaviour is performed, observers will think that the person performing the behaviour occupies a certain social role. When people view themselves as being a certain type of person, they will act in a way that illustrates that they are the kind of person they believe themselves to be. For example, a generous person donates money to charity. Therefore, people who consider themselves generous will donate money to charity. Role beliefs reflect how an individual thinks someone of his or her age, social status, education level, etc. should behave. Together, normative social beliefs and role beliefs represent *perceived social norms*. The role that normative social factors play in determining behaviour leads us to posit the following hypothesis:

H4: Perceived social norms are predictors of intention to use smartphones.

In addition to social norms, people base their behaviour on whether or not an action matches their personal beliefs. These *personal normative beliefs* reflect whether a person feels obligated to perform (or not perform) a given act in order to adhere to his or her own belief system. Based on the TIB, we hypothesise the following:

H5: Personal normative beliefs are predictors of intention to use smartphones.

Whereas personal normative beliefs are based on the way a person is perceived by others, *self-concept/ self-identity* is a private assessment of one's beliefs and values. The self is an active agent in the decision process that drives people to act in accordance with the behaviour that they see appropriate for themselves. One's self-definition motivates behaviour that is consistent with that definition (Triandis 1980, 1989). Self-identity has been shown to influence the acceptance and use of technology (Gagnon et al. 2003); therefore, we hypothesise:

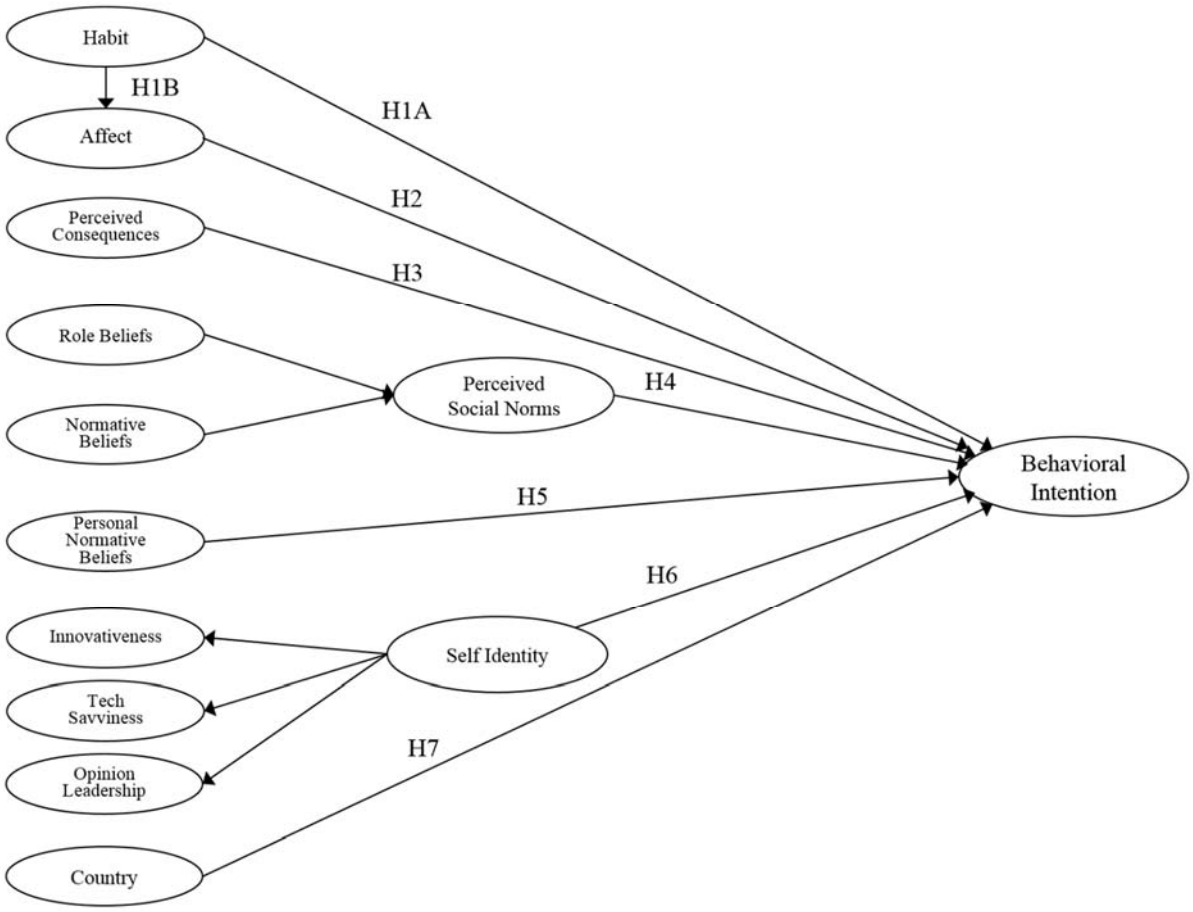
H6: Self-identity is a predictor of intention to use smartphones.

Rogers (2003) argues that people who adopt technology at different points in time exhibit different characteristics and are driven by different motivations. Given that the United States represents an early adopter country with rapid uptake of smartphones and Slovakia represents a late adopter country, we expect a participant's country to significantly influence the intention to adopt a smartphone, leading us to our final hypothesis:

H7: Whether a person lives in an early adopter or late majority country is a predictor of the intention to use smartphones.

The research model showing the constructs and the hypotheses discussed in this section are shown in Figure 1.

Figure 1. Research Model



4 Methodology

This study analyses survey data collected from a two-part field study. Unlike studies that investigate smartphone adoption in countries that are comparable in terms of technological development (e.g. (Jung et al. 2015)), this paper investigates countries that represents early and late majority technology adoption. The first part of the study collected data from university students in the United States during the spring of 2009. There were 250 responses (125 men, 125 women) of whom 152 had a smartphone and 98 did not. Of the surveys returned, four were rejected due to incomplete responses, leaving 246 usable questionnaires. The second part of the study surveyed students in in Slovakia in late 2012. There were 356 respondents (102 men, 252 women) of whom 185 had a smartphone and 171 did not. The surveys were conducted using paper-based questionnaires. In both countries, completion of the questionnaires was optional. No incentives (gifts, extra credit, etc.) were offered to participants.

A student sample was selected for the United States data because it was studying the early adoption of a relatively novel mobile device. Following prior research into wireless adoption (Gimpel et al. 2012), we aimed to reduce extraneous variables and prior studies show that age affects individual technology adoption

(Morris and Venkatesh 2000, McFarland 2001, Yang and Jolly 2008). The selected group has lived their entire lives since the introduction of mainstream personal computing and related technologies (Prensky 2001). They make heavy use of ICT, particularly internet and mobile phone use, and they have therefore incorporated it into their daily lives. They consider technology to be part of the landscape (Oblinger 2003). Equally important, they are consumers whose entrance as decision makers into the marketplace closely coincided with the wide-scale launch of smartphones in the consumer marketplace. To reduce confounding factors when comparing USA and Slovakia data, we targeted a similar sample of university students in Slovakia.

The survey instrument was adapted from existing IT acceptance studies employing the theory of interpersonal behaviour (Bergeron et al. 1995, Gagnon et al. 2003). Habit was measured by prior experience (Bagozzi 1981, Bagozzi and Warshaw 1990, Bergeron et al. 1995, Gagnon et al. 2003) based on whether a participant already owned a smartphone. The intention to purchase a smartphone as one's cellular phone was measured with a single question: "How likely are you to buy a smartphone the next time you buy a cellular phone?" The survey used Likert-type scales ranging from 1-7. Affect was measured on scales ranging from "boring" to "exciting" and "not satisfying at all" to "very satisfying." All other constructs employed a disagree/agree dimensional scale. Based on one of the author's prior qualitative research on smartphone adoption (Bødker et al. 2014), the self-identity construct includes the factors of innovativeness, tech savviness, and opinion leadership, which align with adopter traits described by Rogers (2003). The self-identity measure consists of three pairs of questions, the first evaluating whether each participant considered smartphone users to be tech savvy, opinion leaders, and have innovative minds. The questionnaire subsequently asks whether the participant considers himself or herself to characterise these traits (Gagnon et al. 2003). The survey was translated from English into Slovak, then translated back to English to confirm that the translation was suitable.

Partial Least Squares (PLS) was employed to assess the structural model using the SmartPLS software. PLS places minimal demand on sample size, making it appropriate for this study. Missing values are coded as -1. Mean replacement is used as the missing value algorithm for both PLS and bootstrapping. The PLS algorithm uses the path weighting scheme (the default setting for the weighting scheme) and the default setting "Mean 0, Var 1" for the data metric. Bootstrapping uses the default setting of 500 samples and no sign changes.

We conducted a preliminary confirmatory factor analysis. The initial analysis showed that some items had low correlations within their theoretical construct and were therefore dropped from the analysis. We dropped two items from perceived consequences, leaving 5 questions in the analysis; 1 item from the role

beliefs construct, leaving 3 questions in the analysis; 2 normative beliefs questions, leaving 2 items in the analysis; and 2 items from personal normative beliefs, leaving 4 items in the final analysis. The formative constructs comprising self-identity are each comprised of 2 questions; therefore, lower Cronbach's alphas are expected and do not necessitate action (Carmines and Zeller 1979).

We compare the users and non-users in this study. Because some of our variables do not follow a normal distribution, we apply a Mann-Whitney U-test (Mann and Whitney 1947) to elucidate the differences between users and non-users.

5 Findings and Analysis

This section presents and analyses the results from the PLS analysis of the proposed model and then proposes a more parsimonious model with similar predictive and explanatory power. The section continues with an examination of the differences between the users and non-users in our sample.

5.1 Instrument Validation

We conducted a confirmatory factor analysis for PLS (Gefen and Straub 2005). All items in a construct load highly on distinct factors. Items load highest on their own factors. Internal consistency of constructs is tested using Cronbach's alpha (Nunnally et al. 1967). A value of 0.7 and above is considered acceptable (Nunnally 1978). No Cronbach's alpha is calculated for habit because it consists of one variable and the answer to the question whether someone owns a smartphone should be reliable by default. While normative beliefs falls below this level, an alpha greater than 0.50 can be acceptable when scales are restricted to only a few items (Carmines and Zeller 1979). Consequently, normative beliefs, which is a reflexive part of the perceived social norms construct, remains above the 0.5 value that would be considered unacceptable (George and Mallery 2003).

Table 2. Instrument Validation

	AVE	Composite Reliability	Cronbach's Alpha	Communality	Redundancy
Affect	0.7906	0.8827	0.7477	0.7906	0
Behavioural intention	1	1	1	1	0.5775
Perceived consequences	0.5428	0.8551	0.7894	0.5428	0
Personal normative beliefs	0.5264	0.8115	0.7319	0.5264	0
Perceived social norms	0.5086	0.8365	0.7542	0.5086	0.2413
Normative beliefs	0.7017	0.8244	0.5783	0.7017	0
Role beliefs	0.6681	0.8577	0.7511	0.6681	0
Self-identity	0.4131	0.8075	0.7134	0.4131	0

Tech savvy (formative)	0.5939	0.745	0.3172	0.5939	0.3981
Innovative mind (formative)	0.5842	0.7365	0.2924	0.5842	0.4258
Opinion leader (formative)	0.6614	0.7959	0.4902	0.6614	0.4145

Because formative measures influence the latent constructs, rather than being influenced by them, the internal consistency measured by Cronbach's alpha is not recommended for measuring formative constructs (Churchill Jr 1979, Bollen and Lennox 1991, Hardin et al. 2008) and researchers are discouraged from dropping formative items with low correlation in order to increase alpha scores (Jarvis et al. 2003). According to Jarvis et al. (2003), formative indicators are valid when they are more highly correlated with the measure than with the other constructs in the model. Table 3 compares the correlations among the formative constructs versus the range of correlations with the other constructs in the model. As expected, the formative constructs are more highly correlated with each other than with other constructs, thus establishing their validity.

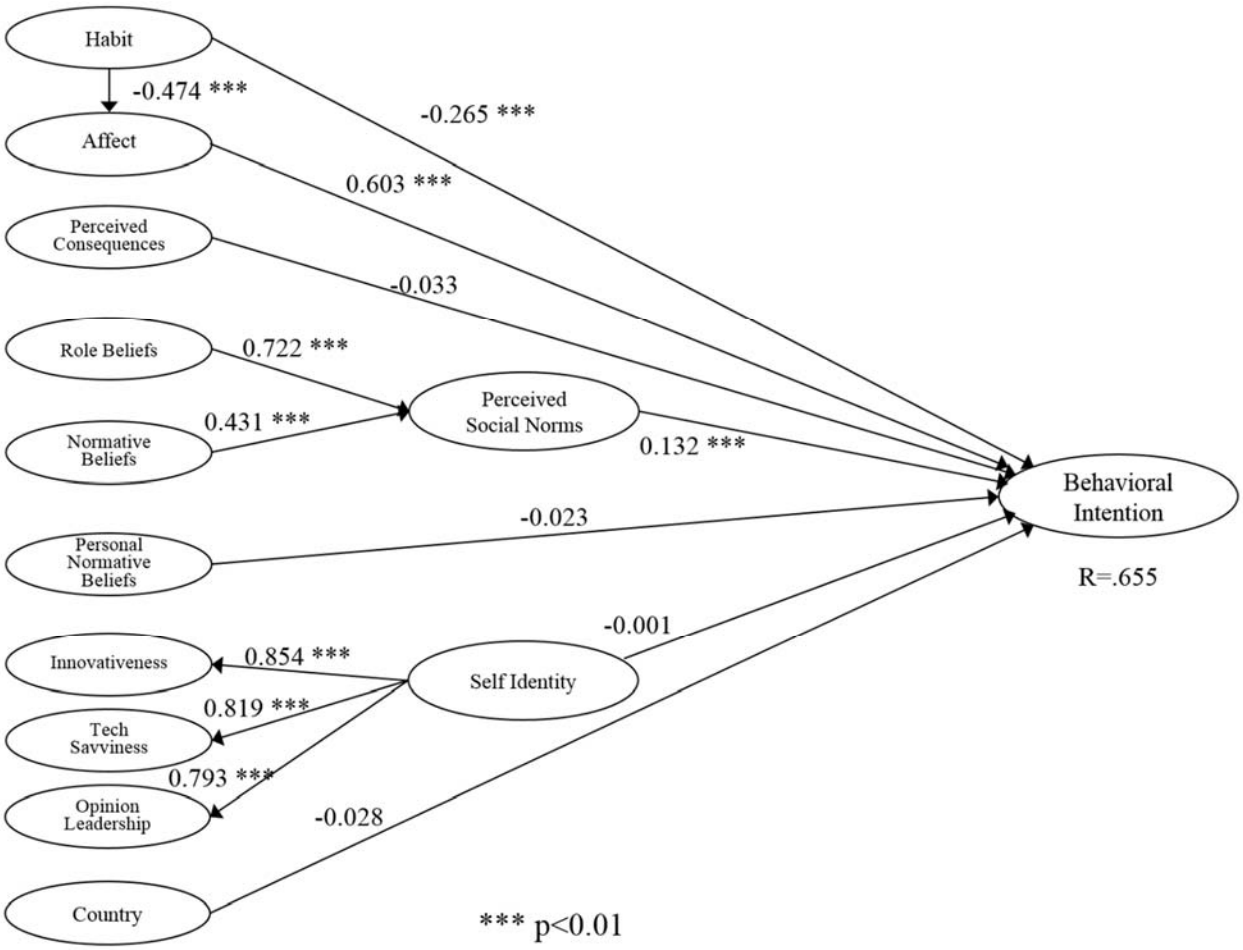
Table 3. Correlations among formative variables, self-identity, and other constructs

	Innovative mind	Tech savvy	Opinion leader	Self-identity	Other Constructs (Range)	
					To	From
Self-identity1	**0.7049**	0.4684	0.2584	**0.5801**	-0.2329	0.4641
Self-identity2	0.4356	**0.7437**	0.3079	**0.5985**	-0.1952	0.4163
Self-identity3	0.4248	0.4288	**0.8439**	**0.6909**	-0.3447	0.4079
Self-identity4	**0.8196**	0.4505	0.4999	**0.7182**	-0.3817	0.4689
Self-identity5	0.4828	**0.7967**	0.3595	**0.662**	-0.1916	0.3599
Self-identity6	0.4053	0.2667	**0.7814**	**0.5939**	-0.4944	0.3653

5.2 Structural Model

PLS analysis shows that our proposed model explains 65.5% of the intention to buy a smartphone as one's next phone.

Figure 2. Path Coefficients of the model



The explanatory power of the model demonstrates that TIB is an acceptable and useful theory for predicting smartphone acceptance. As hypothesized, habit has a direct, significant influence on the intention to use a smartphone. This finding is consistent with other IT acceptance research (Thompson et al. 1994, Kim 2009, Oulasvirta et al. 2012). Similarly, study data support the direct relationship affect can have on intention, similar to the findings of Kim (2009) and Limayem et al. (2003). Additionally, the data support the influence that habit has on affect, which in turn significantly influences the intention to use ICT, a finding shared by Bergeron et al. (1995) and Pee et al. (2008).

While some hypotheses are confirmed, our analysis shows that several hypotheses are not supported. (See Table 4.) According to the data, the personal normative beliefs that reflect whether people feel obligated to perform (or not perform) a given act in order to adhere to their personal belief system do not play a significant role in the intention to purchase and use a smartphone. The data also show that study participants' self-identity does not determine whether they intend to use a smartphone. One plausible explanation for both findings could be that the perceived social norms simply overpower people's personal attitudes. Such an explanation is supported by Chen et al. (2016) and Jung et al. (2015), who also found

that the social normative influence and social influence were highly significant determinants of smartphone use.

Table 4. Summary of Findings

Hypothesis	**Results**
H1a: Habit is a predictor of intention to use smartphones.	Supported
H1b: Habit influences a person's affect about using smartphones.	Supported (at $p<0.10$)
H2: Affect is a predictor of intention to use smartphones.	Supported
H3: Perceived consequences are predictors of intention to use smartphones.	Not supported
H4: Perceived social norms are predictors of intention to use smartphones.	Supported
H5: Personal normative beliefs are predictors of intention to use smartphones.	Not supported
H6: Self-identity is a predictor of intention to use smartphones.	Not supported
H7: The country where a person lives is a predictor of the intention to use smartphoness.	Not supported

A major surprise from the analysis is that perceived consequences do not significantly influence the intentions of current or potential smartphone users. The perceived consequences construct is similar to TAM's perceived usefulness construct. Given the plethora of information systems studies that find "usefulness" drives the intention to use technology, the results of this study warrant closer examination.

Prior applications of Triandis' TIB perceived consequences construct have yielded mixed results. Thompson et al.'s (1991) study of PC use in work situations found a significant relationship between perceived consequences and utilisation. Similarly, Pee et al.'s (2008) study of PCs in non-work contexts found that perceived consequences play a significant role in shaping the intention to use ICT. Lu et al.'s (2005) examination of mobile internet finds that perceived usefulness is a significant driver of use, but they redefine the traditional concept of usefulness to incorporate subjective norms, image, and self-identity, TIB constructs that are usually separate from perceived consequences/usefulness. The findings of other prior applications of TIB are closer to those of the study presented in this paper. Limayen and Hirt's (2003) study of electronic bulletin board use as part of student work found that only one out of six consequences significantly influenced system use. Bergeron et al. (1995) find that perceived consequences do not significantly influence how frequently executives use information systems. Al-Khaldi and Wallace (1999) did not find a significant link between perceived long-term consequences of PC use and actual PC utilisation. Gagnon et al. (2003) did not find a significant link between perceived consequences and physician adoption of telemedicine.

The non-significance of perceived consequences and/or usefulness is not limited to TIB-based studies, but also has a growing presence within mobile technology research. Wireless ICT researchers argue that perceived usefulness may not provide an appropriate tool for studying wireless technologies and services because the impact on everyday routines may be more influential than the technology itself (Bouwman et

al. 2007). Studies have found perceived usefulness has only weak influence on the intention to adopt mobile data services (Hong and Tam 2006) and a negative influence on student acceptance of mobile information systems (Gao et al. 2010). Research into the use of mobile communication tools by police officers found that other considerations, not perceived usefulness, drive use (Bouwman and van de Wijngaert 2009). Other mobile research has found instrumental factors to be non-significant drivers for hedonic tasks like playing mobile games (Fang et al. 2005, Ha et al. 2007). The findings in this study closely resemble prior research that found that the adoption of iPhones is driven by social and emotional factors rather than the instrumental attributes of the device (Hedman and Gimpel 2010). The data in this study suggest that instrumental considerations are neither significant drivers of initial adoption nor continued use. A possible explanation could be that study participants do not evaluate the usefulness of generic technology such as smartphones, whereas they might evaluate a specific application or service. Another plausible explanation could be that smartphones duplicate the functions of other ICT that study participants may own and use (e.g. mobile phone and laptop), therefore mitigating the perception of special utility.

Another major surprise from the analysis is that country – whether an early adopter country at the beginning of the smartphone boom or a late majority county after smartphones have gone mainstream – does not significantly influence behavioural intention. Given that data were collected in different countries at different periods of time, and that prior research comparing different countries found significant differences between nations (Jung et al. 2015), we expected country to be a significant predictor of adoption. We conducted post-hoc analyses to more closely examine whether there are differences between countries. Because some of our variables do not follow normal distribution, we follow Karahanna, Straub, and Chervany (1999) and apply a Mann-Whitney U-test to elucidate the differences between participants in the USA and Slovakia. Table 5 shows the results of the test.

Table 5. Cross-country comparison

	Slovakia	USA	z-value	p-value
Intention to buy	5.221910	5.998446	4.503	<.00001
Affect	5.188202	5.800284	5.594	<.00001
Perceived social norms	4.461236	5.272534	8.357	<.00001
Personal normative beliefs	3.192292	3.739547	4.654	<.00001
Self-identity	3.783240	4.506278	8.071	<.00001
Perceived consequences	4.808901	5.290598	5.087	<.00001

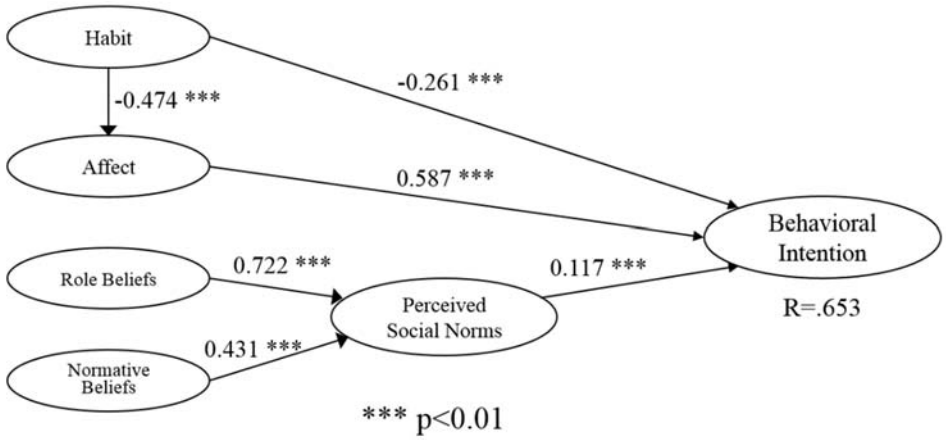
The U-Tests show that significant differences exist between the users in early adopter versus late majority countries despite country playing a non-significant role in shaping the intention to use smartphones. A close look shows that, in general, participants in both countries share similar beliefs about affect, perceived

social norms, personal normative beliefs, and perceived consequences. The differences between participants in each country are about the magnitude (or strength) of their attitudes, rather than an issue of holding different attitudes or beliefs. Self-identity is an exception, with the participants in the early adopter country on average being motivated by their self-identity, while self-identity does not motivate users in the late majority country. Regardless, the PLS analysis shows that self-identity is not a significant driver of the intention to use smartphones.

Because the PLS analysis found the hypothesized influence of country on behavioural intention to be insignificant, we ran a post-hoc analysis to determine whether country has a moderating influence on any of the latent variables in the model. Our analysis determined that country had a significant ($p<0.01$) moderating influence on affect, but not on any other variables. Given that affect is the direct emotional response to the thought of a behaviour, it makes logical sense that people in an early adopter country are more excited by and expect greater satisfaction from using a new technology. As technology becomes less novel and gains wider global acceptance – even if local adoption remains low – emotional reaction to a technology would be expected to drop. Nevertheless, even in the late majority country, affect remains a key factor that drives the use of smartphones.

The model originally proposed includes non-significant factors. Consequently, we re-estimate the model using only the significant predictors (Gagnon et al. 2003). Because many studies may not offer cross-country investigation and because including country as a moderating variable explains only 1.1% more of the variance (R=0.664 versus 0.653), we exclude country from the streamlined model. Our revised model, which includes habit, affect, and perceived social norms, provides a more parsimonious model. PLS analysis shows that the revised model offers greater parsimony and essentially the same explanatory and predictive power.

Figure 3. Path Coefficients of the streamlined model



The PLS analysis of the study data demonstrates the suitability of the TIB for researching the adoption of consumer-oriented ICT such as smartphones. What we have learned is that in a late adopter country, habit (i.e. prior behaviour), affect and perceived social norms, which are comprised of role beliefs and normative beliefs, are the significant determinants of whether a person's next mobile device will be a smartphone. Whether a person is in an early adopter or late majority country has a moderating influence on affect, but in either type of country, affect remains an important driver. Our analysis suggests that a streamlined, more parsimonious operationalisation of the TIB may be appropriate for studying ICT adoption in similar contexts.

5.3 Users vs. Non-users

The data show the suitability of using TIB to explore the adoption and use of ICT. We also have the opportunity to address our fourth research question: *Do potential adopters and users of smartphones hold the same behavioural and normative beliefs?* Table 6 shows the results of a U-Test that shows that significant differences between the two groups exist in every dimension measured.

A closer look at the differences show that those who already own a smartphone indicates that they have a strong intention to continue using a smartphone, whereas non-users are neutral about whether they will buy a smartphone or traditional feature phone. Current users have much stronger affect for smartphones. They attribute a strong sense of satisfaction to their smartphones and are excited about the devices. Non-users also believe they will be satisfied with smartphones and have a sense of excitement; however, the affect they have for smartphones, while positive, is much weaker than those who already own them.

Table 6. U-Test Comparison of Users and Non-Users

	user	non-user	z-value	p-value
Intention to buy	6.467301	4.369467	13.7171	0.00000
Affect	5.987839	4.745952	2.4039	0.01310
Perceived social norms	5.097136	4.406061	2.9362	0.00328
Perceived consequences	5.363978	4.552273	2.7473	0.00588
Personal normative beliefs	3.724368	3.032197	2.6787	0.00725
Self-identity	4.352428	3.735480	2.2837	0.02218

Social beliefs play a significant part in the intention to buy a smartphone. Those who use smartphones have a stronger belief that people at their status level – career, education, income, age – should be using smartphones than those who do not have a smartphone. This shows that socio-demographics influence smartphone adoption, as previously reported by Kang et al. (2014). Similarly, current users believe that others hold smartphone users in high regard, whereas non-owners are more neutral. While these social

beliefs, which comprise the perceived social norms construct, are significant drivers of the intention to use a smartphone, the difference between users and non-users is much smaller than that of affect.

While perceived consequences do not play a significant role in determining whether someone will use a smartphone, users believe that smartphones are more useful than non-users. Users believe smartphones facilitate work-related tasks, increase tech knowledge, facilitate their social life, and make communication more fun. Non-users share these views, but their beliefs are only slightly more positive than an indifferent attitude.

Neither users nor non-users are influenced by personal normative beliefs. At the same time, smartphone users consider themselves to be more tech savvy and innovative than non-users.

6 Discussion and Conclusion

This paper investigates the drivers of the intention to purchase a smartphone by residents in an early adopter and a late majority country. The study, which includes current smartphone users as well as potential adopters, employs Triandis' (1980) theory of interpersonal behaviour to investigate the factors that drive the adoption and use of smartphones by people living in early adopter and late majority countries.

Survey data indicate that habit (prior smartphone ownership), affect (the emotional response to the thought of using a smartphone), and perceived social norms (how one thinks others expect him or her to act) determine a person's behavioural intention. Perceived consequences (usefulness) is found to be non-significant, suggesting that the adoption of personal mobile technologies are driven by different factors than workplace technology. The same drivers motivate people in early adopter and late adopter countries. The biggest differences are not between people in different countries, but between current smartphone users and non-users, who differ in every dimension measured in the study.

6.1 Contributions to Research

This paper makes three contributions to the understanding of mobile adoption and use. First, it elucidates the commonalities and differences in what drives the acceptance of wireless technology in early adopter versus late majority countries. Second, it provides insight into the different drivers that motivate initial adoption versus continued use of smartphones. Third, this paper proposes a streamlined version of the theory of interpersonal behaviour for studying the adoption and use of wireless ICT.

The paper's first three research questions address the drivers of smartphone use in early adopter and late majority countries, as well as the similarities and differences between the two groups. The study finds that

habit, affect, and perceived social norms drive the use – either adoption or continued use – of smartphones in both early adopter and late majority countries. The country has a moderating influence on affect, but affect remains a significant driver of the intention to use smartphones in both types of countries. Although there are significant differences in the drivers of behavioural intention in early adopter and late adopter countries, the differences are not in what drives intention, but in how deeply held the beliefs and attitudes are. Consequently, the theory of interpersonal behaviour is a suitable model for studying the acceptance of wireless ICT when it is new and novel as well as after it has become pervasive and mundane.

The habitual use of smartphones is an important driver of the continued use of smartphones. Smartphone owners are very likely to buy a smartphone the next time they purchase a mobile phone, whereas non-users are neutral about whether they will buy a smartphone or traditional feature phone. Current users have stronger, more favourable beliefs about the use of smartphones. Although this study compares countries at different points in the innovation diffusion curve, individuals within each country also fall within different categories of technology adopter, as predicted by Rogers (1962, 2003).

Based on the analysis of data, this study proposes a streamlined version of the theory of interpersonal behaviour that can be used in future research in the adoption and continued use of wireless ICT. The new model uses habit, affect, and perceived social norms to predict mobile ICT use. This model is more parsimonious than the traditional TIB model. Furthermore, it does not include perceived consequences, which marks a material departure from the TAM and UTAUT theoretical traditions that dominates ICT research. The new model, based on findings from two countries at different stages of technology diffusion, focuses on non-utilitarian factors as called for by prominent scholars (Venkatesh and Brown 2001, Van der Heijden 2004, Magni et al. 2010).

6.2 Implications for Practice

Smartphones have become a ubiquitous mobile technology in many places; however, they are still have strong growth potential in several late majority markets. The study data indicate that those who use feature phones may decide not to buy another one rather than upgrading to a smartphone; whereas once a person upgrades, they will not return to a regular mobile phone. Therefore, the key to smartphone growth is in convincing those using traditional feature phones to upgrade to smartphones. Traditional messages touting capabilities will not convince people to upgrade, because people do not purchase a smartphone because of its utility. Appealing to someone's self-identity, their belief that someone like them should use a smartphone rather than feature phone, will also be ineffective. Instead, marketing messages should build emotional excitement around smartphone and promote positive emotions that could come with owning a smartphone. While current smartphone users have this emotional attachment, it must be nurtured among non-users.

Likewise, marketing campaigns should focus on the increased social status people experience when they switch to a smartphone. This belief is necessary for adoption, but generally is not held by feature phone users. The insight to focus on emotional and status messages also applies to markets already dominated by smartphones. Many advertisements still tout screen resolution, camera quality, etc., even though the decision to buy a new smartphone (and therefore switch brands or buy an updated version of an existing phone) is driven by the social norms that assign it social value and by the emotions it elicits from potential users.

6.3 Limitations and Further Research

The study faces certain limitations. First, conducting survey research in one "early adopter" and one "late majority" country may limit the generalizability of the conclusions. The sample consists of students, who may have a different level of tech-savviness and different financial constraints than the general population. Additionally, a substantially higher proportion of both our samples owned smartphones than their respective populations at large. Furthermore, the cross-sectional study design does not afford the opportunity to study the facilitating conditions that Triandis (1980) argues mediate intended behaviour from actual behaviour.

Future research can compare the streamlined model to the full TIB model to see whether the more parsimonious model provides nearly equal explanatory power. Researchers can also compare the TIB to more mainstream adoption models, such as TRA, TPB, and UTAUT or continued-use models such as the ITC to compare relative explanatory and predictive power, as well as which models are best suited for studying novel versus mundane ICT and personal mobile ICT versus more traditional workplace technologies.

Acknowledgements

This work was carried out with the support by the DREAMS project via a grant from the Danish Agency of Science and Technology (grant number 2106-04-0007). Special thanks to the University of Southern California Institute for Communication Technology Management, the study participants, and the anonymous reviewers for their suggestions and advice.

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