JAIS - JOURNAL OF THE ASSOCIATION FOR INFORMATION SYSTEMS

META-ANALYSIS OF THE UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY (UTAUT): CHALLENGING ITS VALIDITY AND CHARTING A RESEARCH AGENDA IN THE RED OCEAN

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ABSTRACT

There are both formal and informal cries that UTAUT and by association the stream of research on technology adoption has reached its limit, with little or no opportunities for new knowledge creation. Such a conclusion is ironic because the theory has not been sufficiently and suitably replicated. It is possible that the misspecifications in the various replications, applications, and extensions led to the incorrect conclusion that UTAUT was more robust than it really was and opportunities for future work were limited. Although work on UTAUT has included important variables, predictors and moderators, absent a faithful use of the original specification, it is impossible to assess the true nature of the effects of the original and additional variables. The present meta-analysis uses 25,619 effect sizes reported by 737,112 users in 1,935 independent samples to address this issue. Consequently, we develop a clear current state-of-the-art and revised UTAUT that extends the original theory with new endogenous mechanisms from different, other theories (i.e., technology compatibility, user education, personal innovativeness, and costs of technology) and new moderating mechanisms to examine the generalizability of UTAUT in different contexts (e.g., technology type and national culture). Based on this revised UTAUT, we present a research agenda that can guide future research on the topic of technology adoption in general and UTAUT in particular.

Keywords: UTAUT, meta-analysis, random effects meta-analysis, meta-structural equation modeling, moderator analysis, research agenda

INTRODUCTION

The unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003) is one of the most widely cited theories in the information systems (IS) literature, with a reach that has extended well beyond the IS field and in a variety of settings and populations. The original model was developed to explain employee acceptance[1] and use of technology using four predictors—performance expectancy, effort expectancy, social influence, and facilitating conditions—and four moderators—gender, age, experience, and voluntariness. One key extension to UTAUT was by Venkatesh, Thong and Xu (2012), who proposed UTAUT2 by contextualizing UTAUT to a consumer context, with the addition of three predictors—hedonic motivation, price value, and habit—and dropping one of the moderators—voluntariness. The Google Scholar citation count of the original UTAUT paper is about 28,000 and the UTAUT2 paper is about 6,000; the Web of Science citation counts for these two papers are about 9,000 and 2,000, respectively. Although by itself, it does not mean every citation is a replication or an effort to apply or extend UTAUT, the number of studies being conducted is tending toward the thousands (see Venkatesh, Thong, & Xu, 2016). Given the large number of UTAUT studies, there are both formal and informal cries to suggest that UTAUT and perhaps by association the stream of research on technology adoption has reached its limit, with little or no new knowledge to be gained. Such maturity declarations notwithstanding, recently, Venkatesh et al. (2016) lamented that most replications, applications, and extensions were not sufficiently inclusive of the original moderators and thus did not comprehensively examine UTAUT. Potentially addressing this gap were prior meta-analyses on UTAUT such as those by Dwivedi et al. (2019), Taiwo and Downe (2013), and Khechine, Lakhal, and Ndjambou (2016). However, these meta-analyses rely on small databases covering only few users, technologies, and cultures. Although Taiwo and Downe

[1] Consistent with some of the research on this topic, the terms acceptance and adoption are used interchangeably in this paper.

(2013) synthesized empirical results of 37 studies, Khechine et al. (2016) used 74 studies, and Dwivedi et al. (2019) examined 162 studies, none of these meta-analyses examined the UTAUT2 extensions or any other variables used in the various extensions in the literature. Further, these meta-analyses have not only overlooked the moderators in UTAUT, but also other contextual and method characteristics that may explain differences across studies. Thus, there is acute need to understand the robustness, completeness, and accuracy of the original specification.

Given that UTAUT has not actually been sufficiently and suitably replicated—an issue that is of great importance to scientists (Dennis & Valacich, 2014; Tsang & Kwan, 1999)—we could have one of two serious problems. First, it is possible that the misspecifications in the various replications, applications, and extensions led to the incorrect conclusion that UTAUT was more robust than it really was and opportunities for future work were limited. Second, although the extensions have included important variables, predictors and moderators from UTAUT and other theories, absent the original specification, it is impossible to assess the true nature of the effects of the original and additional variables—so as to arrive at a new, more accurate, more complete UTAUT specification.

We contend that the original UTAUT specification and UTAUT2, although useful and capturing important constructs explaining to acceptance and use of technology, still lacks a broader coverage of relevant constructs. We observed that most of the existing papers that have applied UTAUT are in what is termed the red ocean, as they are mostly incremental contributions using nearly the same set or subset of constructs. In principle, we thus agree with the muted formal and vocal informal calls to cease-and-desist work using the theory, albeit *in its original/current form.* Such concerns were earlier raised about the predecessor to UTAUT, i.e., the technology acceptance model (for examples, see Bagozzi, 2007; Benbasat & Barki, 2007). Nonetheless, while acknowledging such concerns, future research directions on acceptance and use in general, with a particular focus on UTAUT and its derivative models, have also been proposed by a number of scholars in a variety of journals. These future research directions have been developed based on a qualitative review of the literature (Venkatesh et al., 2016), meta-analysis (Dwivedi et al., 2019), and/or replication of UTAUT in different contexts (Al-Gahtani, Hubona, & Wang, 2007; Venkatesh & Zhang, 2010).

Considering the number of research endeavors using UTAUT, it behooves us to take stock of the model specification so as to provide an accurate assessment of the robustness of theory and a clear current state-of-the-art and a revised theory that can guide future endeavors on this topic. In order to understand what has been studied in the past, which theories and predictors hold the most promise, and how UTAUT studies can create new and substantial contributions, amidst the current number of UTAUT studies in the red ocean, we conducted a comprehensive meta-analysis on UTAUT. The meta-analysis will lead us to an accurate specification of the theory spanning various contexts such as different user samples (age, gender, consumer/employee), national cultures (power distance, individualism-collectivism, masculinity-femininity, uncertainty avoidance), and technologies (mobile/non-mobile, online/offline, transaction/non-transaction). Our meta-analysis, including proposed predictors and moderators extracted from 1,935 independent samples that have applied UTAUT, will help us arrive at a current, accurate, and robust specification of UTAUT because, unlike previous meta-analyses on UTAUT, we will include all predictors and theories proposed in previous UTAUT studies, the original UTAUT by including the moderators, and examine the contextual application of UTAUT based on technology types, individual characteristics, and national culture. Armed with this specification, we will propose key future research directions. We believe that our meta-analysis will help future researchers to seek out the blue ocean related to technology adoption in general and UTAUT in particular. As stated by Straub (2009), blue ocean does not have to be entirely new research and we are not calling for a new theory to replace UTAUT. Instead, with this meta-analysis, we examine the theoretical boundaries of UTAUT and propose new territory (e.g., new four key variables and context of UTAUT) that future research can examine and identify opportunities to conduct blue ocean research on/using UTAUT.

While reiterating that we believe that fruitful questions related to technology acceptance and use do exist, we believe they will emerge from a new starting point—i.e., a new theoretical specification that will emerge from this work—and rich contextualization (see Alvesson & Kärreman, 2007; Johns, 2006) that considers new, unique contexts such as rural environments (e.g., Venkatesh & Sykes, 2013; where traditional predictors of acceptance were found to be inadequate), cultural considerations (e.g., Al-Gahtani et al., 2007; Venkatesh & Zhang, 2010; where traditional predictors were found to be inadequate in a new culture), technology type (e.g., Sykes & Venkatesh, 2017; where traditional predictors were inadequate in an ERP system context), and personality traits of users (e.g., Barnett et al., 2015; where personality traits were found to influence the acceptance of technology).

META-ANALYSIS

A meta-analysis provides a systematic way to assess the progress of existing theories and serve as a theory extension tool (Carney et al., 2011; Orsingher, Hogreve, & Ordanini, 2016). Although in the past, a meta-analysis was thought to be conclusive and be the definitive or final word on a given topic, that has since shifted because more often than not, it raises more questions than it answers, and thus is now seen as a way to reinvigorate interest in mature research areas and encourage development of novel ideas (Shaw & Ertug, 2017). Owing to the fact that multiple studies on a single phenomenon will always provide more information about the phenomenon than any single study, a meta-analysis provides numerous benefits (McShane & Böckenholt, 2017). First, a meta-analysis allows researchers to comprehensively collect the findings of individual studies and provide an overview of all the predictors found in a specific research topic. As is the case with UTAUT where a majority of the studies have been carried out with relatively small sample sizes, their results could be unique to the examined sample. A meta-analysis enables us to overcome this issue and come up with more robust effects (Sleesman et al., 2012). Second, a meta-analysis explores relationships between a theoretical construct, its predictors and/or outcomes, while correcting any distortion present in measurement errors, sample errors, and other inputs that may lead to conflicting results (Hunter & Schmidt, 2004). Third, a meta-analysis allows researchers to take advantage of the variation in the settings of the individual studies included in it and to quantify the moderating influence of the settings as boundary conditions for the examined relationships in the study (Geyskens et al., 2009; Karna, Richter, & Riesenkampff, 2016). Testing the boundaries of theoretical models further aids researchers in confirming the predictive and explanatory power of theories and make headway in advancing knowledge (Bergh et al., 2016). Fourth, a meta-analysis (specifically, meta-analysis with SEM) enables researchers to conduct a "horse race" and examine the explanatory power of a theoretical model in comparison to other competing models. It also allows for testing intermediate mechanisms in relationships and examining mediation mechanisms regarding their existence, order, direction, and magnitude (Bergh et al., 2016). By getting a better understanding of the relationships between constructs and how they relate with each other across many studies, researchers are better placed to discover innovative problems and reflect on constructs and relationships that ultimately serve as the foundation for new theories (Aguinis et al., 2011; MacInnis, 2011). Fifth, the uncertainty in a meta-analysis will typically be smaller than the uncertainty in the individual studies included in the meta-analysis, thus providing a solution in the case where individual studies provide conflicting results (McShane & Böckenholt, 2017). A meta-analysis can be and has been used to assess and revise various theories in different fields such as technology acceptance model (King & He, 2006), IS success model (Petter &

Mclean, 2009), theories of reasoned action and planned behavior (Madden, Ellen, & Ajzen, 1992; Notani, 1998), transaction cost theory (Geyskens, Steenkamp, & Kumar, 2006), five-factor model of personality (Judge, Heller, & Mount, 2002), leader-member exchange theory (Gerstener & Day, 1997), organizational citizenship behavior theory (LePine, Erez, & Johnson, 2002), expectancy theory (Van Eerde & Thierry, 1996), transformational and transactional leadership theory (Judge & Piccolo, 2004), resource dependence theory (Drees & Heugens, 2013), organizational support theory (Kurtessis et al., 2017), technology-structure relationship theory (Miller et al., 1991), and challenge stressor-hindrance stressor framework (LePine, Podsakoff, & LePine, 2005). These meta-analyses assess whether a theory is still valid and whether after many years of research on a theory, its main tenets are supported (Drees & Heugens, 2013; Van Eerde & Thierry, 1996; Petter & McLean, 2009), integrate one theory with other theories to develop a new theory (Colquitt, LePine, & Noe, 2000), expand a theory by testing assumptions not assessed in past research (Drees & Heugens, 2013; Wu & Lederer, 2009), contrast different theories with each other (Judge & Piccolo, 2004), revise specific constructs in a theory by excluding constructs or distinguishing across types of constructs (Geyskens et al., 2006; LePine et al., 2002), and introduce new contingency variables to a theory (Miller et al., 1991). Against this backdrop, we use a meta-analysis to reexamine UTAUT and extend it in several ways as will be explained next.

LITERATURE REVIEW

Overview of UTAUT

UTAUT was developed based on a comprehensive synthesis of previous technology acceptance and use studies (Venkatesh et al., 2003). The four constructs with main effects on intention in UTAUT, hereinafter UTAUT predictors, that are found to have an influence on the behavioral intention and use of technology are performance expectancy, effort expectancy, social influence and facilitating conditions. Performance expectancy is the degree to which technology provides benefits to users when performing certain activities. Effort expectancy is the degree of ease associated with using the technology. Social influence is the degree to which the user perceives that important others believe he or she should use the technology. Facilitating conditions are the degree to which the user believes there is an organizational and technical infrastructure that supports the use of the technology. According to UTAUT, behavioral intention to use technology is influenced by performance expectancy, effort expectancy, and social influence, whereas technology use is influenced by behavioral intention and facilitating conditions. When extending the theory for consumer contexts, i.e., in UTAUT2, Venkatesh et al. (2012) also included hedonic motivation, habit, and price value as context-dependent predictors. UTAUT further theorizes that age, gender, experience and voluntariness moderate various relationships, whereas UTAUT2 drops voluntariness for consumer settings.

Since its introduction, UTAUT has been applied in a wide range of contexts such as mobile banking (Zhou, Lu, & Wang, 2010), e-government (Venkatesh et al., 2011), and electronic medical record (Hennington & Janz, 2007). Whereas some researchers applied this theory in different contexts without any modification, others integrated it with other theories, thus extending UTAUT/UTAUT2 (Venkatesh et al., 2016). As Venkatesh et al. (2016) note in their review of this theory, UTAUT still offers many promising opportunities for further theoretical development.

First, they emphasize that more research is needed with respect to new UTAUT predictors that can be added to the theory. Some studies tested potential predictors of behavioral intention (Appendix A). Most of these studies examined one or two potential additional variables that raises a concern as it appears to be ad-hoc and thus not systematic (see Venkatesh et al., 2016). Also, most of these studies did not test the additional variables together with all UTAUT predictors. It is thus difficult to assess whether they perform better or worse than established UTAUT predictors. Also, many variables discussed in various other acceptance theories have not been considered as extensions. Generally, the findings for different extensions are mixed and they are based on single-context studies with small sample sizes. Further, it should be noted that most studies proposed new predictors for behavioral intention rather than use (Appendix B). So far, only six studies suggest potential predictors of use. Thus, UTAUT would also benefit from a systematic assessment of potential predictors of use. Again, we found that many predictors of intention or use suggested by other theories have the potential to be added to UTAUT because strong effects were observed in some extension studies. For instance, Eckhardt, Laumer, and Weitzel (2009) enriched the social influence construct with five dimensions based on the source of the influence (i.e., customers, suppliers). Despite the various studies that extend other variables, it remains unclear which of these predictors should be included to increase the amount of explained variance in technology use over and above the variance explained by current predictors. The choice of predictors becomes even more difficult because UTAUT studies frequently produce inconsistent results, with numerous studies reporting rather weak effects. For example, Teo et al. (2015) found that performance expectancy does not affect a user's intention to accept mobile payment, whereas effort expectancy is found to play an important role. This contradicts findings from the original UTAUT that found performance expectancy and not effort expectancy to be the most important predictor of behavioral intention. Some of these inconsistencies could be attributed to researchers not applying the full UTAUT or using sample sizes in their research that are too small (Teo et al., 2015). Nonetheless, it remains unclear how well the existing UTAUT predictors explain technology acceptance and which new constructs add value to the theory.

Second, Venkatesh et al. (2016) encourage further research on the influence of contextual factors in UTAUT and they suggest shifting the focus from examining "UTAUT in context" to a focus on "UTAUT of context". Extension studies examining contextual moderators are rather scarce (Appendix C). Existing studies often focus on only few variables and few moderators. These studies mainly examine lower-level moderators related to the user, rather than higher-level moderators (see Venkatesh et al., 2016), describing the study context. Hence, not many macro-level moderators have been assessed in prior extensions studies. We observed that hardly any studies examined more than two countries representing different cultures or more than two technologies. The UTAUT literature is thus lacking in cross-technology and cross-cultural comparisons. Cross-context theorizing provides insights on the generalizability of a theory and the context dependence of its predictors. These insights are needed because it is unclear whether the importance of UTAUT predictors differs, for instance, across technologies, organizations, or cultures. Although some studies have examined technology type (Wong et al., 2014) and location differences (Al-Gahtani et al., 2007), the literature still lacks a comprehensive assessment of these factors using a large dataset, especially spanning various values of these factors, which is often only available in meta-analyses. It therefore remains unclear which higher-level contextual factors exert moderating influences on UTAUT in addition to its individual-level moderators (e.g., age, gender). Venkatesh et al. (2016) explain that cross-context theorizing provides researchers insights to better interpret empirical findings and to modify UTAUT to better suit different contexts. Kamakura, Kopalle, and Lehmann (2014, p. 121) emphasize the importance of empirical generalization using meta-analysis by explaining that "grouping related studies (replications) can provide a more powerful test of specific theories than any single study as well as help identify boundary conditions for them."

Against this background, our meta-analysis examines two potential areas of extensions to UTAUT, as recommended by Venkatesh et al. (2016): (1) addition of new endogenous mechanisms from different theories and (2) addition of new moderating mechanisms to examine the generalizability of UTAUT in different contexts. The next section provides an overview of these two types of extensions.

UTAUT Extensions/Predictors

Based on a review of the articles included in our meta-analysis, we found that researchers commonly used predictors from seven theories to extend UTAUT. Despite the fact that UTAUT was previously built on some of these theories (e.g., TAM), these studies have commonly used endogenous constructs from diffusion of innovation theory, theory of planned behavior, information systems success model, big-five personality, social-demographic predictors, and risk theory. Variables used to extend UTAUT are studied in Appendixes A and B. As shown in these Appendixes, there are a wide range of variables that have been used to extend UTAUT. Many of these studies have found other predictors (e.g., personal innovativeness) to show an influence in the presence of existing UTAUT variables, suggesting that UTAUT may have potentially excluded some other important predictors. However, given that there are so many variables that have been proposed in these studies, it would not be practical to have a parsimonious model by integrating all these variables into one model and test them in one large-scale data collection effort. Many of these studies also attributed these different results or predictors to different contextual factors such as location or the technology type studied. The next section further explains these moderators.

Moderators Influencing UTAUT Relationships

Moderators Proposed in UTAUT. The original UTAUT states that the importance of different predictors depends on four moderators. These moderators are related to the user, namely the user’s gender, age, and experience, and to the use context, namely voluntariness of technology use (Venkatesh et al., 2003). For example, Venkatesh et al. (2003) found that the strength of the relationship between performance expectancy and intention varied by gender and age, with stronger relationships for men and younger users. They found the relationship between effort expectancy and intention relationship to be moderated by three user characteristics, with stronger effects for women, older users, and more experienced users. Different moderating effects were also observed for other UTAUT relationships.

When developing UTAUT2, Venkatesh et al. (2012) reexamined the moderators in this theory. They dropped voluntariness given that all consumer decisions are voluntary, but still included age, gender, and experience. They proposed that these user characteristics influenced not only the effects of the four predictors proposed in the original UTAUT, but also the new constructs included in UTAUT2 (hedonic motivation, price value, and habit). UTAUT2 thereby contributes to a better understanding about user differences in adopting new technologies that is essential to understand the boundary conditions of the theory. Interestingly, Venkatesh et al. (2012, 2016) note that most studies that apply UTAUT in various technology contexts often include only the main effects and not the moderating variables. Thus, it is unclear to what extent the moderating effects proposed in UTAUT can be generalized to different settings. Our meta-analysis therefore reexamines these moderating effects using a comprehensive dataset covering numerous technologies and users.

Current State of Research on UTAUT Moderators. In their review of UTAUT research, Venkatesh et al. (2016) particularly stressed the need to study more contextual effects. They reviewed the various extensions of UTAUT proposed in the literature and noted that some studies suggest the inclusion of new moderating mechanisms. Most of these extensions still refer to use differences such as the user's technology readiness (Borrero et al., 2014), adopters versus non-adopters (Eckhardt et al., 2009), and ethnicity, religion, language, employment, income, education, and marital status (Liew, Vaithilingam, & Nair, 2014). Few studies can be found that examine other moderators describing the broader contextual setting such as technology type and national culture setting. Regarding technology type, some studies compared specific technologies with each other such as e-learning tools vs. online games (Oh

& Yoon, 2014), different IT service types (Thong et al., 2011), and type of recommender systems (Wang et al., 2012). These technology types provide important insights into technology differences but they cannot be used to comprehensively classify various technologies examined in UTAUT studies. Similarly, few UTAUT studies consider country differences and those few studies usually examine only two countries. For example, studies compare UTAUT differences in Saudi Arabia versus USA (Alaiad, Zhou, & Koru, 2013), South Korea versus USA (Im, Hong, & Kang, 2011), and China versus USA (Venkatesh & Zhang, 2010). Franke and Richey (2010, p. 1275) explain that "[t]ypically, two countries are selected judgmentally to represent different levels of one or more cultural factors." Two-country comparisons have substantial limitations but are common due to practical constraints. Franke and Richey (2010) further explain that studies should avoid these types of comparisons because findings for a particular variable may be due to factors other than the one(s) studied. They instead recommend including a larger number of countries with each country having its own culture profile to ensure that the observed finding can be attributed to the country characteristic of interest.

User Characteristics as Moderators

UTAUT proposes that several user characteristics, namely age, gender, and experience, exert moderating effects on various relationships (Venkatesh et al., 2003). We exclude voluntariness of use because most studies do not report this information and thus the challenges in accurately coding this moderator (Appendix D). Whereas age is proposed to interact with all UTAUT predictors, the remaining characteristics such as gender and experience only interact with selected UTAUT predictors such as performance expectancy and effort expectancy. Despite user characteristics being a key element of UTAUT, subsequent researchers who have used this theory have often ignored these moderation effects (Venkatesh et al., 2016). It remains largely unknown whether the moderating effects of user characteristics also matter in different contextual settings. It may be that many of the existing UTAUT studies do not report such moderating effects because they may have shown nonsignificant effects in their specific study context. Thus, it remains unclear whether the proposed interactions are generalizable across contexts. Similar to UTAUT2, we propose that age and gender exert moderating effects on some relationships in the theory. Information about the average user age and gender is reported by most UTAUT studies and a large number of studies can be compared. We do not derive specific new hypotheses for age and gender, as we expect the same moderating effects as in the original UTAUT, e.g., performance expectancy is most important for men and younger users. Instead, we focus on the potential differences between employees versus consumers because differences across these user groups have not been formally tested.

In examining studies that apply UTAUT in the contexts of *employees* and *consumers*, we found that the constructs that predict behavioral intention and use vary across these categories. In the context of consumers, the UTAUT predictors typically show strong effects (Tan, 2013; Thong et al., 2011; Powell et al., 2012). When studying employees however, some studies have found not all of the constructs are important. Several studies have, for example, found that effort expectancy does not affect employees' behavioral intention toward various technologies (e.g., Lin, Zimmer, & Lee, 2013; Decman, 2015; Šumak & Šorgo, 2016). This is in line with our reasoning because, in organizational settings, the use of technology or systems are often mandated by the organization regardless of how the employees perceive the effort required to use it. For similar reasons, it can be expected that other UTAUT predictors, including performance expectancy (Chen & Chen, 2015) and social influence (Lin et al., 2013), would show weaker effects in studies examining employees' behaviors. Venkatesh et al. (2012) revised UTAUT for consumer contexts arguing that the motivations to use technology differ compared to employee contexts. They introduced hedonic motivation, price value, and habit and we expect these predictors show stronger effects for consumer contexts. Thus, we hypothesize:

H1: The effects of (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) hedonic motivation, (e) price value, and (f) habit on behavioral intention and use will be weaker in employee contexts compared to consumer contexts.

National Culture as Moderator

When discussing future research or study limitations, many UTAUT studies regularly suggest conducting large-scale cross-country comparisons (Teo et al., 2015). We therefore consider national culture as moderator. Culture is defined as "the collective programming of the mind which distinguishes the members of one human group from another" (Hofstede, 1991, p. 5). Culture can influence individuals' social behaviors (Dinev et al., 2009). Past studies have used different approaches when examining the role of culture in understanding acceptance and use. We use Hofstede's (2001) culture model to assess the moderating effects of four culture dimensions because this concept is widely used and has been shown to explain technology use across cultures (Srite & Karahanna, 2006). Existing UTAUT studies examine some of Hofstede's four original culture dimensions or they refer to this concept when comparing two countries (Appendix C). Straub et al. (2002) explain that social identify theory is an important theoretical approach to study culture. According to this theory, individuals are likely to identify themselves to be part of a culture and this has an impact on their use of technologies (Im et al., 2011). Given the importance of culture for an individual's technology adoption decisions, and in response to the call of Venkatesh et al. (2016) for further research on the role of environmental factors on UTAUT, we differentiate across four culture dimensions: (1) power distance, (2) individualism-collectivism, (3) uncertainty avoidance, and (4) masculinity-femininity. We tested the effects of these four original culture moderators but not long-term orientation (Appendix D discusses our rationale for its exclusion)

Power distance refers to the extent to which consumers in a culture expect and accept inequality in a system (Hofstede, 2001). There is an expectation in high power distance cultures that the powerful members take care of the less powerful. We therefore assume that users in high power distance cultures expect the firm to take care of the users' technology problems and provide support (Hofstede, 2001). In relation to UTAUT, it is reasonable to expect some differences between the findings of UTAUT, especially regarding social influence, across cultures with different levels of power distance. In high power distance cultures, individuals would be expected to submit to the influence of those they consider to be in a higher social position than themselves. In such cultures, when people in high power positions adopt a technology or have positive feelings toward it, their subordinates and others in lower positions than them would not be willing to disturb the social norm and disagree with or deviate from them. Thus, the effect of social influence should be stronger in such cultures in comparison to cultures with low power distance where individuals are more independent. This observation is in agreement with the analysis of Sun and Zhang (2006) analysis of the situational limitations of technology acceptance studies, and the findings of Al-Gahtani et al. (2007) who compared users' behavioral intentions in Saudi Arabia and in the U.S., and found social influence to have a stronger effect on behavioral intentions in Saudi Arabia than in the U.S. They explained that this was, among other reasons, due to the difference of power distance in the two countries.

Similarly, in high power distance cultures, when users with low standing in the society are considering a technology, they expect firms to provide organizational and technical infrastructure to support the use of the system. Hofstede (2001) explains that, in high power distance cultures, individuals expect more powerful members of society, including public and private institutions, such as firms and technology services providers, to provide support and structure. Therefore, it is also expected that facilitating conditions will show stronger effects in high power distance cultures. Hofstede, Hofstede and Minkov (2010) provide a further argument about why facilitating conditions gain importance in high power distance cultures. They explain that individuals in high power distance cultures appreciate social status and preferential treatment more than individuals in low power distance cultures do (Hofstede et al., 2010). Provision of support demonstrates that users receive preferential treatment by firms that enhances their reputation (i.e., status). In high power distance cultures, users are therefore more likely to use a technology when facilitating conditions exist that support use of the technology. We found these patterns to be borne out in studies carried out in high power distance cultures (e.g., Ali, Nair, & Hussain, 2016; Khorasanizadeh et al., 2016) and low power distance cultures (e.g., Järvinen, Ohtonen, & Karjaluoto, 2016). Thus, we hypothesize:

H2: The effects of (a) social influence and (b) facilitating conditions on behavioral intention and use will be stronger in high power distance cultures.

Individualism-collectivism refers to the extent that people prefer to act as an individual, rather than as a member of a group, and whether they prioritize their own needs compared to group needs (Hofstede, 2001). Steenkamp and Geyskens (2006, p. 139) further explain that users in "individualistic societies place their personal goals, motivations, and desires ahead of those of others, whereas collectivistic cultures are conformity oriented and show a higher degree of group behavior and concern to promote their continued existence." As a result, some UTAUT predictors are expected to show stronger effects in individualistic, compared to collectivistic, cultures. The UTAUT predictors that will display stronger effects in individualistic cultures are related to the individual's personal goals, motivations, and desires such as performance expectancy and hedonic motivation. While performance expectancy relates to the benefits the individual receives when using a technology, hedonic motivation relates to the fun and pleasure the individual derives when using the technology (Venkatesh et al., 2012). However, factors related to group needs and group behavior are more important in collectivistic cultures. Thus, the effect of social influence will be stronger in collectivistic cultures because this predictor relates to the degree to which the user perceives that important others believe he or she should use the technology (Venkatesh et al., 2003). Some evidence of this is found in the existing literature. In comparative studies between cultures characterized by individualism versus collectivism, performance expectancy gained importance in individualistic cultures, whereas social influence gained importance in collectivistic cultures (Im et al., 2011; Udo, Bagchi, & Maity, 2016; Venkatesh & Zhang, 2010). We also found hedonic motivation to be consistently important in studies carried out in individualistic cultures (Gao, Li, & Luo, 2015; Morosan & DeFranco, 2016; Ozturk et al., 2016).

The cross-cultural literature stresses that users in individualistic cultures show a greater achievement orientation than users in collectivistic cultures (Nelson & Shavitt, 2002). This literature refers to the theory of achievement motivation that argues that personal success is related to reaching individual goals that is more motivating to users in individualistic cultures (McClelland, 1961). In collectivistic cultures, users are more likely to be motivated by socially oriented goals. Among all individualistic cultures, the U.S. is the prototypical example where individuals are achievement oriented (Nelson & Shavitt, 2002). It is important in individualistic cultures to demonstrate "personal success through demonstrating competence according to social standards" (Schwartz, 1992, p. 8). Accordingly, individuals in individualistic cultures will try harder to learn using a new technology independent of the required effort. Consequently, effort expectancy will be less important as a predictor in individualistic, rather than in collectivistic, cultures. Thus, we hypothesize:

H3: The effects of (a) performance expectancy and (b) hedonic motivation on behavioral intention and use will be stronger in individualistic cultures, whereas (c) social influence and (d) effort expectancy will be stronger in collectivistic cultures.

Masculinity-femininity refers to whether the culture embraces values that are typically associated with masculinity or femininity (Hofstede, 2001). Masculine cultures value advancement, competitiveness, and performance, whereas feminine cultures value cooperation, modesty, consensus-oriented, and quality of life (Hofstede, 2001). Srite and Karahanna (2006) explain in this context the process of gender-role identification is related to an individual's espoused masculinity/femininity values. According to this line of inquiry, individuals learn society's gender role standards and expectations, and will acquire attitudes, behaviors, and values that are viewed as gender acceptable and appropriate (Srite & Karahanna, 2006). Because users in masculine cultures are performance oriented and more competitive, they emphasize performance expectancy of technology and focus less on effort expectancy and facilitating conditions. Further, in organizational environments where there is typically a goal-orientation, people in masculine cultures will be more eager to adopt a technology, as it will facilitate them performing their work better (Srite & Karahanna, 2006). Venkatesh and Morris (2000) also suggest that users in masculine cultures will be more concerned with whether the technology will be able to carry out the tasks intended. Taylor and Hall (1982) also propose that masculine cultures more easily connect with instrumental actions such as the achievement of work goals and performance improvement. In feminine cultures, users will be more concerned with effort expectancy and social influence because they are less concerned with instrumental goals and more interested in improving their quality of life and developing relationships with others (Srite & Karahanna, 2006). People in masculine cultures can be characterized as risk takers, being optimistic, and function oriented. People in feminine cultures have a tendency to share, focus on avoiding losses, and being experientially oriented (He, Inman, & Mittal, 2008). In comparisons between masculine and feminine cultures, some studies found that masculine cultures favor performance expectancy, whereas effort expectancy, facilitating conditions, and social influence were more important in feminine cultures (e.g., Im et al., 2011; Jung & Lee 2015; Pramatari & Theotokis, 2009; Yuen et al., 2010). Moreover, Venkatesh and Morris (2000) suggest that the need to stand out and be unique in social circles for individuals in feminine cultures heightens the importance of facilitating conditions for such people. They argue that the prominence of social/affiliation needs for individuals who espouse feminine values increase the importance placed on availability of technology support staff for such individuals. Thus, we hypothesize:

H4: The effect of (a) performance expectancy on behavioral intention and use will be stronger in masculine cultures, whereas the effects of (b) effort expectancy (c) social influence and (d) facilitating conditions will be stronger in feminine cultures.

Uncertainty avoidance refers to “the extent to which the members of a culture feel threatened by uncertain or unknown situations” (Hofstede, 1991, p. 113). Uncertainty avoidance is the degree to which a person prefers structured over unstructured situations (Hofstede, 1980). Individuals in high uncertainty avoidance cultures display a preference for predictability over ambiguity. Users in high uncertainty avoidance cultures are more likely to experience high levels of anxiety when confronted with problems or challenges. Because of this, users in cultures displaying high uncertainty avoidance may show resistance toward efforts promoting technologies that are new or have an element of risk involved in them (e.g., mobile banking). Such users would be more inclined toward traditional services with richer interaction, such as face-to-face communication, rather than technologies where use has high levels of ambiguity (Straub, Keil, & Brenner, 1997). Technology users in high uncertainty avoidance cultures cope with uncertainties by relying more strongly on facilitating conditions. In cultures with low uncertainty avoidance, people are more relaxed and are more willing to take risks, try something new, and are more comfortable in uncertain situations. With regard to persuasion and processing information, people in high uncertainty avoidance cultures are better able to process arguments and require less heuristic assistance (Chaiken, 1980), whereas individuals in low uncertainty avoidance cultures typically require more heuristic assistance (e.g., facilitating conditions and social influence) and are less willing to engage in systematic processing of information (e.g., personal assessment of new technologies)

(Sorrentino et al., 1988). One would expect that higher levels of facilitating conditions would need to be present for users be able to overcome the uncertainty involved in accepting new technologies in high uncertainty avoidance cultures (Thatcher et al., 2007). Similarly, when it comes to accepting technologies, people in such cultures are likely to conform with the social influence they perceive from the people in their surroundings. Relying on social influences gives users in high uncertainty avoidance cultures reassurance about technology use. Jung and Lee (2015) found facilitating conditions to be important in determining students' behavioral intention in high uncertainty avoidance cultures, whereas for students in low uncertainty avoidance cultures, it was unimportant. They also found that social influence had a greater effect on students from high uncertainty avoidance cultures. In contrast, in other studies conducted on users from high uncertainty avoidance cultures, social influence was consistently found to have weaker effects (Martins, Oliveira, & Popovič, 2014; Oliveira et al., 2016). Our meta-analysis can unearth the cumulative effect. It is more important to users in high uncertainty avoidance cultures that technology is easy to use because it helps them to better understand the technology. Users who do not fully understand technology may feel uncomfortable with the uncertainty in the situation. Thus, we hypothesize:

H5: The effects of (a) facilitating conditions, (b) social influence and (c) effort expectancy on behavioral intention and use will be stronger in high uncertainty avoidance cultures.

Technology Characteristics as Moderators

Despite the maturity of technology acceptance research, many studies have not considered the effects of technology types (Im, Kim, & Han, 2008). As proposed by Venkatesh et al. (2016), technology type is a dimension of context that can be applied to UTAUT research. UTAUT was developed during a time when the Internet was still growing and not as widely used as it is today. Thus, the literature is lacking a comparison of the usefulness of UTAUT for Internet versus non-Internet technologies. Meuter et al. (2000)

developed a technology classification based on a comprehensive literature review. They classify different technologies depending on their main purpose (transaction versus non-transaction technologies) and the interface (online versus offline technologies). Meuter et al. (2000) use this classification to explore the expectations of technology users. We adapt this classification in this meta-analysis and extend it using a third criterion. Balasubramanian, Peterson, and Jarvenpaa (2002) argue that mobile technologies differ from non-mobile technologies due to their flexibility to receive services independent of time and space. Thus, users may also have different expectations about mobile, compared to non-mobile, technologies. Using these three criteria allows us to classify most technologies examined in prior UTAUT research and test the generalizability of this theory across these broad technology categories.[2] Thus, we consider three main types of technology in our meta-analysis: (1) transaction- vs. non-transaction-based technologies, (2) Internet- vs. non-Internet-based technologies, and (3) mobile- vs. non-mobile-based technologies. It should be noted that one specific technology studied may belong to more than one of the mentioned categories. For example, mobile banking services used for transferring money is classified as a transaction, Internet-based, mobile technology.

For *transaction versus non-transaction* technologies, we examine if technologies used to conduct financial transactions differ from technologies not supporting such transactions (Escobar-Rodríguez & Carvajal-Trujillo, 2014). Users may have different expectations depending on this technology moderator (Meuter et al., 2000). For example, transaction technologies are related to potential financial losses that make the performance expectancy of the technology gain importance (Blut et al., 2016). In addition to the potential negative consequences of use, technologies differ regarding their extent of process standardization,

[2] Blut Wang, and Schoefer's (2016) meta-analysis examined 96 studies testing various factors influencing the acceptance of self-service technology. They found differences depending on the purpose of technology (i.e., transaction technology) and interface (i.e., Internet technology). They did not consider mobile technologies.

with transaction technologies being more standardized (Goodhue, 1995; Meuter et al., 2000). Thus, we assume facilitating conditions to have weaker effects for transaction technologies since they are more standardized. Due to the uncertainties of use, users frequently use the same technology with which they are familiar that in turn leads to the development of habits. Users also satisfy their hedonic consumption needs with transaction technologies—for example, shopping online allows users to buy products that address their hedonic needs and the process of shopping online itself is possibly hedonic consumption. Thus, hedonic motivation gains importance. For non-transaction-based technologies, facilitating conditions may be more important because the technologies are less standardized and serve various purposes (Chiu & Wang, 2008). In the context of transaction-based technologies, Baptista and Oliveira (2015) found habit and performance expectancy to be the strongest predictors of intention, and habit to be the strongest predictor of use. AbuShanab, Pearson and Setterstrom (2010) similarly found performance expectancy to be the strongest predictor of intention of transaction technologies such as Internet banking. Thus, we hypothesize:

H6: The effect of (a) performance expectancy, (b) hedonic motivations, and (c) habits on behavioral intention and use will be stronger for transaction technologies, whereas (d) facilitating conditions will be stronger for non-transaction technologies.

Regarding *Internet versus non-Internet* technologies also, we propose user expectations to differ according to this technology moderator (Meuter et al., 2000). We propose that social norms gain importance for Internet technologies. A number of these technologies have been integrated into social networking sites and apps that help in connecting people and social groups (Blut et al., 2016). Thus, the social norms of the user's social groups are more likely to influence the use of Internet-based technologies. Further, Internet technologies are less tangible than non-Internet technologies because there is hardly any physical aspect of the technology for the user to evaluate (Koernig, 2003). As such, users have more difficulty in comprehending how to use the technology and require more support from the firm, thus making the user's effort expectancy and facilitations conditions gain importance in users' decision-making. Some studies suggest similar effects. For example, in studies related to e-government service, effort expectancy was the strongest predictor of intention (Lian, 2015) and social influence was also found to be an important predictor of intention (Krishnaraju, Mathew, & Sugumaran, 2016). Thus, we hypothesize:

H7: The effects of (a) effort expectancy, (b) facilitating conditions, and (c) social influence on behavioral intention and use will be stronger for Internet, rather than non-Internet, technologies.

We also propose differences for *mobile versus non-mobile* technologies because user expectations may differ due to this moderator (Balasubramanian et al., 2002). Mobile technologies have both changed how users interact with and accept new technology. Although mobile technologies allow more flexibility and independence of space and time in the use of a technology (Balasubramanian et al., 2002), users are more dependent on this technology because they have fewer alternative technologies they can use when being mobile. When mobile, users cannot easily switch to alternative technologies when the focal technology is not working or when they struggle to use the technology. They may have other, alternative technologies available at home or at work but they rely on mobile technology more when away from home or work. Thus, performance of mobile technology, as well as effort expectancy and facilitating conditions, will be important. At home or work, they may be able to switch to alternative technologies, but when being mobile, the technology has to perform reliably, it has to be easy to use, and support will be more beneficial for the user. In studies on mobile learning, Milošević et al. (2015) found performance expectancy to be the strongest predictor of intention. Wang, Wu, and Wang (2009) also reported the same, with effort expectancy being the second strongest predictor (second to performance expectancy). Facilitating conditions was also found to affect intention to adopt mobile apps (Hew et al., 2015). Thus, we hypothesize:

H8: The effects of (a) performance expectancy, (b) effort expectancy, and (c) facilitating conditions on behavioral intention and use will be stronger for mobile, rather than non-mobile, technologies.

METHOD

Data Collection and Coding

We followed the approach of Hunter and Schmidt (2004) and Gerow et al. (2014) by initially conducting our literature search using keywords in various electronic databases (e.g., ABI/INFORM, JSTOR, Proquest, Academic Search, Scopus, Web of Science, ACM Digital Library, Science Direct and EBSCO/Business Source Premier). Conference proceedings, dissertations, and these were all included in the search in order to avoid bias toward higher effect sizes (Gerow et al., 2014). Therefore, we included the AIS Electronic Library (to collect AIS conference proceedings), IEEE Xplore, and the ProQuest Dissertations & Theses and WorldCat Dissertations and Theses database in our search. In addition, we examined the initial articles on UTAUT (Venkatesh et al., 2003; Venkatesh et al., 2012) and examined that studies referred to these articles. We complemented this search with further web searches to compile a comprehensive list of empirical studies on UTAUT. To ensure we captured all relevant articles, we also conducted a manual search of leading IS journals (e.g., AIS Basket of Eight journals) and business journals that were outlets for UTAUT research. We used Google Scholar to identify articles that referenced papers we had already identified and we e-mailed 1,258 authors in our list of papers to see if they had additional correlation tables that had not been published.

We used three criteria to determine the suitability of the collected studies for inclusion in the meta-analysis. First, the studies had to be empirical (e.g., survey, experiment or both) at the user/employee unit of analysis. Second, correlation coefficients must be reported or other statistical information that can be used to calculate correlations. Third, the study had to report on an independent dataset to ensure that we did not include studies relying on the same dataset twice in our meta-analysis. Appendix D provides more details about this screening process. In total, we gathered 1,451 usable articles. These articles included 1,149 studies published in journals, 268 studies from conference proceedings, 17 dissertations, and 17 unpublished studies. The study characteristics (e.g., effect sizes, sample sizes, type of technology) were extracted by two independent coders, with an inter-rated agreement of 98%. In those few cases where coding of effect sizes was unclear, the coding was discussed among the authors and resolved. When classifying effect sizes, the coders were given the construct definitions and aliases in Appendix E. They received definitions for moderators that they used to classify study contexts and once again, there was high inter-rater agreement (Appendix D).

Integration of Effect Sizes

The meta-analysis uses correlation coefficients as effect sizes because they are scale independent and they are reported in most of the collected studies. In those cases when correlations were not reported in the paper, we transformed regression coefficients to correlations when possible (Peterson & Brown, 2005). Some samples reported more than one correlation of the same association between two constructs usually because of multiple measurements of the same constructs. In these cases, we calculated composite scores and reported them as a single study, as suggested by Hunter and Schmidt (2004). We also adjusted the respective reliability coefficients using Mosier's (1943) formula. In total, we gathered 25,619 effect sizes reported in 1,935 independent samples in 1,451 articles. The cumulative size across collected samples was 737,112 users covering 77 countries worldwide. When empirical studies are characterized by methodological imperfections, such as measurement error (imperfect reliability), Borenstein et al. (2009) recommend conducting a psychometric meta-analysis that corrects estimates for these flaws by following the approach proposed by Hunter and Schmidt (2004). We therefore followed the suggestions by Hunter and Schmidt (2004). We first used reliability coefficients to correct for measurement error in the dependent and the independent variables. Hunter and Schmidt (2004) suggest dividing each correlation by the square root of the product of the respective reliabilities of the two constructs of interest. Then, we weighted the reliability adjusted correlations by sample size to address the sampling error. We calculated standard errors and 95% confidence intervals for each sample size weighted and reliability-adjusted correlation.

To assess the need for moderator analysis, we assessed the homogeneity of the effect size distribution using the Q-test that is a χ^2 test of homogeneity (Hunter & Schmidt, 2004). A significant Q-test indicates the need for moderator analysis. We also calculated credibility intervals that show the distribution of effect sizes (Hunter & Schmidt, 2004). Wide credibility intervals also suggest variation in effect sizes and the need for moderator analysis to account for unexplained variance (Whitener, 1990). Finally, we calculated the percent of variance in observed correlations (PVA) that is attributable to sampling error and other artifacts. Hunter and Schmidt (2004) suggest moderator tests for PVAs lower than 75%.

The robustness of our results and the possibility of publication bias was assessed using Rosenthal's (1979) fail safe N (FSN). The FSN refers to the number of studies averaging null results necessary to lower a significant relationship to a barely significant level (p=.05). When developing this criterion, Rosenthal proposed tolerance levels and suggested that FSNs should be greater than 5 x k + 10 with k=number of correlations. High FSNs provide some evidence regarding the robustness of the results and highlights that the results are less likely to be influenced by publication bias. In addition to these statistics, we calculated the power of the employed statistical tests (Muncer, Craigie, & Holmes, 2003).

Calculation of the Structural Equation Model (SEM)

We tested UTAUT and the different extensions using SEM because this testing approach considers the interrelationships among all constructs at the same time. We used the coded effect sizes to compile a correlation matrix among all variables. This correlation matrix was used as input to LISREL 9.2 to test the different extensions of UTAUT. SEM uses the harmonic mean of all sample sizes as the sample size for the calculations (N=1,665). Viswesvaran and Ones (1995) suggest using the harmonic mean because it leads to more conservative SEM results than the arithmetic mean of sample sizes. The constructs in the SEM are measured with single indicators. Because measurement errors have already been corrected when integrating effect sizes, the error variances of constructs are set to zero. These analyses are frequently conducted in various meta-analyses (e.g., Palmatier et al., 2006).

Moderator Analysis

We used a subgroup analysis to assess the effects of moderators. Specifically, Hunter and Schmidt (2004) discuss two types of subgroup analyses depending on the type of moderator variable. For dichotomous moderator variables, they suggest splitting the data set by the moderator variable and conducting a separate meta-analysis within each subset of studies. For continuous moderators, Hunter and Schmidt (2004) suggest correlating the potential moderators with the coded effect sizes. They explain that "[w]hen moderators are continuous, the subgrouping method has the disadvantage of requiring dichotomization of the continuous variables to produce the subgroups, thus losing information. When there is only one operator to be examined and it is continuous, simple correlation can be used." (p. 390). Thus, we correlated each continuous moderator with the effect sizes.

We coded the data for moderators. The dichotomous moderators were coded as dummy variables, including the user type (1=consumer, 0=employee), mobile technology (1=mobile, 0=non-mobile), online technology (1=online, 0=offline), and transaction technology (1=transaction, 0=non-transaction). We also coded the data for continuous moderators. We extracted the average user age for each sample (M=34.83 years) and the percentage of women (M=48.78 percent). The studies had data from 77 different countries in our meta-analysis and for 58 of those countries, we could match the country with Hofstede's

(2001) culture dimensions. Similar to other meta-analyses, we used the country information reported in each publication to match the coded correlations with scores for each of Hofstede's culture dimensions from a secondary data source. Specifically, we matched the four dominant culture values reported by Hofstede, Hofstede, & Minkov (2010) with the coded correlations similar to Samaha et al. (2014). The values of the culture dimensions in our meta-analysis range from 11 to 100 for power distance, from 14 to 91 for individualism/collectivism, from 5 to 96 for masculinity/femininity, and from 8 to 100 for uncertainty avoidance. In cases where we could not match the country scores with our data, we used the mean country scores for each culture dimension.

In addition to these substantive moderators, we coded method moderators including the study year and the sampling approach as a dummy variable (1=student sample; 0=non-student). The year when the study was published is included as moderator because the literature indicates that some factors may lose importance/relevance over time (Venkatesh & Bala, 2008). Similarly, we assume that factors not related to a specific technology (i.e., personal innovativeness, education) show weaker effects over time, as users have dealt with a large number of different technologies, whereas factors specific to a technology gain importance (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, price value, and costs). We also consider potential differences between student and non-student samples. Student samples tend to be more homogeneous than non-student samples (Pan & Zinkhan, 2006). Due to this homogeneity, the error variance of the constructs measured in student samples is lower compared to non-student samples that in turn lead to stronger effect sizes (Peterson, 2001). More information about the data coding, effect size integration, SEM, and moderator analysis is reported in Appendix D.

RESULTS

Results of Univariate Analyses

The final results of effect size integration are shown in Table 1.[3] This table shows the results for the final model including the UTAUT predictors and the four suggested extension variables. We found all relationships between the predictor variables shown in Table 1 to be related to behavioral intention and use. We have excluded effect size outliers when integrating effect sizes because they have the potential to impact the findings.

Original UTAUT. The results in Table 1 suggest that among the original UTAUT relationships, most studies examined the effects of performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation on intention. The strongest effects on intention can be observed for habit (sample-sized weighted-reliability adjusted correlation [rc]=.66), performance expectancy (rc=.64), and hedonic motivation (rc=.53). Fewer studies examined the effects of these predictors on use. In addition to behavioral intention (rc=.50), we found strong effects for habit (rc=.56) and performance expectancy (rc=.46) on use. The FSNs exceed the tolerance criterion suggested by Rosenthal (1979), thus suggesting the results were robust and less likely to be influenced by publication bias. The tests also show sufficient power. Also, the Q-test of homogeneity suggests substantial variance in effect sizes, giving an indication of contextual differences and the need for moderator analysis. Also, the credibility intervals were rather wide, suggesting the need for moderator analysis. Finally, the PVAs were lower than 75%, suggesting that a relatively small percentage of variance in effect sizes was attributable to sampling and measurement errors. Taken together, this pattern of results suggests the need for moderator analysis.

UTAUT Extensions. Regarding the four extensions variables, we found that more studies examined relationships predicting intention rather than predicting use. The strongest

[3] The results of effect size integration for all extension variables are reported in Appendix F.

relationships with intention can be observed for compatibility (rc=.66), personal innovativeness (rc=.35), and education (rc=.18). Particularly, compatibility of technology (rc=.44) and personal innovativeness of the user (rc=.36) also showed strong effects on use. Costs of technology showed smaller effect sizes in the univariate analyses. Three of the costs and education credibility intervals included zero, suggesting that the true costs values could be negative or positive in some cases. The moderator analysis provides insights when the positive and negative effects are more likely.[4] For all relationships, the FSNs exceeded the tolerance criterion, suggesting the results to be robust. The power of tests was sufficient. Again, all conducted tests of homogeneity (i.e., Q-test of homogeneity, credibility intervals, PVAs) suggest the need to examine moderators.

As suggested by Grewal, Puccinelli, and Monroe (2018), we also reported the results of the full data set with effect size outliers (Appendix G). The findings were largely similar. The effects of most extensions were slightly stronger after removing outliers. Further, we assessed whether the results differ across different measurements of UTAUT and extension constructs. For example, we compared effect sizes using narrow UTAUT definitions (e.g., performance expectancy) with effect sizes using aliases (e.g., usefulness) and did not observe any significant differences (Appendix H).

[4] The moderator results in Table 4 suggest that the credibility interval for education-use relationship did not include zero for employees [.00; .12] and transaction technologies [.13; .13]. Also, the intervals of education-intention relationship did not include zero for employees [.08; .28], non-Internet technologies [.13; .13], mobile technologies [.03; .15], and student samples [.15; .78]. Finally, the CR interval of the costs-behavioral intention relationship did not include zero for employees [-.83; -.10].

Table 1. Univariate Results

Relationship	k	N	rc	SD	$_{-95\%}$CI	$_{+95\%}$CI	$_{-80\%}$CR	$_{+80\%}$CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PVA
Behavioral Intention (BI)															
Performance expectancy → BI	907	410591	.64*	.20	.63	.65	.39	.89	12694*	26868467	4545	>.999	.039	.041	3.5%
Effort expectancy → BI	781	360834	.51*	.21	.50	.53	.24	.78	12820*	12797262	3915	>.999	.045	.047	4.0%
Social influence → BI	603	302874	.43*	.20	.41	.44	.17	.68	9941*	7326087	3025	>.999	.041	.043	4.5%
Price value → BI	88	34248	.52*	.18	.48	.56	.29	.75	860*	196045	450	>.999	.031	.034	6.6%
Hedonic motivation → BI	208	101318	.53*	.22	.50	.56	.26	.81	3747*	1486817	1050	>.999	.047	.048	3.4%
Facilitating conditions → BI	320	194804	.39*	.19	.37	.41	.14	.64	5715*	1821910	1610	>.999	.038	.039	4.4%
Habit → BI	43	19709	.66*	.18	.61	.72	.43	.89	509*	85638	225	>.999	.033	.034	3.8%
Compatibility → BI	82	84059	.66*	.09	.64	.68	.55	.77	584*	340416	420	>.999	.008	.008	5.5%
Education → BI	22	9649	.18*	.19	.10	.26	-.06	.42	269*	1933	120	>.999	.036	.039	7.8%
Personal innovativeness → BI	96	27415	.35*	.25	.30	.40	.03	.67	1332*	84425	490	>.999	.063	.067	6.0%
Costs → BI	80	38281	-.12*	.32	-.19	-.05	-.53	.29	2778*	14010	410	>.999	.102	.105	2.9%
Use (U)															
Performance expectancy → U	303	110855	.46*	.23	.43	.48	.17	.75	4364*	1593168	1525	>.999	.051	.054	5.0%
Effort expectancy → U	258	94033	.36*	.21	.34	.39	.09	.64	3332*	749490	1300	>.999	.046	.049	6.4%
Social influence → U	196	73128	.32*	.20	.29	.35	.06	.57	2275*	351390	990	>.999	.040	.043	7.5%
Price value → U	23	9492	.34*	.17	.27	.42	.12	.57	223*	6537	125	>.999	.030	.033	8.6%
Hedonic motivation → U	70	29057	.40*	.22	.35	.46	.13	.68	1055*	82260	360	>.999	.047	.049	5.2%
Facilitating conditions → U	158	61873	.37*	.20	.34	.40	.11	.63	1911*	289470	800	>.999	.041	.044	6.7%
Habit → U	24	10437	.56*	.19	.48	.64	.32	.81	295*	19538	130	>.999	.037	.039	4.9%
Compatibility → U	36	10591	.44*	.25	.36	.52	.12	.76	501*	18332	190	>.999	.062	.065	5.3%
Education → U	15	6636	.09*	.10	.04	.15	-.04	.22	63*	169	85	>.999	.010	.014	23.6%
Personal innovativeness → U	20	4828	.36*	.23	.26	.47	.07	.66	200*	2949	110	>.999	.053	.058	8.3%
Costs → U	17	6992	-.26*	.17	-.35	-.18	-.48	-.04	167*	1885	95	>.999	.030	.033	9.2%
Behavioral intention → U	192	67497	.50*	.26	.46	.54	.17	.83	3385*	740408	970	>.999	.065	.068	3.8%

k=number of effect sizes; N=cumulative sample size; rc=sample-sized weighted-reliability adjusted correlation; SD = sample size weighted observed standard deviation of correlations; CI=95%-confidence interval; CR=80% credibility interval; Q=Q statistic; FSN=fail-safe N; Power=power statistics; V_{rho}=variance of population correlation; V_r=variance of observed correlation; PVA= percent of variance in observed correlations due to sampling error and other artifacts; * p<.05.

Results of Structural Equation Modeling

We used SEM to test whether inclusion of the four predictors improves UTAUT (i.e., technology compatibility, user education, personal innovativeness, and costs of technology). We tested further extensions discussed in the UTAUT literature (Appendix I-K). We considered 72 constructs in the full descriptive analyses and 32 constructs as potential extensions using SEM. The final model only considers the four extensions that explain most variance in the dependent variables. We used the correlation matrix, shown in Table 2, as input in LISREL to calculate several models (Models 1-8, Table 3). Table 3 shows the results of these tests.[5] The calculated models were assessed in terms of explained variance and model fit. As shown in Model 1, we first replicated UTAUT2, as proposed by Venkatesh et al. (2012). Then, we tested four models, each by adding one of the four extension variables (Models 2-5). Finally, we combined all four extensions to assess their joint influence together with UTAUT constructs (Models 6-8). As can be seen, the model fit of all calculated models was good. Model 8 explained the most variance in behavioral intention (74.1%) and use (47.2%).

Table 2. Correlations among UTAUT Constructs

		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1.	Use	1.00												
2.	Behavioral intention	.50	1.00											
3.	Compatibility	.44	.66	1.00										
4.	Costs	-.26	-.12	-.02†	1.00									
5.	Effort expectancy	.36	.51	.70	-.07†	1.00								
6.	Education	.09	.18	.21	-.04	.15	1.00							
7.	Hedonic motivation	.40	.53	.57	-.04†	.50	-.04†	1.00						
8.	Facilitating conditions	.37	.39	.37	-.29	.46	.31	.52	1.00					
9.	Habit	.56	.66	.21	-.17†	.39	.09	.42	.39	1.00				
10.	Social influence	.32	.43	.37	-.08†	.36	.21	.43	.28	.48	1.00			
11.	Personal innovativeness	.36	.35	.51	-.31	.37	.15	.40	.30	.11	.27	1.00		
12.	Performance expectancy	.46	.64	.70	-.07†	.60	.17	.58	.41	.45	.44	.33	1.00	
13.	Price value	.34	.52	.50	.00†	.30	.06†	.43	.33	.40	.41	.36	.37	1.00

Note. Harmonic mean across all collected effects is 1,665. † p>.05. The table is based on the data set without effect size outliers.

[5] We also calculated the models using the data set with effect size outliers (Appendix L); results are comparable.

Replication of UTAUT. As shown in Model 1 in Table 3, the replication of UTAUT2 showed that our estimates using all available empirical studies led to results largely similar to what was found in the original study developing UTAUT2 (Venkatesh et al., 2012). The estimated model explained 63.2% of variance in intention (original study: 44%) and 36.2% (original study: 35%) of use. Similar to Venkatesh et al. (2012), we found strong effects of the same predictors on intention, including performance expectancy (.31 vs .21 in original study), effort expectancy (.10 vs .16), hedonic motivation (.08 vs .23), price value (.21 vs .14), and habit (.40 vs .32). Some relationships were slightly weaker in our meta-analysis, presumably due to the large number of different technologies being examined. For example, we found weaker effects for social influence (-.05 vs .14) and facilitating conditions (-.04 vs .16) in our meta-analysis than in the original UTAUT2 study. Similar to Venkatesh et al. (2012), we found strong effects for habit (.40) and performance expectancy (.31). In predicting use, the results of our meta-analysis were also comparable to the original UTAUT2 study. Comparing the meta-analysis and the original UTAUT2 study, we found the strongest effects for habit (.37 vs .24) and behavioral intention (.20 vs .33), whereas the effect of facilitating conditions was weakest (.15 vs .15).

Extending UTAUT: Behavioral Intention. The extended UTAUT, shown in Model 8, showed that 7 out of 11 tested constructs were related to intention. More specifically, we found relationships for performance expectancy (β=.06), price value (β=.03) and habit (β=.59) that have been proposed by Venkatesh et al. (2012). In addition, our meta-analysis suggests the inclusion of compatibility (β=.62) and education (β=.03). Personal innovativeness and technology costs were nonsignificant. Interestingly, the effects of UTAUT predictors effort expectancy and social influence were weak and showed a negative effect when the extension variables were included. The effect of performance expectancy was rather weak in the combined model (Model 8). The effect of effort expectancy turned negative when compatibility was added (Model 2). Similarly, hedonic motivation turned nonsignificant when compatibility was included. Facilitating conditions had weak or negative effects across all individual extensions (Models 2-5). Several of the new predictors explained intention across the various technologies and users examined in the meta-analysis.

Extending UTAUT: Use. The revised UTAUT in Model 8 showed that the effects of intention and facilitating conditions on use were marginal. Facilitating conditions turned nonsignficant when including all extensions in the model. Habit is the only UTAUT predictor that showed a strong effect on use (β=.56). This effect was consistent in all tested models. Among the included new predictors, compatibility (β=.37), technology costs (β=-.14), and personal innovativeness (β=.13) showed strong associations with use. The effect of education was marginal. Having a closer look at the individual extensions, we observe that intention loses importance when compatibility (Model 2) was included. The new predictors explain use better than several of the original UTAUT constructs.

Table 3. Results of Structural Equation Modeling

		Individual Models					Integrated Models		
	UTAUT2 (Venkatesh et al. 2012)	**Model 1: UTAUT2 Replication**	**Model 2: Compatibility Extension**	**Model 3: Education Extension**	**Model 4: Innovativeness Extension**	**Model 5: Costs Extension**	**Model 6: Integrated Model (2)**	**Model 7: Integrated Model (3)**	**Model 8: Integrated Model (4)**
Behavioral intention (R^2)	**44%**	**63.2%**	**73.9%**	**64.2%**	**64.1%**	**63.3%**	**74.0%**	**74.0%**	**74.1%**
Performance Expectancy	.21*	.31*	.06*	.29*	.31*	.31*	.06*	.06*	.06*
Effort Expectancy	.16*	.10*	-.18*	.09*	.07*	.10*	-.18*	-.18*	-.17*
Social Influence	.14*	-.05*	-.06*	-.07*	-.05*	-.05*	-.06*	-.07*	-.07*
Facilitating conditions	.16*	-.04*	-.01	-.09*	-.05*	-.05*	-.02	-.02	-.03
Hedonic motivation	.23*	.08*	-.01	.13*	.06*	.09*	.00	.00	.01
Price value	.14*	.21*	.03	.22*	.19*	.22*	.03*	.03	.03*
Habit	.32*	.40*	.59*	.41*	.43*	.39*	.59*	.60*	.59*
Compatibility	—	—	.64*	—	—	—	.63*	.62*	.62*
Education	—	—	—	.11*	—	—	.03*	.03*	.03*
Personal innovativeness	—	—	—	—	.11*	—	—	.03*	.02
Costs	—	—	—	—	—	-.04*	—	—	-.02
Use (R^2)	**35%**	**36.2%**	**43.3%**	**36.2%**	**41.4%**	**38.0%**	**43.5%**	**45.8**	**47.2%**
Behavioral Intention	.33*	.20*	-.16*	.20*	.09*	.20*	-.15*	-.16*	-.17*
Facilitating Conditions	.15*	.15*	.07*	.16*	.09*	.11*	.08*	.05*	.02
Habit	.24*	.37*	.55*	.37*	.44*	.36*	.55*	.56*	.56*
Compatibility	—	—	.40*	—	—	—	.41*	.33*	.37*
Education	—	—	—	-.03	—	—	-.04*	-.04*	-.04*
Personal innovativeness	—	—	—	—	.26*	—	—	.18*	.13*
Costs	—	—	—	—	—	-.14*	—	—	-.14*
Chi^2(df)	—	61.22(5)	75.16(5)	59.70(5)	47.53(5)	83.83(5)	80.22(5)	107.00(5)	90.34(5)
CFI	—	.991	.992	.992	.994	.988	.992	.990	.992
GFI	—	.992	.991	.993	.994	.990	.991	0.989	.992
SRMR	—	.021	.014	.018	.013	.022	.013	.014	.011

* $p < .05$.

Results of Moderator Analysis

The SEM results suggested that the effects of some UTAUT predictors became marginal when using data from all empirical UTAUT studies and including additional predictors. It seems that the original constructs do not have unconditional effects on intention and use. The moderator analysis helps in explaining whether specific contexts exist when these UTAUT predictors are more likely to demonstrate the expected effect. Some UTAUT predictors show conditional effects in our meta-analysis. We report the moderator results for original UTAUT constructs and the different extensions in Table 4 for dichotomous moderators and in Table 5 for continuous moderators.[6] For dichotomous moderators, we report the weighted and corrected correlations (rwc) next to the moderator variable ($rwc_{high\ moderator}$ vs $rwc_{low\ moderator}$) and the correlation (r) between moderator variable and effect size for continuous moderators. Similar to Gerow et al. (2014), we complemented the subgroup results for dichotomous moderators in Table 4 with additional significance tests to examine differences across moderator levels.

UTAUT Predictors. Results of the moderator tests in Tables 4 and 5 suggested that *performance expectancy* was more likely to influence use for transaction technologies than for non-transaction technologies (H6a: rwc=.57 vs rwc=.44, Table 4) and mobile than non-mobile technologies (H8a: .51 vs .45). The relationship was stronger in high power distance cultures (r=.14, Table 5) and weaker in individualistic (H3a: -.17) and masculine cultures (H4a: -.10). Performance expectancy had stronger effects on behavioral intention in low power distance cultures (-.05) and in individualistic cultures (H3a: .08). We discuss these and other moderating effects in Table 6. The moderator results also suggest that *effort expectancy* gained importance in predicting use for transaction vs. non-transaction technologies (.46 vs .35) and mobile vs. non-mobile technologies (H8b: .44 vs .35). The relationship was stronger in high power distance cultures (.16) and collectivistic cultures (H3d: -.22). For the

[6] Appendix M-N show the results of moderator tests for the full data set and Appendix O-P contrast results of the analyses with and without effect size outliers to display the differences across analyses.

relationship between effort expectancy and behavioral intention, we observed moderating effects for mobile versus non-mobile technologies (H8b: .53 vs 51); also, the relationship was stronger for feminine cultures (H4b: -.09). *Social influence* gained importance in use for transaction technologies (.42 vs .30), Internet technologies (H7c: .34 vs. .27), mobile technologies (.38 vs .30), and collectivistic cultures (H3c: -.12). It gained importance in predicting behavioral intention for transaction technologies (.51 vs .42), mobile technologies (.52 vs .39), and collectivistic cultures (H3c: -.12). We found *price value* had stronger effects on use for high power distance cultures (.33). There were no moderating effects for the relationship between price value and intention. *Hedonic motivation* had a stronger effect on use for transaction technologies (H6b: .51 vs .36). It also had stronger effects on intention for transaction technologies (.62 vs. .52). *Facilitating conditions* showed stronger effects on use for men (-.19) and collectivistic cultures (-.17); it showed stronger effects on intention for transaction technologies (H6d: .50 vs .38), mobile technologies (H8c: .53 vs .36), high power distance cultures (H2b: .14), collectivistic cultures (-.14), and feminine cultures (H4d: -.15). Finally, *habit* was a stronger predictor of use for Internet technologies (.59 vs. .31), high power distance cultures (.51), and collectivistic cultures (-.55); habit was a stronger predictor of intention for high power distance cultures (.36), collectivistic cultures (-.25), and low uncertainty avoidance cultures (-.36).

UTAUT Extensions. The effects of the four extensions (i.e., compatibility, education, personal innovativeness, and costs) on intention and use were moderated by study context. *Compatibility* with the user's lifestyle had stronger effects on use for collectivistic cultures (-.44); it also had stronger effects on intention for women (.18). *Education* also showed some interaction effects. It showed stronger effects on use for women (.64) and low uncertainty avoidance cultures (-.71). It had stronger effects on intention in collectivistic cultures (-.51). The relationship between *personal innovativeness* and use was stronger for transaction technologies (.65 vs .28), younger users (-.37), and collectivistic cultures (-.42). Its relationship with intention was stronger for mobile technologies (.43 vs .28). Finally, *technology costs* showed stronger negative effects on use for transaction technologies (-.41 vs -.19), Moreover, it showed stronger negative effects on intention for transaction technologies (-.47 vs -.05), non-mobile technologies (-.28 vs -.05), low power distance cultures (.20), feminine cultures (.23), and high uncertainty avoidance cultures (-.28).

Method Moderators. We also assessed the effects of study year and sampling approach. As expected, student samples were found to display stronger effect sizes than nonstudent samples for some relationships (e.g., facilitating conditions, social influence, and hedonic motivation). Also, we found numerous effects of study year, with effect sizes being stronger in recent years (e.g., performance expectancy, effort expectancy, and social influence). Similar moderating influences can be observed for other relationships.

Table 4. Subgroup Analysis for Dichotomous Moderators

IV	DV	k	N	rc	SD	$_{-95\%}$CI	$_{+95\%}$CI	$_{-80\%}$CR	$_{+80\%}$CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PAV	F	Sig.
Performance expectancy	Use	303	110855	.46*	.23	.43	.48	.17	.75	4364*	1593168	1525	>.999	.051	.054	5.0%		
	Consumer	201	83387	.47*	.22	.44	.50	.19	.75	3117*	805393	1015	>.999	.049	.051	4.6%	1.76	.19
	Employee	102	27468	.43*	.24	.38	.48	.12	.73	1222*	132962	520	>.999	.057	.061	6.3%		
	Transaction	44	16749	.57*	.20	.51	.63	.31	.83	520*	56177	230	>.999	.040	.042	4.9%	12.63	.00[a]
	Non-transaction	259	94106	.44*	.23	.41	.47	.15	.73	3660*	1050812	1305	>.999	.051	.054	4.1%		
	Internet	201	75487	.47*	.23	.44	.50	.18	.76	2958*	735519	1015	>.999	.051	.054	4.4%	.97	.33
	Non-Internet	102	35368	.44*	.23	.39	.48	.15	.73	1393*	163588	520	>.999	.051	.054	5.5%		
	Mobile	60	19161	.51*	.20	.46	.56	.26	.76	578*	77946	310	>.999	.039	.041	6.8%	3.78	.05
	Non-mobile	243	91694	.45*	.23	.42	.48	.15	.74	3742*	966108	1225	>.999	.053	.056	4.8%		
	Student	96	33984	.44*	.20	.40	.48	.18	.70	1065*	141374	490	>.999	.041	.044	6.7%	.26	.61
	Non-student	207	76871	.47*	.24	.43	.50	.16	.77	3291*	785148	1045	>.999	.056	.058	4.5%		
Effort expectancy	Use	258	94033	.36*	.21	.34	.39	.09	.64	3332*	749490	1300	>.999	.046	.049	6.4%		
	Consumer	178	73018	.37*	.22	.33	.40	.09	.65	2653*	407568	900	>.999	.047	.050	5.5%	.09	.77
	Employee	80	21015	.35*	.20	.31	.40	.10	.61	677*	51599	410	>.999	.040	.044	9.8%		
	Transaction	33	12357	.46*	.22	.39	.54	.18	.74	454*	21564	175	>.999	.047	.050	5.2%	6.96	.01[a]
	Non-transaction	225	81676	.35*	.21	.32	.38	.08	.62	2777*	516623	1135	>.999	.044	.047	6.8%		
	Internet	167	61894	.38*	.21	.35	.41	.11	.65	2168*	345891	845	>.999	.045	.048	6.2%	2.92	.09
	Non-Internet	91	32139	.33*	.21	.28	.38	.06	.60	1123*	76978	465	>.999	.045	.048	6.9%		
	Mobile	53	17901	.44*	.24	.37	.50	.14	.74	765*	45424	275	>.999	.056	.059	5.2%	6.89	.01
	Non-mobile	205	76132	.35*	.20	.32	.38	.09	.61	2480*	425716	1035	>.999	.042	.045	6.9%		
	Student	85	26723	.37*	.22	.32	.42	.09	.65	969*	73201	435	>.999	.048	.051	7.2%	.23	.63
	Non-student	173	67310	.36*	.21	.33	.40	.09	.63	2363*	354049	875	>.999	.045	.048	6.0%		
Social influence	Use	196	73128	.32*	.20	.29	.35	.06	.57	2275*	351390	990	>.999	.040	.043	7.5%		
	Consumer	133	53764	.32*	.21	.28	.35	.05	.58	1774*	171862	675	>.999	.043	.046	6.5%	.00	.96
	Employee	63	19364	.32*	.18	.27	.36	.09	.55	500*	31701	325	>.999	.032	.036	10.9%		
	Transaction	25	9570	.42*	.17	.36	.49	.21	.64	225*	9764	135	>.999	.028	.031	8.3%	8.28	.00[a]
	Non-transaction	171	63558	.30*	.20	.27	.33	.04	.55	1952*	243874	865	>.999	.040	.043	7.7%		
	Internet	128	44968	.34*	.22	.31	.38	.06	.63	1691*	160714	650	>.999	.049	.052	6.4%	5.60	.02[a]
	Non-Internet	68	28160	.27*	.15	.23	.31	.08	.46	513*	36756	350	>.999	.022	.026	12.0%		
	Mobile	46	15614	.38*	.21	.32	.44	.11	.64	514*	24806	240	>.999	.043	.046	7.3%	4.77	.03
	Non-mobile	150	57514	.30*	.19	.27	.33	.05	.55	1707*	189339	760	>.999	.038	.041	7.8%		
	Student	64	22369	.31*	.19	.26	.36	.06	.56	627*	32463	330	>.999	.037	.041	8.9%	.00	.99
	Non-student	132	50759	.32*	.20	.28	.35	.06	.58	1647*	170103	670	>.999	.041	.044	6.9%		
Price value	Use	23	9492	.34*	.17	.27	.42	.12	.57	223*	6537	125	>.999	.030	.033	8.6%		
	Consumer	19	8092	.37*	.17	.29	.45	.15	.59	179*	5380	105	>.999	.028	.031	8.6%	2.40	.14
	Employee	4	1400	.20*	.12	.07	.33	.05	.35	19*	53	30	>.999	.014	.018	20.2%		
	Transaction	10	3200	.38*	.23	.23	.53	.08	.68	135*	1140	60	>.999	.055	.058	5.9%	.56	.46

IV	DV	k	N	rc	SD	$_{-95\%}$CI	$_{+95\%}$CI	$_{-80\%}$CR	$_{+80\%}$CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PAV	F	Sig.
	Non-transaction	13	6292	.33*	.13	.25	.40	.16	.49	85*	2204	75	>.999	.016	.019	13.1%		
	Internet	18	6959	.35*	.19	.25	.44	.10	.59	203*	3793	100	>.999	.037	.040	7.4%	.03	.87
	Non-Internet	5	2533	.34*	.10	.25	.43	.22	.46	21*	366	35	>.999	.009	.012	20.5%		
	Mobile	12	5024	.35*	.17	.24	.45	.13	.57	119*	1806	70	>.999	.030	.032	8.4%	.00	.96
	Non-mobile	11	4468	.34*	.17	.23	.45	.12	.57	105*	1461	65	>.999	.030	.033	8.8%		
	Student	8	2478	.44*	.16	.32	.55	.23	.64	50*	989	50	>.999	.025	.028	11.8%	2.61	.12
	Non-student	15	7014	.31*	.17	.22	.40	.10	.53	153*	2427	85	>.999	.028	.030	8.5%		
Hedonic motivation	Use	70	29057	.40*	.22	.35	.46	.13	.68	1055*	82260	360	>.999	.047	.049	5.2%		
	Consumer	63	27038	.41*	.22	.35	.46	.13	.69	1004*	356	325	>.999	.048	.050	4.9%	.25	.62
	Employee	7	2019	.35*	.17	.22	.49	.13	.57	47*	356	45	>.999	.029	.033	12.5%		
	Transaction	19	8960	.51*	.17	.43	.58	.29	.72	193*	356	105	>.999	.027	.029	6.5%	7.75	.01[a]
	Non-transaction	51	20097	.36*	.22	.30	.42	.08	.64	761*	356	265	>.999	.048	.051	5.6%		
	Internet	59	23848	.42*	.22	.37	.48	.15	.70	871*	356	305	>.999	.047	.049	5.1%	2.38	.13
	Non-Internet	11	5209	.31*	.19	.20	.43	.07	.56	147*	356	65	>.999	.037	.039	6.6%		
	Mobile	22	8362	.45*	.24	.34	.55	.14	.75	371*	356	120	>.999	.058	.061	4.4%	.90	.35
	Non-mobile	48	20695	.39*	.20	.33	.45	.13	.65	670*	356	250	>.999	.041	.044	5.7%		
	Student	23	7403	.47*	.21	.38	.56	.20	.75	272*	356	125	>.999	.046	.049	5.9%	2.71	.10
	Non-student	47	21654	.38*	.21	.32	.44	.11	.65	748*	356	245	>.999	.045	.047	5.1%		
Facilitating conditions	Use	158	61873	.37*	.20	.34	.40	.11	.63	1911*	289470	800	>.999	.041	.044	6.7%		
	Consumer	101	44640	.38*	.20	.34	.42	.12	.64	1348*	136916	515	>.999	.041	.043	6.1%	.52	.47
	Employee	56	17233	.36*	.20	.30	.41	.09	.62	559*	28173	290	>.999	.042	.046	8.4%		
	Transaction	21	8684	.44*	.17	.36	.52	.22	.66	208*	7629	115	>.999	.030	.033	7.5%	2.33	.13
	Non-transaction	136	53189	.36*	.21	.32	.40	.10	.62	1671*	203002	690	>.999	.042	.045	6.8%		
	Internet	98	37069	.38*	.19	.34	.42	.13	.63	1061*	111794	500	>.999	.038	.041	7.5%	.22	.64
	Non-Internet	59	24804	.36*	.22	.30	.42	.09	.64	847*	41422	305	>.999	.046	.049	5.8%		
	Mobile	26	9429	.39*	.16	.32	.45	.18	.59	190*	8531	140	>.999	.026	.029	11.1%	.17	.68
	Non-mobile	131	52444	.37*	.21	.33	.41	.10	.64	1720*	198486	665	>.999	.044	.047	6.3%		
	Student	46	18011	.43*	.24	.36	.50	.13	.73	714*	30661	240	>.999	.056	.059	5.0%	5.32	.02
	Non-student	111	43862	.35*	.18	.31	.39	.11	.59	1145*	131612	565	>.999	.034	.037	8.1%		
Habit	Use	24	10437	.56*	.19	.48	.64	.32	.81	295*	19538	130	>.999	.037	.039	4.9%		
	Consumer	20	9157	.55*	.20	.46	.64	.30	.81	283*	13914	110	>.999	.040	.042	4.3%	.31	.58
	Employee	4	1280	.61*	.09	.51	.71	.50	.73	10*	472	30	>.999	.008	.011	23.0%		
	Transaction	8	3851	.58*	.12	.49	.67	.42	.74	49*	2401	50	>.999	.015	.017	9.2%	.06	.82
	Non-transaction	16	6586	.55*	.22	.44	.66	.26	.83	245*	8226	90	>.999	.050	.052	4.1%		
	Internet	22	9056	.59*	.15	.53	.66	.40	.79	168*	17106	120	>.999	.023	.025	7.2%	5.56	.03
	Non-Internet	2	1381	.31	.25	-.05	.66	-.02	.63	60*	–	–	>.999	.063	.065	2.9%		
	Mobile	10	4883	.56*	.15	.46	.65	.37	.75	82*	3592	60	>.999	.022	.023	7.4%	.00	1.00
	Non-mobile	14	5554	.56*	.22	.44	.68	.28	.85	213*	6362	80	>.999	.049	.051	3.9%		

IV	DV	k	N	rc	SD	-95% CI	+95% CI	-80% CR	+80% CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PAV	F	Sig.
	Student	9	2636	.57*	.19	.44	.70	.32	.81	73*	1969	55	>.999	.036	.039	7.4%	.02	.88
	Non-student	15	7801	.56*	.19	.46	.66	.31	.80	222*	9084	85	>.999	.037	.038	4.0%		
Compatibility	Use	36	10591	.44*	.25	.36	.52	.12	.76	501*	18332	190	>.999	.062	.065	5.3%		
	Consumer	22	7294	.42*	.25	.31	.53	.09	.74	359*	7027	120	>.999	.065	.068	4.7%	.45	.51
	Employee	14	3297	.49*	.23	.37	.61	.20	.78	133*	2646	80	>.999	.051	.055	7.3%		
	Transaction	5	2197	.41*	.23	.20	.61	.11	.70	89*	556	35	>.999	.054	.056	4.4%	.12	.74
	Non-transaction	31	8394	.45*	.25	.36	.54	.13	.77	410*	12479	165	>.999	.063	.067	5.6%		
	Internet	21	6655	.44*	.26	.33	.55	.11	.77	335*	6911	115	>.999	.066	.069	4.6%	.01	.91
	Non-Internet	15	3936	.44*	.23	.32	.56	.14	.74	166*	2717	85	>.999	.055	.059	6.8%		
	Mobile	12	4231	.43*	.23	.30	.56	.14	.72	172*	2329	70	>.999	.053	.055	5.2%	.02	.90
	Non-mobile	24	6360	.45*	.26	.34	.55	.11	.78	328*	7570	130	>.999	.068	.071	5.4%		
	Student	12	3329	.44*	.22	.31	.57	.16	.72	121*	1772	70	>.999	.047	.051	7.4%	.00	.98
	Non-student	24	7262	.44*	.26	.33	.55	.11	.77	380*	8678	130	>.999	.068	.072	4.7%		
Education	Use	15	6636	.09*	.10	.04	.15	-.04	.22	63*	169	85	>.999	.010	.014	23.6%		
	Consumer	9	3766	.12*	.12	.03	.21	-.03	.28	48*	97	55	>.999	.015	.018	18.4%	1.21	.29
	Employee	6	2870	.06*	.05	.00	.12	.00	.12	10	5	40	.942	.002	.005	58.2%		
	Transaction	3	2334	.13*	.00	.09	.17	.13	.13	2	29	25	>.999	.000	.001	100.0%	.50	.49
	Non-transaction	12	4302	.08*	.12	.00	.16	-.08	.24	58*	51	70	.996	.016	.020	20.5%		
	Internet	11	5385	.09*	.08	.03	.15	-.01	.19	36*	71	65	>.999	.006	.009	30.7%	.13	.72
	Non-Internet	4	1251	.11	.17	-.07	.28	-.11	.32	27*	–	–	.988	.028	.033	14.5%		
	Mobile	1	976	.10	.00	–	–	–	–	–	–	–	–	–	–	–	.00	.96
	Non-mobile	14	5660	.09*	.11	.03	.16	-.05	.24	63*	129	80	>.999	.012	.016	22.0%		
	Student	3	398	.21	.29	-.14	.56	-.16	.59	24*	–	–	.995	.085	.096	11.8%	1.37	.26
	Non-student	12	6238	.09*	.07	.04	.14	-.01	.18	35*	123	70	>.999	.005	.008	33.8%		
Personal innovativeness	Use	20	4828	.36*	.23	.26	.47	.07	.66	200*	2949	110	>.999	.053	.058	8.3%		
	Consumer	12	2941	.43*	.25	.28	.58	.10	.75	147*	1525	70	>.999	.065	.069	6.2%	2.42	.14
	Employee	8	1887	.26*	.12	.15	.36	.10	.41	28*	226	50	>.999	.016	.021	26.2%		
	Transaction	3	1046	.65*	.22	.40	.91	.37	.94	40*	369	25	>.999	.049	.051	3.5%	12.77	.00[a]
	Non-transaction	17	3782	.28*	.15	.20	.35	.09	.46	73*	1222	95	>.999	.022	.027	20.9%		
	Internet	14	3573	.36*	.26	.22	.50	.03	.69	184*	1531	80	>.999	.067	.071	6.3%	.00	1.00
	Non-Internet	6	1255	.36*	.11	.25	.47	.22	.50	16*	224	40	>.999	.012	.018	31.5%		
	Mobile	5	1620	.32*	.14	.18	.45	.14	.49	27*	250	35	>.999	.019	.023	16.1%	.26	.62
	Non-mobile	15	3208	.38*	.26	.25	.52	.05	.72	169*	1468	85	>.999	.068	.073	7.2%		
	Student	4	1140	.24*	.00	.18	.30	.24	.24	3	60	30	>.999	.000	.004	100.0%	1.38	.25
	Non-student	16	3688	.40-	.25	.27	.53	.08	.72	181*	2144	90	>.999	.063	.068	7.0%		
Costs	Use	17	6992	-.26-	.17	-.35	-.18	-.48	-.04	167*	1885	95	>.999	.030	.033	9.2%		
	Consumer	16	6856	-.26-	.17	-.34	-.17	-.47	-.04	159*	1605	90	>.999	.029	.032	9.2%	.75	.40
	Employee	1	136	-.54-	.00	–	–	–	–	–	–	–	–	–	–	–		

IV	DV	k	N	rc	SD	$_{-95\%}$CI	$_{+95\%}$CI	$_{-80\%}$CR	$_{+80\%}$CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PAV	F	Sig.
	Transaction	5	2156	-.41*	.16	-.56	-.26	-.61	-.21	44*	303	35	>.999	.025	.028	8.8%	6.41	.02[a]
	Non-transaction	12	4836	-.19*	.13	-.27	-.11	-.36	-.02	72*	667	70	>.999	.017	.021	15.8%		
	Internet	12	5015	-.30*	.18	-.40	-.19	-.53	-.07	125*	1177	70	>.999	.032	.035	8.4%	1.65	.22
	Non-Internet	5	1977	-.17*	.12	-.29	-.05	-.32	-.02	25*	78	35	>.999	.014	.018	18.9%		
	Mobile	9	3086	-.19*	.13	-.29	-.10	-.36	-.02	47*	288	55	>.999	.017	.021	18.2%	1.83	.20
	Non-mobile	8	3906	-.32*	.18	-.45	-.19	-.55	-.08	101*	688	50	>.999	.033	.036	6.9%		
	Student	4	967	-.28*	.21	-.49	-.06	-.54	-.01	34*	91	30	>.999	.043	.049	10.7%	.02	.88
	Non-student	13	6025	-.26*	.17	-.35	-.16	-.47	-.05	133*	1133	75	>.999	.028	.030	8.9%		
Behavioral intention	Use	192	67497	.50*	.26	.46	.54	.17	.83	3385*	740408	970	>.999	.065	.068	3.8%		
	Consumer	133	51872	.51*	.27	.46	.56	.17	.85	2827*	402323	675	>.999	.071	.074	3.1%	.78	.38
	Employee	58	15625	.47*	.21	.42	.53	.20	.74	546*	51103	300	>.999	.044	.048	7.6%		
	Transaction	25	9453	.63*	.26	.53	.74	.29	.97	522*	22244	135	>.999	.070	.072	2.3%	9.31	.00[a]
	Non-transaction	166	58044	.48*	.25	.44	.52	.16	.79	2712*	505858	840	>.999	.061	.064	4.3%		
	Internet	121	45124	.55*	.26	.51	.60	.22	.88	2331*	366087	615	>.999	.067	.070	3.1%	15.94	.00[a]
	Non-Internet	70	22373	.39*	.21	.34	.44	.12	.66	776*	65175	360	>.999	.044	.048	7.2%		
	Mobile	37	12913	.54*	.20	.47	.60	.28	.80	411*	33503	195	>.999	.042	.044	5.6%	1.25	.27
	Non-mobile	154	54584	.49*	.27	.45	.53	.15	.83	2959*	458774	780	>.999	.071	.073	3.6%		
	Student	66	20812	.44*	.26	.38	.51	.11	.77	1040*	67657	340	>.999	.067	.070	4.7%	3.52	.06
	Non-student	125	46685	.52*	.25	.48	.57	.20	.85	2274*	360288	635	>.999	.063	.065	3.5%		
Performance expectancy	Behavioral intention	907	410591	.64*	.20	.63	.65	.39	.89	12694*	26868467	4545	>.999	.039	.041	3.5%		
	Consumer	715	361081	.64*	.20	.63	.66	.39	.90	11325*	18357936	3585	>.999	.040	.041	3.0%	1.58	.21
	Employee	192	49510	.61*	.18	.58	.64	.38	.84	1330*	807772	970	>.999	.033	.036	7.6%		
	Transaction	136	47884	.62*	.18	.59	.65	.38	.85	1283*	602267	690	>.999	.034	.036	5.4%	.55	.46
	Non-transaction	771	362707	.64*	.20	.63	.66	.39	.90	11392*	19424595	3865	>.999	.040	.041	3.3%		
	Internet	661	326160	.64*	.20	.63	.66	.38	.91	10829*	15226349	3315	>.999	.042	.043	2.9%	1.06	.30
	Non-Internet	246	84431	.62*	.17	.60	.64	.41	.83	1832*	1641708	1240	>.999	.028	.030	7.1%		
	Mobile	253	102239	.61*	.19	.59	.64	.37	.85	2678*	2088051	1275	>.999	.034	.036	5.1%	3.01	.08
	Non-mobile	654	308352	.65*	.20	.63	.66	.39	.90	9942*	13975514	3280	>.999	.040	.042	3.1%		
	Student	342	109594	.61*	.17	.59	.63	.39	.84	2643*	3203687	1720	>.999	.030	.033	6.8%	2.33	.13
	Non-student	565	300997	.65*	.20	.63	.67	.39	.91	9980*	11515871	2835	>.999	.042	.043	2.6%		
Effort expectancy	Behavioral intention	781	360834	.51*	.21	.50	.53	.24	.78	12820*	12797262	3915	>.999	.045	.047	4.0%		
	Consumer	617	319000	.52*	.21	.50	.54	.25	.79	11279*	9038179	3095	>.999	.045	.047	3.5%	3.11	.08[a]
	Employee	164	41834	.47*	.21	.44	.50	.20	.74	1476*	325850	830	>.999	.043	.047	7.8%		
	Transaction	110	39184	.50*	.20	.47	.54	.25	.76	1208*	265628	560	>.999	.039	.041	6.1%	.16	.69
	Non-transaction	671	321650	.51*	.21	.50	.53	.24	.79	11610*	9374791	3365	>.999	.046	.048	3.7%		
	Internet	567	288784	.51*	.21	.50	.53	.24	.79	10382*	7403196	2845	>.999	.045	.047	3.5%	.01	.94
	Non-Internet	214	72050	.51*	.21	.48	.53	.24	.77	2434*	733292	1080	>.999	.044	.047	5.8%		
	Mobile	221	87994	.53*	.21	.51	.56	.26	.81	2964*	1087703	1115	>.999	.045	.047	4.7%	4.07	.04

IV	DV	k	N	rc	SD	$_{-95\%}$CI	$_{+95\%}$CI	$_{-80\%}$CR	$_{+80\%}$CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PAV	F	Sig.
	Non-mobile	560	272840	.51*	.21	.49	.52	.23	.78	9817*	6422620	2810	>.999	.045	.047	3.7%		
	Student	290	93117	.52*	.21	.50	.55	.26	.79	3083*	1553038	1460	>.999	.043	.045	6.0%	1.53	.22
	Non-student	491	267717	.51*	.21	.49	.53	.24	.78	9725*	5433579	2465	>.999	.046	.047	3.3%		
Social influence	Behavioral intention	603	302874	.43*	.20	.41	.44	.17	.68	9941*	7326087	3025	>.999	.041	.043	4.5%		
	Consumer	480	272451	.43*	.20	.41	.44	.17	.68	8910*	5270846	2410	>.999	.041	.042	4.0%	.00	.98
	Employee	123	30423	.43*	.21	.39	.47	.17	.70	1030*	168674	625	>.999	.042	.046	9.0%		
	Transaction	89	32454	.51*	.21	.46	.55	.24	.78	1164*	184783	455	>.999	.045	.047	5.0%	9.61	.00[a]
	Non-transaction	514	270420	.42*	.20	.40	.43	.16	.67	8585*	5183389	2580	>.999	.039	.041	4.5%		
	Internet	441	242722	.42*	.21	.41	.44	.16	.69	8404*	4470792	2215	>.999	.043	.044	3.9%	.00	.96
	Non-Internet	162	60152	.43*	.18	.40	.46	.20	.66	1536*	350606	820	>.999	.033	.036	8.0%		
	Mobile	194	83692	.52*	.19	.49	.54	.28	.76	2290*	881570	980	>.999	.036	.038	5.6%	40.29	.00[a]
	Non-mobile	409	219182	.39*	.20	.37	.41	.14	.65	6970*	3124578	2055	>.999	.039	.041	4.6%		
	Student	226	72373	.47*	.18	.45	.50	.24	.71	1933*	868153	1140	>.999	.034	.037	8.3%	8.90	.00[a]
	Non-student	377	230501	.41*	.21	.39	.43	.15	.67	7857*	3149955	1895	>.999	.042	.044	3.6%		
Price value	Behavioral intention	88	34248	.52*	.18	.48	.56	.29	.75	860*	196045	450	>.999	.031	.034	6.6%		
	Consumer	83	32955	.52*	.17	.48	.56	.30	.74	777*	178959	425	>.999	.029	.031	6.9%	.15	.70
	Employee	5	1293	.52*	.29	.26	.78	.15	.89	84*	385	35	>.999	.086	.089	3.8%		
	Transaction	18	5574	.54*	.24	.43	.66	.23	.86	251*	7958	100	>.999	.059	.062	4.4%	.43	.51
	Non-transaction	70	28674	.51*	.16	.47	.55	.31	.72	606*	124936	360	>.999	.026	.028	7.5%		
	Internet	75	29912	.51*	.17	.47	.55	.29	.73	715*	140400	385	>.999	.030	.032	6.8%	.62	.43
	Non-Internet	13	4336	.55*	.20	.44	.67	.29	.81	141*	4620	75	>.999	.042	.044	5.5%		
	Mobile	52	20253	.53*	.15	.49	.58	.34	.73	392*	69144	270	>.999	.023	.025	8.2%	.68	.41
	Non-mobile	36	13995	.50*	.21	.43	.57	.23	.76	460*	32299	190	>.999	.044	.046	5.3%		
	Student	26	6954	.57*	.13	.52	.63	.40	.74	105*	15285	140	>.999	.018	.021	14.3%	2.16	.15
	Non-student	62	27294	.50*	.18	.46	.55	.27	.74	735*	101783	320	>.999	.034	.036	5.6%		
Hedonic motivation	Behavioral intention	208	101318	.53*	.22	.50	.56	.26	.81	3747*	1486817	1050	>.999	.047	.048	3.4%		
	Consumer	196	98467	.53*	.22	.50	.57	.26	.81	3700*	1370709	990	>.999	.047	.049	3.2%	.04	.85
	Employee	12	2851	.53*	.14	.45	.62	.35	.71	47*	2348	70	>.999	.019	.023	16.0%		
	Transaction	30	14692	.62*	.20	.55	.69	.37	.88	475*	43239	160	>.999	.040	.041	3.1%	5.03	.03[a]
	Non-transaction	178	86626	.52*	.22	.49	.55	.24	.80	3172*	1022799	900	>.999	.046	.048	3.6%		
	Internet	176	93361	.53*	.22	.50	.56	.26	.81	3418*	1177405	890	>.999	.046	.048	3.2%	.34	.56
	Non-Internet	32	7957	.56*	.22	.48	.65	.28	.85	323*	17997	170	>.999	.050	.054	5.8%		
	Mobile	86	34343	.57*	.20	.53	.61	.32	.82	1048*	243138	440	>.999	.038	.040	4.7%	3.37	.07
	Non-mobile	122	66975	.52*	.22	.48	.56	.23	.80	2653*	527330	620	>.999	.050	.051	2.9%		
	Student	88	24570	.62*	.19	.58	.66	.38	.86	714*	202425	450	>.999	.036	.038	6.2%	10.53	.00[a]
	Non-student	120	76748	.51*	.22	.47	.55	.23	.78	2846*	591890	610	>.999	.047	.048	2.7%		
Facilitating conditions	Behavioral intention	320	194804	.39*	.19	.37	.41	.14	.64	5715*	1821910	1610	>.999	.038	.039	4.4%		
	Consumer	234	174553	.39*	.19	.36	.41	.15	.62	4732*	1204179	1180	>.999	.035	.036	3.9%	.56	.46

IV	DV	k	N	rc	SD	$_{-95\%}$CI	$_{+95\%}$CI	$_{-80\%}$CR	$_{+80\%}$CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PAV	F	Sig.
	Employee	86	20251	.41*	.25	.36	.47	.09	.73	975*	63641	440	>.999	.063	.068	6.9%		
	Transaction	48	21065	.50*	.23	.43	.56	.20	.79	850*	53869	250	>.999	.053	.055	3.8%	10.43	.00[a]
	Non-transaction	272	173739	.38*	.19	.35	.40	.14	.61	4668*	1248980	1370	>.999	.034	.036	4.7%		
	Internet	214	162277	.39*	.19	.36	.41	.15	.63	4476*	999815	1080	>.999	.035	.037	3.8%	.02	.87
	Non-Internet	106	32527	.40*	.22	.35	.44	.11	.68	1238*	122314	540	>.999	.050	.054	6.8%		
	Mobile	69	29557	.53*	.21	.48	.58	.25	.80	1010*	127601	355	>.999	.045	.047	4.4%	27.98	.00[a]
	Non-mobile	251	165247	.36*	.18	.34	.39	.13	.59	4222*	984986	1265	>.999	.032	.034	4.8%		
	Student	103	40776	.50*	.19	.47	.54	.26	.75	1124*	208269	525	>.999	.036	.038	6.2%	27.80	.00[a]
	Non-student	217	154028	.36*	.18	.33	.38	.12	.59	4103*	797986	1095	>.999	.034	.035	4.3%		
Habit	Behavioral intention	43	19709	.66*	.18	.61	.72	.43	.89	509*	85638	225	>.999	.033	.034	3.8%		
	Consumer	37	17858	.67*	.17	.61	.72	.45	.89	421*	66714	195	>.999	.030	.031	3.9%	.00	.99
	Employee	6	1851	.63*	.26	.43	.84	.31	.96	87*	1174	40	>.999	.066	.068	3.5%		
	Transaction	10	4448	.73*	.11	.66	.80	.59	.87	44*	6176	60	>.999	.012	.013	8.1%	1.55	.22
	Non-transaction	33	15261	.64*	.19	.58	.71	.40	.89	447*	45789	175	>.999	.037	.039	3.5%		
	Internet	36	17248	.68*	.14	.64	.73	.50	.86	277*	65612	190	>.999	.020	.021	5.4%	2.88	.10
	Non-Internet	7	2461	.50*	.33	.26	.75	.09	.92	183*	1325	45	>.999	.107	.110	2.6%		
	Mobile	15	10107	.68*	.14	.61	.75	.51	.86	155*	16037	85	>.999	.019	.019	3.9%	.37	.55
	Non-mobile	28	9602	.64*	.22	.56	.72	.36	.92	347*	27533	150	>.999	.048	.050	4.0%		
	Student	18	5871	.64*	.24	.52	.75	.33	.94	256*	10813	100	>.999	.058	.060	3.5%	.37	.55
	Non-student	25	13838	.67*	.15	.61	.73	.48	.86	248*	35560	135	>.999	.022	.023	4.3%		
Compatibility	Behavioral intention	82	84059	.66*	.09	.64	.68	.55	.77	584*	340416	420	>.999	.008	.008	5.4%		
	Consumer	67	81725	.67*	.08	.65	.69	.56	.77	493*	280965	345	>.999	.007	.007	5.2%	3.77	.06[a]
	Employee	15	2334	.55*	.19	.45	.65	.31	.79	69*	2836	85	>.999	.036	.042	13.6%		
	Transaction	17	6251	.70*	.12	.64	.76	.55	.86	77*	12252	95	>.999	.015	.016	8.7%	1.02	.32
	Non-transaction	65	77808	.66*	.08	.64	.68	.55	.77	499*	223433	335	>.999	.007	.007	5.1%		
	Internet	62	78393	.66*	.08	.64	.68	.56	.77	465*	229864	320	>.999	.006	.007	5.1%	.71	.40
	Non-Internet	20	5666	.64*	.16	.57	.71	.44	.84	116*	10799	110	>.999	.025	.027	8.3%		
	Mobile	34	9427	.62*	.17	.56	.67	.40	.83	216*	32563	180	>.999	.028	.031	8.2%	2.56	.11
	Non-mobile	48	74632	.67*	.07	.65	.69	.58	.76	352*	162342	250	>.999	.005	.005	5.2%		
	Student	27	10336	.73*	.14	.68	.79	.55	.91	156*	30975	145	>.999	.020	.021	6.6%	7.27	.01[a]
	Non-student	55	73723	.65*	.07	.63	.68	.56	.75	387*	165958	285	>.999	.006	.006	5.5%		
Education	Behavioral intention	22	9649	.18*	.19	.10	.26	-.06	.42	269*	1933	120	>.999	.036	.039	7.8%		
	Consumer	16	8937	.18*	.19	.08	.28	-.07	.43	261*	1415	90	>.999	.038	.040	5.9%	.00	.98
	Employee	6	712	.18*	.08	.08	.29	.08	.28	9	35	40	>.999	.006	.017	64.8%		
	Transaction	0	–	–	–	–	–	–	–	–	–	–	–	–	–	–		
	Non-transaction	22	9649	.18*	.19	.10	.26	-.06	.42	269*	1933	120	>.999	.036	.039	7.8%		
	Internet	16	8967	.18*	.20	.09	.28	-.07	.43	265*	1550	90	>.999	.038	.041	5.8%	.08	.78
	Non-Internet	6	682	.13*	.00	.07	.20	.13	.13	4	16	40	.961	.000	.007	100.0%		

IV	DV	k	N	rc	SD	$_{-95\%}$CI	$_{+95\%}$CI	$_{-80\%}$CR	$_{+80\%}$CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PAV	F	Sig.
	Mobile	2	4450	.09*	.05	.02	.17	.03	.15	9*	24	20	>.999	.002	.003	22.3%	4.01	.06
	Non-mobile	20	5199	.25*	.23	.15	.36	-.04	.55	214*	1509	110	>.999	.052	.056	8.5%		
	Student	5	1276	.46*	.25	.24	.68	.15	.78	64*	215	35	>.999	.061	.064	5.5%	9.59	.01[a]
	Non-student	17	8373	.13*	.13	.07	.20	-.03	.30	113*	847	95	>.999	.016	.019	14.8%		
Personal innovativeness	Behavioral intention	96	27415	.35*	.25	.30	.40	.03	.67	1332*	84425	490	>.999	.063	.067	6.0%		
	Consumer	76	22938	.35*	.26	.29	.41	.02	.68	1182*	58761	390	>.999	.067	.070	5.3%	.04	.84
	Employee	20	4477	.34*	.20	.24	.43	.08	.60	150*	2300	110	>.999	.042	.047	11.3%		
	Transaction	12	3996	.37*	.45	.12	.63	-.20	.95	588*	2097	70	>.999	.200	.203	1.6%	.17	.68
	Non-transaction	84	23419	.35*	.20	.30	.39	.09	.60	743*	59843	430	>.999	.039	.044	9.5%		
	Internet	70	20599	.35*	.27	.29	.42	.01	.70	1147*	47627	360	>.999	.072	.076	5.1%	.02	.88
	Non-Internet	26	6816	.34*	.18	.27	.41	.11	.57	185*	5205	140	>.999	.033	.038	11.8%		
	Mobile	37	12330	.43*	.21	.37	.50	.17	.70	403*	20441	195	>.999	.042	.045	6.9%	8.44	.00[a]
	Non-mobile	59	15085	.28*	.26	.21	.35	-.05	.62	816*	21734	305	>.999	.069	.074	6.4%		
	Student	30	8888	.42*	.17	.36	.48	.21	.63	196*	10538	160	>.999	.027	.031	11.7%	3.04	.08
	Non-student	66	18527	.32*	.28	.25	.39	-.04	.67	1089*	35248	340	>.999	.076	.080	5.2%		
Costs	Behavioral intention	80	38281	-.12*	.32	-.19	-.05	-.53	.29	2778*	14010	410	>.999	.102	.105	2.9%		
	Consumer	76	37598	-.12*	.32	-.19	-.05	-.53	.29	2717*	13254	390	>.999	.102	.105	2.8%	.02	.89
	Employee	4	683	-.14	.34	-.49	.20	-.58	.29	61*	–	–	.979	.116	.124	6.4%		
	Transaction	16	5652	-.47*	.29	-.61	-.32	-.83	-.10	355*	3593	90	>.999	.082	.085	3.2%	21.43	.00[a]
	Non-transaction	64	32629	-.05	.28	-.12	.02	-.41	.31	1821*	–	–	>.999	.079	.082	3.5%		
	Internet	66	25358	-.16*	.37	-.25	-.07	-.62	.31	2503*	11982	340	>.999	.133	.137	2.6%	2.80	.10[a]
	Non-Internet	14	12923	-.03	.15	-.11	.05	-.22	.15	187*	–	–	.961	.021	.023	7.5%		
	Mobile	45	27331	-.05	.29	-.14	.03	-.42	.31	1584*	–	–	>.999	.082	.085	2.9%	8.41	.00[a]
	Non-mobile	35	10950	-.28*	.34	-.39	-.16	-.71	.16	922*	5119	185	>.999	.114	.118	3.4%		
	Student	20	5182	-.31*	.28	-.44	-.19	-.67	.04	317*	2329	110	>.999	.078	.083	5.5%	4.41	.04[a]
	Non-student	60	33099	-.09*	.31	-.17	-.01	-.49	.32	2290*	4872	310	>.999	.098	.101	2.6%		

k=number of effect sizes; N=cumulative sample size; rc=sample-sized weighted-reliability adjusted correlation; SD = sample size weighted observed standard deviation of correlations; CI=95%-confidence interval; CR=80% credibility interval; Q=Q statistic; FSN=fail-safe N; F=F-test; * p<.05. a. The confidence intervals and the F-test display similar results for moderator test.

Table 5. Results of Subgroup Analysis for Continuous Moderators

IV	DV		Age	Female	PDI	IND-COL	MAS-FEM	UA	Year
Performance expectancy	Use	r	-.06	.00	.14	-.17	-.10	.02	.12
		Sig.	.16	.48	.01	.00	.04	.39	.02
		k	303	303	303	303	303	303	303
Effort expectancy	Use	r	.06	.08	.16	-.22	-.08	-.04	.14
		Sig.	.16	.10	.01	.00	.09	.28	.01
		k	258	258	258	258	258	258	258
Social influence	Use	r	-.05	-.06	.05	-.12	-.05	-.04	.29
		Sig.	.24	.21	.23	.04	.25	.31	.00
		k	196	196	196	196	196	196	196
Price value	Use	r	-.17	-.04	.33	-.29	-.30	.05	.36
		Sig.	.22	.43	.05	.09	.09	.40	.05
		k	23	23	23	23	23	23	23
Hedonic motivation	Use	r	-.10	.09	.16	-.15	-.04	-.16	.04
		Sig.	.20	.23	.09	.12	.38	.10	.36
		k	70	70	70	70	70	70	70
Facilitating conditions	Use	r	.03	-.19	.10	-.17	-.03	.02	.12
		Sig.	.35	.01	.11	.02	.34	.38	.07
		k	157	157	157	157	157	157	157
Habit	Use	r	-.09	.06	.51	-.55	-.18	-.26	.39
		Sig.	.34	.39	.01	.00	.20	.11	.03
		k	24	24	24	24	24	24	24
Compatibility	Use	r	.05	-.02	.23	-.44	-.04	.10	.08
		Sig.	.38	.45	.09	.00	.42	.28	.33
		k	36	36	36	36	36	36	36
Education	Use	r	.23	.64	-.14	-.33	.29	-.71	.45
		Sig.	.20	.01	.31	.11	.14	.00	.05
		k	15	15	15	15	15	15	15
Personal innovativeness	Use	r	-.37	.18	.00	-.42	-.26	.31	.02
		Sig.	.05	.22	.49	.03	.13	.09	.47
		k	20	20	20	20	20	20	20
Costs[a]	Use	r	-.18	.09	.31	-.10	.12	-.32	-.35
		Sig.	.25	.37	.11	.35	.33	.11	.09
		k	17	17	17	17	17	17	17
Behavioral intention	Use	r	-.01	.06	.02	-.09	.02	.03	.05
		Sig.	.43	.21	.41	.12	.41	.32	.25
		k	191	191	191	191	191	191	191
Performance expectancy	Behavioral intention	r	.05	.05	-.05	.08	-.01	.01	.07
		Sig.	.06	.08	.05	.01	.36	.33	.02
		k	907	907	907	907	907	907	907
Effort expectancy	Behavioral intention	r	.05	.02	.02	-.04	-.09	.05	.09
		Sig.	.07	.26	.32	.13	.01	.06	.00
		k	781	780	781	781	781	781	781
Social influence	Behavioral intention	r	.00	-.01	.06	-.12	-.02	.05	.18
		Sig.	.46	.43	.06	.00	.29	.13	.00
		k	603	603	603	603	603	603	603
Price value	Behavioral intention	r	-.15	.07	.00	-.07	-.13	.11	.02
		Sig.	.08	.25	.50	.27	.12	.15	.41
		k	88	88	88	88	88	88	88
Hedonic motivation	Behavioral intention	r	.05	.01	.02	.07	.05	-.02	.10
		Sig.	.23	.43	.37	.17	.23	.37	.08
		k	208	208	208	208	208	208	208
Facilitating conditions	Behavioral intention	r	-.03	-.02	.14	-.14	-.15	.02	.11
		Sig.	.29	.34	.01	.01	.00	.37	.03
		k	320	320	320	320	320	320	320
Habit	Behavioral intention	r	.06	-.04	.36	-.25	-.06	-.36	.13
		Sig.	.35	.41	.01	.05	.36	.01	.20
		k	43	43	43	43	43	43	43

IV	DV		Age	Female	PDI	IND-COL	MAS-FEM	UA	Year
Compatibility	Behavioral intention	r	-.08	.18	-.02	.10	-.14	.09	.27
		Sig.	.25	.05	.43	.18	.10	.22	.01
		k	82	82	82	82	82	82	82
Education	Behavioral intention	r	.13	.26	.16	-.51	.06	-.19	-.18
		Sig.	.29	.12	.24	.01	.39	.20	.21
		k	22	22	22	22	22	22	22
Personal innovativeness	Behavioral intention	r	-.03	-.08	-.06	.03	-.14	.10	.07
		Sig.	.40	.21	.28	.38	.09	.17	.26
		k	96	96	96	96	96	96	96
Costs[a]	Behavioral intention	r	-.10	-.05	.20	-.09	.23	-.28	.03
		Sig.	.18	.34	.04	.20	.02	.01	.41
		k	80	80	80	80	80	80	80

r=correlation between continuous moderator and effect size; k=number of effect sizes. PDI = power distance of country culture; IND-COL=individualism versus collectivism of culture; MAS-FEM=masculinity versus femininity of culture; UA=uncertainty avoidance of culture.

a. The main effect of costs is negative and this is important to consider when interpreting the moderator results.

Table 6. Interpretation of Moderator Results

Moderator	Results	Interpretation
Age	Personal innovativeness is more relevant to younger users predicting use. No further differences were observed.	➢ Personal innovativeness was important for younger users because their technology preferences have yet to be shaped (Spitzer, 2006; Rahi & Ghani, 2018).
Women	While education gains relevance for women when predicting use, facilitating conditions loses relevance. Compatibility gains relevance for women when predicting intention.	➢ Women tend to display greater self-criticism, thus making education gain importance. They emphasize work-life balance, thus making compatibility with their values and past experiences gain relevance. ➢ Women tend to view technology as a tool that can increase productivity, whereas men tend to view technology as more of a toy for fun (Bain & Rice, 2006). Men show greater interest in technology, making them want to interact more with the technology provider and use their support (Igbaria, Greenhaus, & Parasuraman, 1991).
Consumers	We observed only marginal or nonsignificant effects of this moderator on the relationship between UTAUT predictors (H1a-H1f) and both behavioral intention and use.	➢ There were few differences when UTAUT was applied in the context of consumer or employee use of technology. ➢ UTAUT can be applied and generalized across studies that examine consumer or work-related contexts.
Power distance	The effects of effort expectancy, price value, and habit on use were stronger for countries with higher power distance. The effects of facilitating conditions (H2b) and habit on intention were stronger for countries with higher power distance, whereas the effect of costs was weaker. Performance expectancy was more relevant in predicting use in high power distance countries, whereas it was less so for behaviorial intention. No effect was observed for social influence (H2a).	➢ In higher power distance cultures, individuals conform more and are less independent (Matusitz & Musambira, 2013). Users in high power distance cultures have greater expectations of the firm to support and enable technology use because the firm is perceived as being more powerful than in low power distance cultures; thus, effort expectancy, facilitating conditions, and price value were both important predictors. They seem to care less about the costs. ➢ For the same reason, performance expectancy was more relevant in predicting use in high power distance countries; however, the weaker effect on intention is surprising. ➢ Due to the greater reliance on powerful members of society (e.g., firms), users were more likely to develop a habit to use the technology.
Individualism-collectivism	The effects of effort expectancy (H3d), social influence (H3c), facilitating conditions, habit, compatibility, and personal innovativeness on use were weaker for individualistic countries. The effects of social influence (H3c), facilitating conditions, habit, and education on intention were weaker for individualistic countries. Performance expectancy (H3a) was weaker for individualistc countries in predicting use but when it comes to behavioral intention, it had a stronger effect. No effect was observed for hedonic motivation (H3b).	➢ Users in individualistic cultures in general prioritize need satisfaction and they are more willing to use new technology (Hofstede, 2001). ➢ In collectivistic cultures, users would be less likely to challenge the norm (Im et al., 2011) and use technology whose use is habitual, has high compatibility with existing technologies, and has a good set of facilitating conditions. ➢ In collectivistic cultures, people tend to follow others' decisions. However, with greater personal innovativeness, they are more likely to seek information on their own and be more willing to be independent decision makers when deciding to use new technology (Lee, Trimi, & Kim, 2013). ➢ In collectivistic cultures, where people will usually follow the norm, those who find technology easy to use will still decide to use a technology without conforming to others (Chong, Chan, & Ooi, 2012). It is more important that users have good education.
Masculinity-femininit	Performance expectancy (H4a) had a weaker effect on use in masculine culture countries. The effects of effort expectancy (H4b), facilitating conditions (H4d), and costs on intention were weaker in masculine culture countries.	➢ Users in masculine cultures are more likely to explore the use of technology and are more likely to be interested in performance accomplishments (Im et al., 2011). Thus, users reflect less on whether the technology would be challenging to use or not, and whether support is offered. Instead, they try the latest technology or try to use more complex functions to maintain an edge over others (Ma &

Moderator	Results	Interpretation
	No effect was observed for social influence (H4c).	Turel, 2019). ➢ Interestingly, performance expectancy had a stronger effect in feminine cultures, suggesting that users in these cultures assess technology more critically and expect it to provide benefits to users. Users focus on feminine values such as quality of life (Huang, Choi, & Chengalur-Smith, 2010), and hence cost of a new technology is important to them because users could spend the money in more pleasurable ways.
Uncertainty avoidance	The effect of education on use was weaker in high uncertainty avoidance countries. The effect of habit on intention was weaker in high uncertainty avoidance countries, whereas the effects of costs were stronger. No effect were observed for facilitating conditions (H5a), social influence (H5b), and effort expectancy (H5c).	➢ In high uncertainty avoidance cultures, users do not tolerate uncertainty (Im et al., 2011); relying on technology costs (Lu, Yao, & Yu, 2005) helps to cope with uncertainty because higher costs often imply better product quality (Agarwal & Teas, 2002). ➢ Users from low uncertainty avoidance cultures do not need detailed technology information (Im et al., 2011); they are also going to use it once it becomes a habit for them. Interestingly, education gains importance in the use of technology in these cultures; some education may be needed to enjoy the use of technology.
Transaction	The effects of performance expectancy (H6a), effort expectancy, social influence, hedonic motivations (H6b), personal innovativeness, and costs on use were stronger for transaction technologies. The effects of social influence, hedonic motivations (H6b), facilitating conditions (H6d), and costs on intention were stronger for transaction technologies. No significant difference was found for habit (H6c).	➢ Transaction technologies are associated with financial risks and users are more likely to use them if they find it useful and easy to use, with good facilitating conditions, and if people important to them also use the technology (Chong, 2013; Loh et al., 2020). Innovative users are also more likely to use the technology. Users also consider the cost of the transactional technology because it is an indicator for quality/secure transactions (Loh et al., 2020). ➢ Users are also more likely to use transactional technology if they find it enjoyable, as the technology is often related to online shopping (Ramayah & Ignatius, 2005).
Internet	The effect of social influence (H7c) and habit on use were stronger for Internet technologies. No effects were observed for effort expectancy (H7a) and facilitating condition (H7b).	➢ Users employ online technologies, such as social media, to foster social relationships and engage in social comparisons. ➢ Using the Internet has now become a habit for most users, and it is being used for both work and daily life (Haythornthwaite & Wellman, 2002).
Mobile	The effects of performance expectancy (H8a), effort expectancy (H8b), and social influence on use gain importance for mobile technologies when compared to non-mobile technologies. The effects of effort expectancy (H8b), social influence, facilitating conditions (H8c), and personal innovativeness on intention gained importance for mobile technologies; costs lost importance for mobile technologies.	➢ Mobile technologies offer new service concepts to users making innovativeness trait gain relevance (Chong et al., 2012). ➢ Mobile technologies improve connectivity, and people tend to use these technologies if their social circle and people who are important to them also use these technologies (Chong et al., 2012). ➢ Mobile technologies are often consumer focused (Venkatesh et al., 2012). Consumers who enjoy using a mobile technology care less about costs. Mobile technologies are improving constantly making performance expectancy, effort expectancy, and facilitating conditions gain importance (Hew et al., 2015).

DISCUSSION

Although UTAUT is a theory that is of great importance in IS, in recent times, an increasing number of cries have suggested that research on UTAUT and other acceptance theories may have reached their limit regarding insights to be gained. Given the widespread misspecification of prior replications and extensions of this theory, and the narrow focus and limited database of prior meta-analyses, the present work assessed whether UTAUT is a robust theory or whether a new UTAUT specification is in order. More specifically, our meta-analysis clarified whether and which of the central tenets of UTAUT were supported. We then formulated a state-of-the-art, revised UTAUT that can guide future research. The revised UTAUT extended the theory with four additional predictors that were found to be more influential for many technologies than even some of the theory's original predictors and UTAUT 2 predictors. Also, UTAUT should be extended by considering additional contextual differences that characterizes the specific context in which the theory is employed. The effects in the revised UTAUT depend not only on user characteristics as moderators, but also on national culture and technology type as moderators, thus underscoring the need for more cross-context UTAUT theorizing.

Theoretical Contributions

Our results suggest that the current conceptualizations of UTAUT and UTAUT2 have limitations. The results suggest that four new predictor variables—i.e., technology compatibility, user education, personal innovativeness, and costs of technology—explain substantial variance in intention and use above and beyond the variance explained by current predictors. Our findings indicates that the new predictors cover aspects that are not considered either in UTAUT or UTAUT2. As such, when employing UTAUT in future technology studies, researchers should consider the revised UTAUT that includes these four new predictors. Despite advances in IT, technology compatibility remains an important issue for users or organizations that plan to adopt new technology. Often, when there is a new radical technological innovation, an organization may find it a challenge to embrace the new technology (Hill & Rothaermel, 2003). This is especially true when a new technology is part of an existing platform or ecosystem, or when an organization has made a strategic commitment to implement a system with its partners (e.g., supply chain partners), thus making the adoption of the new technology to be highly inflexible.

Although some demographic characteristics were used in prior UTAUT studies, user education and personal innovativeness were shown to be the most important user characteristics that can influence adoption decisions. Finally, users were found to consider the monetary cost of buying/using the technology to be important. We found this effect for consumer and organizational technologies. Similar to consumers, employees seem to consider the costs of technology although employees may not need to pay for the technology themselves. Thus, it is important to incorporate cost of technology in the theory even in organizational contexts.

Our meta-analysis also suggests that several of the original UTAUT predictors show weaker effects when including new predictors, emphasizing the relative importance of new predictors. Without considering these four predictors, scholars cannot fully understand the factors determining technology use. We identified these factors using a systematic approach that considered a large number of potential [extension] variables. Although prior research on UTAUT assessed additional predictors on an ad-hoc basis usually by testing one additional predictor, our meta-analysis found that the new predictors outperform the alternative [extension] variables (Appendixes J-K). Our meta-analysis thereby clarified which of the potential extensions should be considered in future UTAUT studies. Interestingly, the new predictors mainly relate to users and their personal circumstances. These findings contribute to the debate about the importance of user-oriented technology design versus selecting the "right" users. It seems that user characteristics explain more variance in technology use than technology beliefs do.

Moreover, synthesizing the research across numerous study contexts, our meta-analysis found substantial variance in the UTAUT relationships. This variance in relationships suggests the presence of moderating variables exerting an influence. This is an important finding because it has been common practice to only examine the main effects in UTAUT, while neglecting contextual differences and moderator effects. This result also suggests that there is not just one UTAUT specification with a universal set of predictors that applies to all contexts. Instead, the theory's ability to predict technology use depends on the specific context. Although we found that some relationships in the revised UTAUT are generalizable across users, technologies, and cultures, most relationships differ in strength across these contexts and they are not easily generalizable (many relationships with intention and use are moderated; Tables 4 and 5). This finding also emphasizes the need for the importance of cross-context theorizing when trying to understand technology use. Thus, scholars should always consider moderators when applying UTAUT and they can also use the results of the moderator tests to compare their findings with ours. Scholars can use our findings to explain why certain predictors turn out to be less important in their studies.

More specifically, our meta-analysis found contextual differences not only across user types, but also across different technology types—i.e., mobile vs. non-mobile, online vs. offline, and transaction vs. non-transaction. We classified the large number of technologies examined in prior UTAUT research using this broad classification. As expected, there were a wide range of technologies studied in prior research. In our research, due to the exploratory nature of our meta-analysis, we were able to group previous technologies studied in UTAUT into different categories. Despite having many types of technologies being examined by UTAUT, the three types of technologies were found to have substantial contextual differences, thus providing us clearer insights into the boundary conditions of the theory. Although some UTAUT studies have tested technology differences before, the employed technology type variables were too narrow to cover all types of technologies. The revised UTAUT shows the benefits of employing a widely applicable technology classification. Thus, scholars can use this comprehensive classification to compose a UTAUT specification that predicts technology use in different contexts. Although the two key predictors, i.e., performance expectancy and effort expectancy, were found to have relatively weak effects across many technology types, these two variables gain importance when studying mobile technologies. Thus, studies examining mobile technologies should focus on these variables. Similar conclusions can be drawn for other technology types (i.e., Internet technologies and transaction technologies).

National culture has to also be considered when using UTAUT because culture variables moderate key UTAUT relationships, as indicated by the number of significant moderation effects in our moderator tests. Because prior research had conducted simple two-country comparisons, scholars were aware of the importance of cultural differences. Our work built on such prior research and clarified which specific culture variables speak to the contextualization of UTAUT. We found that all four culture dimensions, proposed by Hofstede (2001), exert a moderating effect. Most cultural differences were observed for individualism-collectivism and power distance, but some differences were also observed for masculinity-femininity and uncertainty avoidance. Scholars can use these findings to tailor UTAUT for different cultures. For example, in highly collectivistic cultures, such as South Korea, certain predictors, such as effort expectancy, social influence, and education, gain importance. Again, scholars can use these results to retrospectively explain why certain predictors show weaker effects in a specific study. Certain predictors may display weaker effects in a specific cultural setting due to the user socialization.

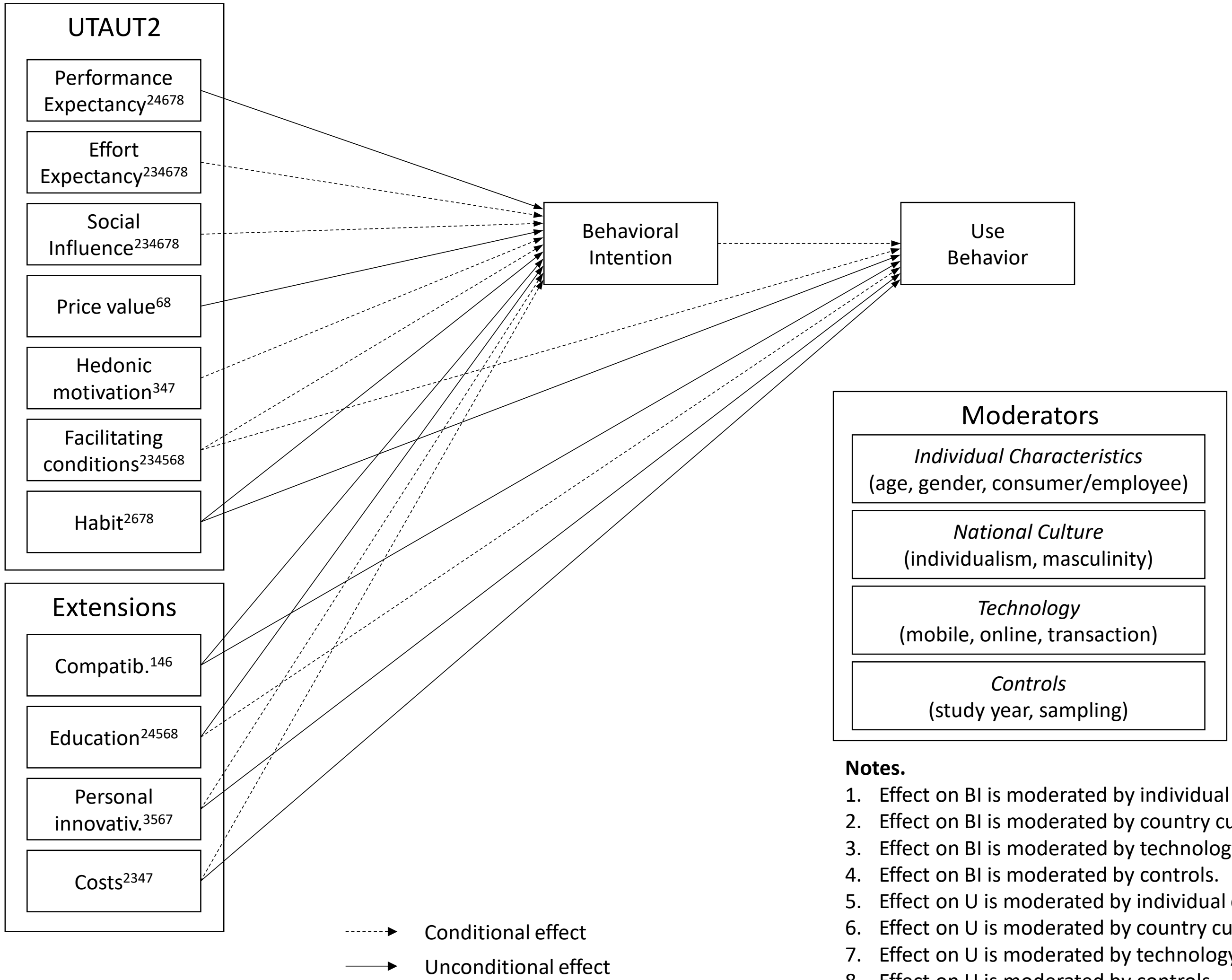
We also observe that many UTAUT predictor show stronger effects in later studies applying this theory compared to early studies. Venkatesh and Bala (2008) explained that, as users gain more experience with technology, various factors related to the specific technology (i.e., adjustment factors) gain importance (see also Venkatesh, 2000). Since many UTAUT factors were found to vary over time, it seems that the experiences with various technologies are without difficulty transferable to a specific technology, thus making the user adjustment effect rather strong.

Key conclusions from our results are summarized in Table 7. Figure 1 shows the revised UTAUT that complements the current UTAUT specification with four additional predictors and considers further moderators characterizing the study context. This revised theory explains more variance in intention and use than UTAUT and UTAUT2 do. This theory also provides detailed insights into the contextual importance of the eleven predictors explaining behavioral intention and use and provides insights into the generalizability of this theory.

Table 7. Recommended Practices for UTAUT Research

Finding	Recommendation
UTAUT predictors and outcomes	
1. The original UTAUT and UTAUT2 predictors are related to intention and use, but the effects are weaker than expected.	➢ Scholars should use the full set of UTAUT variables, whenever possible; excluding some predictors may yield inaccurate findings related to the relative importance of different predictors of use. ➢ However, scholars can use the moderator results to assess when specific predictors are more important than others in different contexts.
2. Results in Table 3 suggest that four new predictors explain substantial variance in use.	➢ UTAUT studies should include technology compatibility, user education, personal innovativeness, and costs of technology as predictors because they are more important than most original predictors.
3. The new predictors were identified in a systematic testing approach assessing 23 potential extensions in several SEMs.	➢ Scholars should include the four new predictors rather than the other tested extensions (Appendices J-K) because they are more likely to explain use.
4. Inclusion of new predictors makes some original UTAUT predictors lose importance.	➢ This finding implies that the new predictors are of unconditional importance, whereas the original predictors are of conditional importance.
Contextualization of UTAUT research	
5. We found substantial variation in effect sizes (Table 1) that can be explained by moderators (Tables 4 and 5).	➢ This finding stresses that UTAUT studies should always consider contextual differences, requiring cross-contextual theorizing. The minimum expectation is that studies include the individual characteristics as moderators (i.e., age and gender).
6. We found several interaction effects between three technology types and UTAUT predictors (Table 4).	➢ Studies testing a larger number of different technologies should use the technology types (mobile technology, online technology, and transaction technology) as moderators. ➢ Scholars can also use the results of our moderator tests to explain contradictory findings in their own research. It may be that one predictor is less important in their study due to the examined technology type.
7. We found UTAUT effects to depend on four culture variables (power distance, individualism-collectivism, masculinity-femininity, and uncertainty avoidance; Table 5).	➢ Research should consider the country and the four corresponding culture variables when interpreting their results. User socialization in a specific culture impacts technology perception and use. National culture may explain the varying importance of predictors in different studies.
8. The importance of some UTAUT predictors varies over time (Table 5).	➢ Scholars should consider the time at which a specific technology is available to users. Many UTAUT predictors gained importance over time.

Figure 1. UTAUT: A Synthesis of Extensions



Notes.
1. Effect on BI is moderated by individual characteristics.
2. Effect on BI is moderated by country culture.
3. Effect on BI is moderated by technology.
4. Effect on BI is moderated by controls.
5. Effect on U is moderated by individual characteristics.
6. Effect on U is moderated by country culture.
7. Effect on U is moderated by technology.
8. Effect on U is moderated by controls.

Scientific Implications

With our meta-analysis, we intended to shed new light on directions for research that can continue to enhance our understanding of technology adoption and UTAUT. Table 8 summarizes our key recommendations for future research and we elaborate on them here. First, scholars should examine *theoretically meaningful predictors*. Our meta-analysis found habit to be the most important predictor among the set of original predictors. Although the literature differentiates between types of user behavior, they have received little attention so far. Users may purchase technologies impulsively due to a sudden urge or use technology because of addiction. A recent meta-analysis on consumer impulse formation identified key predictors and psychological processes that led to an individual's urge to engage in impulsive behavior (Iyer et al., 2020). This literature will help in extending UTAUT to include impulsive technology use. Similarly, compulsive behavior is another stream in consumer research that scholars should examine to further extend UTAUT. Research is also needed on situational predictors of technology use such as whether the user is alone when using technology or whether a friend or family member observes, helps or participates in the technology use. Other situational factors may be the user's monetary budget restrictions and time pressure. It would be interesting to assess the interplay between these restrictions and other predictors such as the user's impulsiveness to use technology.

Second, research should pay more attention to *variables at the group/organization level*. Most extensions considered in various UTAUT studies are based on individual-level theories. However, scholars should assess whether individual-level predictors impact outcomes of technology use at other levels such as the group (e.g., team performance) and firm (e.g., firm performance). Similarly, group-level predictors (e.g., team composition) and firm-level predictors (e.g., manager's leadership style) may influence technology outcomes at the individual level. Studies should examine cross-level moderation effects as well as multi-level mediation. Organizational studies stress that multi-level theories help overcoming the division of micro and macro camps in organizational research. These theories typically describe “some combination of individuals, dyads, teams, businesses, corporations, and industries” (Klein, Tosi, & Cannella, 1999, p. 243). Such theories may provide IS scholars a deeper and richer portrait of technology use and help linking constructs that were previously unlinked in IS literature like individual-level technology use predictors and organizational-level outcomes such as competitive advantage and firm performance.

Third, scholars are encouraged to better *understand UTAUT mechanisms*. Our meta-analysis suggests four new predictors to add to UTAUT. These new endogenous mechanisms, i.e., technology compatibility, user education, personal innovativeness, and costs of technology, have important implications for future research. These four predictors relate to different theories that should be used by scholars to deepen our understanding about technology adoption. For example, more research is needed on the antecedents of the four mechanisms and trait theory is a fruitful way of providing insights on how traits like personal innovativeness form and change. It is important to understand how key traits evolve and which other user traits may have an influence on technology use. Mowen’s (2000) 3M model of motivation and personality may be interesting to consider, including hierarchical personality models assuming that more abstract, cross-situational traits impact narrow situation-specific behavioral tendencies of an individual that then influence behavior—here, technology use. Similarly, more research is needed about the process of habit formation and whether firms can contribute to this process.

Fourth, we encourage scholars to extend research on *outcomes of technology use*. Most of the collected studies examined intention and use. It seems promising to also examine the influence of UTAUT predictors on other outcome variables. Transformative research suggests that technology has the potential to contribute to user’s well-being. Thus, it may be interesting to examine non-traditional outcomes emphasized in this literature stream (e.g., literacy, decreasing disparity, health, happiness). Also, future research should examine assimilation, diffusion, and routinization of technology use that are not examined much in studies that have employed UTAUT, although they are reasonably well researched in adoption studies at the organizational level. It is also worth examining whether the predictors display curvilinear effects on these outcomes, as has been shown with some of the UTAUT predictors on individual-level outcomes (e.g., Brown, Venkatesh, & Goyal, 2012, 2014; Venkatesh & Goyal, 2010).

Fifth, the study of *novel mediators and moderators* is a promising avenue for future research. One interesting mediator discussed in recent IS research and related literature is brand equity of the firm (e.g., Xu, Thong, & Venkatesh, 2014). Managers often introduce technology not only to provide services to users, but also to improve the firm's brand image. Technology use may improve brand equity that in turn impacts brand loyalty. Other novel mediators may be customer experience (sensory, affective, behavioral, intellectual; Brakus, Schmitt, & Zarantonello, 2009) and customer engagement (cognitive, affective, behavioral; Hollebeek et al., 2019). Regarding moderators, scholars could draw from theories in related fields. The concept of cross-national differences may be useful in this context. This concept suggests that country markets differ regarding several characteristics that have the potential to impact the importance of different predictors in the revised UTAUT to explain use (Swoboda, Puchert, & Morschett, 2016). According to Berry, Guillén, and Zhou (2010), these differences include factors like (1) economic factors, (2) legislative system, (3) composition of the country's population, and (4) political system. Studies should also examine the interplay between predictors in the revised UTAUT model and a country's heterogeneity measuring the ethnic, linguistic, and religious fractionalization in the country on behavioral intention and technology use.[7] For example, it may be that social influence had weaker effects on use in

[7] Ethnic fractionalization reflects the number of different ethnic groups, languages, and religions in one country.

diverse countries because societal ties between different groups are weaker. Also, it may be more difficult to communicate the performance benefits of technology in more diverse countries making performance expectancy lose importance as a predictor of use in diverse countries. Also, we noticed that many UTAUT studies do not report information on voluntariness of technology use. Appropriate reporting and testing of this moderator is essential in order to accurately test the theory and the situational contingency (i.e., voluntariness) specified in it.

Sixth, more research is needed to *broaden the conceptualization of predictors and moderators*. Related literature suggests various conceptualizations of key UTAUT predictors. Scholars should test alternative measurements of these predictors. For instance, our findings suggest that the four new predictors relate to user characteristics (i.e., education and personal innovativeness) and their personal circumstances (i.e., compatibility with lifestyle and costs of technology). It may be interesting to differentiate not only different types of user lifestyles that may vary across the user's private and work life, but also different social groups with which the user identifies. Similar extensions should be assessed for other user characteristics. With respect to moderators, we suggest incorporating more research and theories from cross-cultural psychology. While existing research on culture and technology use stress the importance of national culture for understanding user behavior, this research stream would greatly benefit from examining more novel conceptualizations of culture. Culture can generally be measured not only at the national-level similar to the present meta-analysis, but also at the individual user level (Rai, Maruping, & Venkatesh, 2009). These cultural orientations of users may be better suited to explain variance in UTAUT relationships than national culture is—Lenartowicz and Roth (2001, p. 150) explain that individual cultural orientations predict individual behavior better than national culture "unless collective cultural values are strongly shared by the members of the cultural group" (see Hoehle, Zhang, &

Venkatesh, 2015). Related to this, Triandis and Gelfand (1998) distinguished between different individual-level cultural orientations including horizontal and vertical individualism and collectivism. Nowadays, it is also common for users to belong to and to be influenced by more than one culture (multiculturalism) compared to users who belong to just one culture (monoculturalism). Further, scholars should develop novel technology classifications. Our meta-analysis extends Meuter et al.'s (2000) classification and uses it to explain variance in different UTAUT relationships. We encourage scholars to engage in more cross-contextual research by collecting data covering a larger number of technologies and start classifying them given that the classification used in our meta-analysis seemed to be useful in explaining variations in UTAUT relationships. Scholars should build on work on goal-directed systems and task-technology fit to develop more nuanced classifications of technology types (Novak, Hoffman, & Duhachek, 2003; Goodhue & Thompson, 1995)

Seventh, more research is needed on the *changing importance of predictors* over time. Although longitudinal studies are proposed, as well as collecting data for behavioral intention and use, not many studies are doing it. One promising area to study is how UTAUT predictors change over time during the lifecycle of users' experiences/interactions with technology, especially over longer time horizons compared to what is typical (e.g., about 5 months in Venkatesh et al., 2003). Research should assess whether we need a specification of UTAUT for various stages of use beyond the conceptualization of experience and its impact on UTAUT relationships, as reported in Venkatesh et al. (2003), and Venkatesh et al. (2012). The role of time (Venkatesh et al., 2006; Venkatesh et al., 2021), with latent growth modeling as one approach (e.g., Bala & Venkatesh, 2013) could be used to enrich our understanding.

Finally, scholars are encouraged to *use different research designs* in their studies. UTAUT would benefit from using a purposeful sampling approach to examine theoretically interesting study participants and technologies not covered in the meta-analysis. For example, future research could apply and extend the revised UTAUT when studying the acceptance of novel technologies such as chat bots or social robots. Studies could examine the specific characteristics of chat bots and social robots (e.g., anthropomorphism, negative attitude toward robots) as predictors/moderators in UTAUT. Using qualitative studies may provide further insights into surprising moderating effects found in this meta-analysis, thus helping us discover reasons for these patterns (for mixed methods research guidelines, see Creswell, 2002; Venkatesh, Brown, & Sullivan, 2016; Venkatesh, Brown, & Bala, 2013).

CONCLUSION

Our meta-analysis synthesized research on UTAUT to assess the robustness of this theory and assess the inclusion of important variables, predictors, and moderators. Our findings highlight that the theory is less robust than it is often assumed to be. We assessed the impact of 23 potential extensions using SEM and found UTAUT to benefit from the inclusion of four new endogenous mechanisms from different theories (i.e., technology compatibility, user education, personal innovativeness, and costs of technology). Inclusion of these predictors makes some of the original predictors lose importance. Moreover, we contribute to a better understanding about the generalizability and concomitant contextualization of UTAUT in different contexts by identifying various moderators (e.g., technology type, national culture). We use the insights gained from this comprehensive synthesis of extant research to arrive at a new UTAUT specification. Against this backdrop, we present directions for future research that can continue to enhance UTAUT and leverage it meaningfully.

Table 8. Research Agenda on UTAUT

Issues	Key Illustrative Recommendations
Examine theoretically meaningful predictors	• Drivers characterizing impulsive behavior (e.g., urge to use technology) • Drivers characterizing compulsive behavior (e.g., Internet addiction) • Assess situational predictors in UTAUT (e.g., user alone or accompanied, time-pressure, financial restrictions) • Test interactions between predictors (e.g., user traits, such as impulsiveness, and situational predictors such as financial resources)
Expand the focus on variables at higher levels (e.g., group, organization)	• Examine the effects of individual-level variables (e.g., technology use) on outcomes at a higher level (e.g., organization's competitive advantage, firm performance) • Assess cross-level direct effects of variables residing at higher levels, such as the team (e.g., leadership style, team composition, team climate) or organization (firm resources, dynamic capabilities), as predictors of use • Test interactions between higher-level predictors (e.g., leadership style) and lower-level moderators (user innovativeness) • Theorize more complex interaction effects such as between collectivism in a country (culture) and economic situation (GDP) • Assess multi-level mediation between user characteristics on technology use and then, the impact of technology use on firm performance • Examine more levels of analysis, including individuals, dyads, teams, businesses, corporations, and industries
Use novel theories to understand UTAUT mechanisms	• Examine formation of new predictors like personal innovativeness (e.g., abstract traits impact specific traits; Mowen, 2000) • Examine established predictors (e.g., whether firms can encourage habit formation by offering incentives for use)
Use novel theories to extend outcomes of technology use	• Identify non-traditional outcomes variables from transformative research (e.g., literacy, decreasing disparity, health, happiness) • Differentiate between assimilation, diffusion, and routinization of use • Assess curvilinear effects in UTAUT (e.g., optimal stimulation level theory suggests such effects for hedonic motivation)
Use novel theories to extend range of mediators and moderators	• Use novel theories from other fields to study mediators (e.g., brand equity, customer experience, customer engagement; Brakus et al., 2009; Hollebeek et al., 2019). • Employ theories from international business research to assess novel moderators (e.g., concept of cross-national differences; Swoboda et al., 2016) • Use theories considering the heterogeneity of users in countries (e.g., country's ethnic, linguistic, and religious diversity)
Broaden the conceptualization and operationalization of key variables	• Broaden conceptualization of predictors (e.g., different types of lifestyles and habits) • Broaden conceptualization of moderators (e.g., identification of users with multiple cultural affiliations; culture concept proposed by Triandis and Gelfand, 1998) • Employ broader technology classifications (e.g., location-sensitivity of service, time criticality of service, and control of service recipient; Balasubramanian et al., 2002) • Test new technology classifications (e.g., based on goal-directed systems and task-technology fit literature)
Investigate changing importance of predictors	• Assess whether UTAUT specifications differ for initial compared to various levels of experience, especially over longer time windows
Use different research designs	• Sample and study theoretically meaningful technologies (e.g., anthropomorphism of chat bots and social robots) • Employ more observational studies and qualitative studies; employ latent growth modeling to study longitudinal effects

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APPENDIX A. COMPARISON OF META FINDINGS WITH EXISTING UTAUT EXTENSIONS (DV: BEHAVIORAL INTENTION)

Predictor variable	Present meta-analysis	Alaiad et al. (2013)	Alshare and Mousa (2014)	Brown, Dennis, and Venkatesh (2010)	Carter and Schaupp (2008)	Casey and Wilson-Evered (2012)	Chiu and Wang (2008)	Guo and Barnes (2011, 2012)	Hess, Joshi, and McNab (2010)	Hong et al. (2011)	Lian and Yen (2014)	Loose, Weeger, and Gewald (2013)	Martins et al. (2014)	McKenna, Tuunanen, and Gardner (2013)	McLeod, Pippin, and Catania (2009)	Miltgen, Popovič, and Oliveira (2013)	Oh and Yoon (2014)	Oliveira et al. (2014)	Saeed (2013)	Schaupp, Carter, and McBride (2010)	Sun et al. (2014)	Venkatesh et al. (2011)	Wang et al. (2012)	Wang et al. (2014)	Xiong, Qureshi, & Najjar (2013)	Yuen et al. (2010)
Compatibility [a]	.62*															.15*										
Attitude [a]	.23*																					.45* .50*			.44*	.66* .49*
Task relevance [b]	-.20*																									
Education [b]	.18*																									
Trust [a]	.15*	.42*			.24*	.19 .06										.25*	.18*	.36*			.09*	.08* -.01	.22*			
Output quality [a]	.14*																							.30*		
Image [a]	.13*										.06															
Anxiety [a]	-.12*						-.17*							.04											.00	.00 .00
Competence [b]	.10*																									
General risk [a]	-.10*						-.02				.08*	-.30*			.33 .23*	-.11*				-.19*						
Self-efficacy [a]	.08*				.14*		.17*							.29*												.00 .00
Security risk [a]	.07*		-.37*												.03 .24									-.36*		
Experience [a]	.05*			.07 .03	-.43*														.67* .05							
Service quality [b]	.05*																									
Voluntariness [b]	-.05*																									
Costs [b]	-.04*																									
Personal innovativeness [a]	.04*					.10				-.01						.21*										

										.13*																
Age [a]	.03			.04 .07																						
Satisfaction [a]	.03									.19* .04											.15*					
Innovativeness of IT [b]	-.02																									
PBC [a]	-.01																		.69* .12							
Playfulness [a]	.00						.33*																			
Information quality [b]	.00																									
Others																										
Advancement [a]								-.10 *																		
Customization [a]								.29 *																		
Perceived value									.69* .04 .14*																	
Utility value [a]							.11*																			
Attainment value [a]							.20*																			
Delay in response [a]							.04																			
Status [a]								.13*																		
Use barrier [a]											.04															
Value barrier [a]											.31*															
Tradition barrier [a]											.11*															
Threats [a]												-.26*														
Flow experience [a]																	.18*									
Firm reputation [a]																		-.04								.09* .00
Optimism bias [a]																				.76*						
Tie strength [a]																					0.14*					
Job-fit [a]																									.00	
Examined full UTAUT	**Yes**	**No**	**No**	**Yes**	**No**	**No**	**Yes**	**No**	**No**	**Yes**	**No**	**No**	**Yes**	**Yes**	**No**	**No**	**Yes**	**Yes**	**No**	**No**	**No**	**No**	**No**	**No**	**No**	**No**

PBC=Perceived behavioral control. a. Variable considered in previous extensions; b. Variable not considered in previous extensions. * p <.05.

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APPENDIX B. COMPARISON OF FINDINGS WITH EXISTING EXTENSIONS (DV: USE)

Predictor variable	Present meta-analysis	Bourdon and Sandrine (2009)	Brown et l. (2010)	Lallmahomed et al. (2013)	Liew et al. (2014)	Oliveira et al. (2014)	Zhou et al. (2010)
Personal innovativeness [b]	.39*						
Compatibility [b]	.34*						
Service quality [b]	.30*						
Task relevance [b]	.29*						
Competence [b]	.25*						
Output quality [b]	.24*						
Satisfaction [b]	.24*						
Experience [a]	.22*		.04 -.06				
Performance expectancy [b]	.17*						
Image [b]	.14*						
Costs [b]	-.11*						
Self-efficacy [b]	-.11*						
Information quality [b]	.12*						
Attitude [b]	.10*						
Hedonic motivation [b]	.09*						
Perceived behavioural control [b]	-.09*						
Anxiety [b]	.06*						
Playfulness [b]	.06*						
General risk [b]	.05*						
Price value [b]	.05*						
Age [a]	.03		.04 .07				
Effort expectancy [b]	.03						
Innovativeness of IT [b]	.03						

Education [b]	.02						
Trust [b]	.01						
Security risk [b]	.00						
Voluntariness [b]	.00						
Social influence [b]	.00						
Others							
Culture [a]		-.05					
Organizational Structure [a]		.19*					
Time available [a]		.55* .19*					
Incentives [a]		-.21*					
Cognitive absorption [a]				.58*			
Volume frequency intensity [a]				.11*			
Deep structure use [a]				.49*			
Economic benefit [a]					.29* .17*		
Social benefit [a]					-.12 .70*		
Task technology fit [a]						.10	.30*
Examined full UTAUT	**Yes**	**No**	**No**	**Yes**	**No**	**Yes**	**No**

a. Variable considered in previous extensions; b. Variable not considered in previous extensions. * p <.05.

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APPENDIX C. COMPARISON OF MODERATOR APPROACH WITH EXISTING MODERATOR EXTENSIONS

Author (year)	# predictors	Age	Gender	Consumer	PDI	IND	MAS	UA	Mobile	Online	Transaction	Other
Alshare and Mousa (2014)	3				x	x	x	x				Espoused culture values
Al-Gahtani et al. (2007)	4	x	x									Experience; Culture (United States vs. Saudi Arabia)
Borrero et al. (2014)	4		x									Technology readiness
Brown et al. (2010)	4	x	x									Experience
Dasgupta and Gupta (2012)	4		x									
Guo and Barnes (2012)	1											Habit
Hess et al. (2010)	3											Facilitating conditions
Im et al. (2011)	5											Culture (Korea vs. USA)
Lian and Yen (2014)	9		x									
Liew et al. (2014)	6	x	x									Ethnicity, religion, language, employment, income, education, and marital status
Lu, Yu, and Liu (2009)	3	x	x									Income and location
Martins et al. (2014)	4	x	x									
McLeod et al. (2009)	6											Professionals vs. novices
Niehaves and Plattfaut (2010)	4		x									Income, education, and migration background
Oh and Yoon (2014)	6											E-learning vs. online game
Park, Lee, and Li (2011)	4											Organizational facilitating conditions
Thong et al. (2011)	4	x	x									IT service type; Adoption vs. continued use
Venkatesh et al. (2008)	2	x	x									Experience
Venkatesh and Zhang (2010)	4	x	x									Experience; voluntariness; Culture (USA vs. China)
Wang et al. (2014)	7											User groups (silent vs. social users)
Wang et al. (2012)	4											Type of recommender system; type of product
Yuen et al. (2010)	8											Country (USA/Australia vs Malaysia)
Present meta-analysis	**31**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	**x**	

PDI=power distance of national culture; IND=individualism-collectivism; MAS=masculinity-femininity; UA=uncertainty avoidance.

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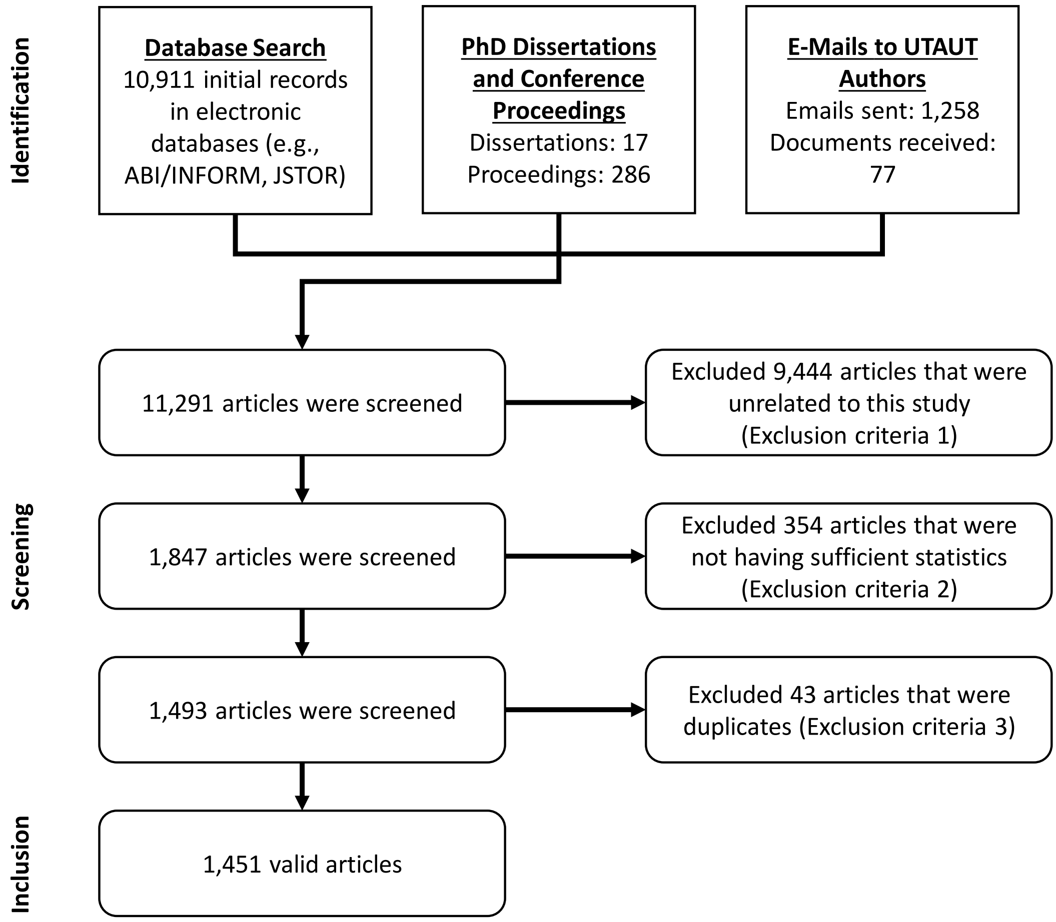
APPENDIX D. METHOD APPENDIX

[1] ***Data collection***

When collecting the data for this meta-analysis, we used several criteria to decide whether to include a specific study. First, the study had to be empirical (e.g., survey, experiment or both) at the individual (e.g., user/employee) level of analysis. Thus, we excluded qualitative papers that applied UTAUT (e.g., Li, 2010; Ye et al., 2008), those that are conceptual or reviewed UTAUT literature (e.g., Bhatti et al., 2017), and empirical studies at other levels of analysis (e.g., Brown et al., 2010; Neufeld, Dong, & Higgins, 2007). Studies had to use at least one of the four main predictors of UTAUT in the study to be included in the meta-analysis. Studies that referred to the theory but did not measure any of its constructs were excluded from the meta-analysis (e.g., Angst & Agarwal, 2009; Benbasat & Barki, 2007). A total of 9,444 studies (83.64% of 11,291 screened articles) did not meet this criterion. Second, correlation coefficients had to be reported in these papers between constructs. If the information was not presented, we examined if there are other statistics that could be used to calculate these effect sizes (e.g., regression coefficients, t-values). If these or other statistics were not available in the article, we e-mailed authors to see if they have such information that they can send to us. Another 354 studies (19.17% of 1,847 screened articles) were excluded because they did not report sufficient data (e.g., Debuse, Lawley, & Shibl, 2008; van Setten et al., 2006). Third, the article had to provide an independent dataset (Gerow et al., 2014). Therefore, if the authors had articles that contained the same dataset, they were excluded to avoid biasing the study through multiple counting (Gerow et al., 2014). We excluded 43 studies (2.88% of 1,493 screened articles) due to this criterion (e.g., Hu et al., 2009; Xu, 2014). The process of identifying, screening, and including studies is illustrated in the figure below:



[2] ***Classification of effect sizes***

When classifying effects sizes, coders were given construct definitions and aliases (Appendix E).

Hunter and Schmidt (2004, p. 470) explain that: "[I]nitially, meta-analyses in a given research area should probably be narrow and focused enough to correspond to the major constructs recognized by researchers in that area. Then, as understanding develops, later meta-analyses may become broader in scope if that is shown to be theoretically appropriate." Cooper (2017) adds to this discussion and argues that when the definition is too narrow, meaningful studies are likely to be left out. The present meta-analysis uses a rather narrow definition of key constructs. Because our meta-analysis focuses on UTAUT, the constructs included in the meta-analysis measure core variables in this theory (e.g., performance expectancy). However, we also included studies that examined usefulness and treated this construct as an alias because performance expectancy and usefulness have the same roots and are treated as conceptually identical (see Venkatesh et al., 2003). We did the same for the other UTAUT variables. Excluding usefulness from the meta-analysis would give an incomplete picture about the importance of UTAUT drivers. For the UTAUT extensions, we initially differentiated across 72 different extension variables when coding and classifying variables for the meta-analysis to ensure that the constructs definitions are sufficiently narrow.

[3] ***Coding of study moderators***

For 1,236 of 1,935 samples, we could collect information about the user's average age. Similarly, gender information was coded for 1,484 samples, and country information was coded for 1,808 samples. Our meta-analysis covers 77 countries including Abu Dhabi, Australia, Austria, Bahrain, Bangladesh, Belgium, Bosnia and Herzegovina, Brazil, Cambodia, Cameroon, Canada, Chile, China, Côte d'Ivoire, Croatia, Egypt, Finland, France, Germany, Ghana, Greece, Guinea, Hong Kong, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Jordan, Kazakhstan, Kuwait, Lebanon, Lithuania, Macao, Malaysia, Maldives, Mauritius, Mexico, Mozambique, Netherlands, New Zealand, Nigeria, Norway, Oman, Pakistan, Palestine, Peru, Philippines, Portugal, Qatar, Romania, Russia, Saudi Arabia, Serbia, Singapore, Slovenia, Somalia, South Africa, South Korea, Spain, Sudan, Sweden, Switzerland, Taiwan, Tanzania, Thailand, Tunisia, Turkey, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Vietnam, and Yemen. We used Hofstede's (2001) cultural dimensions to describe these countries' cultural profile. The coded studies also covered different technologies. Two coders assessed these technology contexts. The overall agreement rate was 98% for (i.e., 96% for mobile technology, 99% for online technology, and 99% for transaction technology). They used the following definitions when classifying technologies. Mobile technologies refers to "the application of small, portable and wireless computing and communication devices, including laptops with wireless LAN technology, mobile phones, and Personal Digital Assistants (PDAs) with Bluetooth, which let consumers utilize various Internet services anytime and anywhere" (Park & Yang, 2006, p. 24; Balasubramanian et al., 2002). Internet technologies refer to "web-based communication technologies – such as browsers, websites, search engines, online forums, e-mail, blogs, and wikis – that enable the easy exchange and retrieval of digitised content" (Whelan et al., 2010, p. 401). Finally, transaction technologies "enables customers to order, buy, and exchange resources with companies… [Examples] are Charles Schwab's online trading service, Amazon.com, and the SABRE Group's Travelocity, an Internet-based travel ticketing service" (Meuter et al., 2000, p. 52). While 439 samples examined mobile technologies, 1,496 samples examined non-mobile technologies. In 1,410 samples, the technology was examined in an online context, whereas in 525 samples, technology was examined in an offline setting. Finally, in 271 samples, the researchers examined technologies supporting transactions between the buyer and seller, whereas in 1,664 samples, non-transaction technologies were examined.

[4] ***Coding of additional moderators***

We considered examining two more moderators: (1) long-term orientation of culture and (2) voluntariness of technology use. First, various meta-analyses from different fields still use only the four culture dimensions—i.e., excluding long-term orientation—to assess the impact of cultural differences on an individual's behavior. For example, Samaha, Beck, and Palmatier (2014) used the four dimensions to assess the role of culture in international relationship marketing, likewise, Blut et al. (2015) examined the impact of the four original culture dimensions on the perception of website characteristics; and Pick and Eisend (2016) similarly examined switching costs. These studies focused on the four original culture dimensions because of their representation in the literature. For this reason, we did not hypothesize any effects of long-term orientation in our meta-analysis and also used the original culture dimensions. However, we still explored the moderating effects of long-term orientation and found performance expectancy (r=.10), effort expectancy (r=.11), hedonic motivation (r=.20), compatibility (r=.44), and personal innovativeness (r=.45) showed stronger effects on use in high long-term orientation cultures. Social influence (r=.07) and education (r=.36) also showed stronger effects on intention in high long-term orientation cultures, whereas hedonic motivation (r=-.12) and compatibility (r=-.21) showed weaker effects. It seems that users in high long-term orientation cultures are more considerate of technology use and place greater emphasis on many predictors. Second, we considered testing voluntariness of technology use. However, we decided against it. Venkatesh et al. (2012) argued that this moderator is less relevant for consumer technologies when they developed UTAUT2. They excluded voluntariness from this theory arguing that "[r]elative to the original conceptualization of UTAUT, we drop voluntariness as a moderating variable. This change is necessary to make UTAUT applicable in the context of a voluntary behavior, such as the one we are studying (i.e., voluntary technology acceptance and use among consumers). While in general, voluntariness can be perceived as a continuum from absolutely mandatory to absolutely voluntary, consumers have no organizational mandate and thus, most consumer behaviors are completely voluntary, resulting in no variance in the voluntariness construct" (Venkatesh et al. 2012, p. 159). As our meta-analysis includes many consumer technologies, we removed voluntariness as a relevant construct from the model. Also, we examined how many of the collected studies reported information about mandatory versus voluntary technology use. Most studies did not report this information and where the information is provided the description is often vague. We found that 65% of all studies (e.g., Abdullah, Ward, & Ahmed 2016) did not report any information on this moderator. 5% of studies (e.g., El Ouirdi et al. 2016) indicated that the use context includes both voluntary and mandatory use. Many studies did not clearly explain whether the context is voluntary or not. Around 22% of the studies (e.g., Miltgen, Popovič, & Oliveira 2013) mentioned the voluntariness of technology use. A number of studies even measured it as a continuum ranging from voluntary to mandatory use. Only, 8% of studies (Kim, Chan, & Gupta 2016) examined mandatory use contexts. Given that there is a lack of sufficient data accurately reporting whether the technologies studied were in a voluntary or mandatory context, it was also not practical to include them in our meta-analysis. Meta-analyses are frequently used to comment on analysis and reporting practices in the examined research domain. Thus, we have explained in the discussion section that given that majority of UTAUT studies did not report sufficient information on voluntariness of technology use, future studies should report and test this traditional moderator to conduct a more accurate and complete test of the theory.

[5] ***Integration of Effect Sizes***

The more recent meta-analyses do not use Fisher z-transformation when integrating effect sizes. It is argued that this transformation overestimates true effect sizes by 15-45% (Field, 2001). Hence, we also do not use this transformation. When calculating the integrated effect sizes, we also tested the statistical power of our tests. Statistical power is described as the probability of not rejecting a false null hypothesis (Type II error, defined by β) and it is therefore defined as (1–β). It is interpreted as the probability that a statistical test will correctly reject a false null hypothesis. Muncer et al. (2003) propose that a test has sufficient power to detect meaningful effect sizes, if power values are larger than .5.

[6] ***Testing Publication Bias***

Nearly all significant relationships were found to be robust against publication bias. In a few cases, the FSN is lower than the tolerance level mainly because of only a few observations being available (i.e., visibility, income, tenure). The average file-drawer N across all individual relationships is 927,688 for behavioral intention and 87,151 for use. Thus, in most cases, the tolerance criterion suggested by Rosenthal (1979) is fulfilled. The Chi^2 test of homogeneity is significant in most cases, supporting heterogeneity.

[7] ***Results of Power Tests***

We tested the power in our meta-analysis using two different sample sizes (N). We used the cumulative sample size N to calculate the power. The results of the power tests exceed the .5 level, suggesting that our analyses have sufficient power (Ellis, 2010).

[8] ***Results of Moderator Analysis***
In addition to the moderators discussed in the main text, we tested whether the quality of the publication outlet affects the results. We used a comprehensive journal ranking to split the studies into two groups and used this dummy variable to explore differences (Academic Journal Guide 2015). The results did not show any differences between the analyses.

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APPENDIX E. DEFINITIONS OF CONSTRUCTS USED IN THE META-ANALYSIS

Predictor	Definition	Alias(es)
Accessibility	The degree to which the system and the information it contains can be accessed with relatively low effort (Kim & Han, 2011).	—
Age	The age of the user.	—
Agreeableness	A compassionate interpersonal orientation (Devaraj, Easley, & Crant, 2008).	—
Alternative attractiveness	The individual judgment on whether the problem that the new system is aimed to address can be solved by other existing methods (Zhang, Guo, & Chen, 2011).	Competitive pressure, quality of alternatives
Altruism	The willingness to help others without expecting benefits in return (Hsu & Lin, 2008).	—
Anxiety	The degree of an individual's apprehension, or even fear, when she/he is faced with the possibility of using computers (Venkatesh, 2000).	Technology anxiety, computer anxiety, fear
Attitude	An individual's positive or negative feelings (evaluative affect) about performing the targeted behavior (Fishbein & Ajzen, 1975).	—
Behavioral intention	The strength of one's intention to perform a specified behavior (Fishbein & Ajzen, 1975).	Continuance intention, use intention
Compatibility	The degree to which an innovation is perceived as being consistent with existing values, needs, and experiences of potential adopters (Moore & Benbasat, 1991).	Perceived fit
Competence	The user's potential to fully utilize information and communication technology in order to better his or her performance of specific job tasks (Munro et al., 1997).	Abilities, skills, knowledge, expertise
Conscientiousness	The degree of organization, persistence, and motivation in goal-directed behavior (Devaraj et al., 2008).	—
Convenience	Time and effort saving associated with technology use (Berry, Seiders, & Grewal, 2002).	—
Costs	The extent to which a user perceives that using a technology is costly (Zhang, Zhu, & Liu, 2012).	Cost effectiveness, price, financial costs, switching costs
Customization	Technology's ability to tailor itself or to be tailored by each user (Lee & Benbasat, 2004).	personalization
Demonstrability	The degree to which the results of using an innovation are perceived to be tangible (Moore & Benbasat, 1991).	Result demonstrability
Education	The education level of the user.	—
Effort expectancy	The degree of ease associated with using the technology (Venkatesh et al., 2003).	Ease of use
Escapism	The extent to which the system will help players escape unpleasant realities or distract his/her attention from problems and pressures (Hirschman & Holbrook, 1982).	—
Experience	A user's prior experience using technology in general (Meuter et al., 2005).	Familiarity, past use
Extraversion	Being sociable, gregarious, and ambitious (Devaraj et al., 2008).	—
Facilitating conditions	A user's perceptions of the resources and support available to perform a behavior (Venkatesh et al., 2003).	—

Fairness	The extent to which users feel that their invested efforts are fair when compared to the final outcomes of technology use (McColl-Kennedy & Sparks, 2003).	—
Gender	Gender of the user.	—
General risk	Users' perceptions of general uncertainty and expectations of adverse results arising from system use (Fu, Farn, & Chao, 2006).	Risk
Habit	The extent to which people tend to perform behavior automatically because of learning (Venkatesh et al., 2012).	—
Hedonic motivation	The fun or pleasure derived from using a technology (Venkatesh et al., 2012).	Enjoyment, hedonic benefits, hedonic value
Identification	Whether the users see their link with the company as an important part of their identity (Bhattacharya & Sen, 2003).	—
Image	The degree to which an individual perceives that use of an innovation will enhance his or her status in his or her social system (Moore & Benbasat, 1991).	Reputation
Impulsiveness	Reflecting an enduring disposition to act impulsively in a given context (Rook, 1987).	—
Incentive structures	The benefits that an individual obtains from engaging in a potentially risky behavior (Rogers, Prentice-Dunn, & Gochman, 1997).	Reward, sanction (R)
Income	Income of the user.	—
Information quality	A combination of end-user's perceptions of accuracy, content, format, and timeliness (Moores, 2012).	Information satisfaction, information overload (R)
Innovativeness of IT	Innovativeness refers to the degree of change in the technology relative to prior technologies (Stock & Tatikonda, 2000).	Perceived novelty, newness
Interactivity	Ability of technology to facilitate two- or multi-way communications for relationship building (Udo & Marquis, 2002).	Interaction quality
Involvement	The degree to which the user perceives a technology and its use to be personally relevant (Santosa, Wei, & Chan, 2005).	User involvement
Locus of control	The extent to which a person thinks to be in control of eternal events that affect him/her (Rotter, 1966).	Controllability, perceived control
Loyalty	An individual's deeply held affective commitment toward the service (Beatty & Kahle, 1988).	—
Management support	The effort on encouragement to use and support for use driven by management (Urbach, Smolnik, & Riempp, 2010).	Supervisor support
Market complexity	The degree to which the business environment is perceived as relatively difficult to understand (Rogers & Shoemaker, 1971).	—
Mood	Intense feelings that are directed at someone or something (Fishbach & Labroo, 2007).	—
Need for interaction	The desire to retain personal contact with others (particularly frontline service employees) during a service encounter (Dabholkar, 1996).	—

Network externalities	The phenomenon in which the value of using a technology increases with the number of other users using the same technology (Kauffman, McAndrews, & Wang, 2000).	—
Neuroticism	Emotional instability, characterized by general insecurity, anxiousness, and hostility (Devaraj et al., 2008).	—
Observability	Observability refers to how visible the use of the technology is to those around (Rogers, 1983).	—
Openness	Flexibility of thought and tolerance of new ideas (Devaraj et al., 2008).	Openness to experience
Optimism	Optimism refers to the generalized expectation of positive versus negative outcomes in important domains of life (Ho & Kwok, 2010).	—
Organizational climate	Refers to the unique organizational environment which supports IT acceptance (Kim, 2009).	Organizational culture, team climate
Output quality	The degree to which an individual believes that the system performs his or her job tasks well (Venkatesh & Davis, 2000).	—
Perceived behavioral control	Refers to one's perceived control of performing the behavior (Orbeil, Hodgldns, S., & Sheeran, 1997).	—
Performance expectancy	Performance expectancy is defined as the degree to which technology will provide benefits to users when performing certain activities (Venkatesh et al., 2003).	Usefulness, relative advantage
Personal innovativeness	Represents an individual characteristic reflecting a willingness to try out any new technology (Agarwal & Karahanna, 2000).	Resistance to change (R), technology readiness
Playfulness	The degree of cognitive spontaneity in microcomputer interactions (Venkatesh, 2000).	—
Price value	Refers to the individual's cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them (Dodds, Monroe, & Grewal, 1991).	—
Privacy risk	Potential loss of control over personal information, such as when information about the user is used without knowledge or permission (Featherman & Pavlou, 2003).	Confidentiality, privacy concerns
Relationship quality	The overall assessment of the strength of a relationship between two parties (Crosby, Evans, & Cowles, 1990).	—
Reliability	The degree to which the system is dependable over time (Kim & Han, 2011).	Assurance
Responsiveness	Extent to which service providers respond proactively by efficient, straightforward, and timely communication (Parasuraman, Zeithaml, & Berry, 1988).	—
Satisfaction	An affective state that is the emotional reaction to technology experience (Spreng, MacKenzie, & Olshavsky, 1996).	Expectation confirmation, disconfirmation (R)
Security risk	Perceptions about security regarding the means of payment and the mechanism for storing and transmission of information (Kolsaker & Payne, 2002).	Security concerns
Self-efficacy	The degree to which an individual believes that he or she has the ability to perform a specific task/job using the system (Venkatesh, 2000).	Computer self-efficacy, Internet self-efficacy
Service quality	The quality of the support that system users receive from IT personnel (Petter, DeLone, & McLean,	—

	2008).	
Social identity	The perception of belonging to a social group (Hsu & Lin, 2008).	—
Social influence	Social influence is the degree to which the user perceives that important others believe he or she should use the technology (Venkatesh et al., 2003).	Peer expectations, expected social conformity, norms
Social status	Refers to a person's position in society relative to others (Black, 2014).	—
Task relevance	The degree to which an individual believes that the target system is applicable to his or her task/job (Venkatesh & Davis, 2000).	Job relevance, task technology fit, task significance
Tenure	Organizational tenure of the user.	—
Trialability	The degree to which an innovation may be experimented with before adoption (Moore & Benbasat, 1991).	—
Trust	A psychological expectation that others will be sincere in keeping promises and will not behave opportunistically in expectation of a promised service (Ooi & Tan, 2016).	Benevolence, integrity, trustworthiness
Use	Actual system use in the context of technology acceptance (Davis, 1989).	Actual use, adoption, continuance usage
Visibility	The perception of the actual visibility of the innovation itself as opposed to the visibility of outputs (Moore & Benbasat, 1991).	—
Voluntariness	The degree to which the use of innovation is perceived as being voluntary, or of free will (Moore & Benbasat, 1991).	—

Note: (R) reverse coded.

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APPENDIX F. DESCRIPTIVE RESULTS OF VARIOUS ENDOGENOUS MECHANISMS

Relationship	k	N	rc	SD	$_{-95\%}$CI	$_{+95\%}$CI	$_{-80\%}$CR	$_{+80\%}$CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PVA
Behavioral intention (BI)															
Performance expectancy (UTAUT) → BI	925	417994	.62*	.23	.61	.64	.33	.92	17074*	26487305	4635	>.999	.052	.054	2.7%
Effort expectancy (UTAUT) → BI	795	365756	.50*	.24	.48	.52	.20	.80	16068*	12583653	3985	>.999	.056	.058	3.3%
Social influence (UTAUT) → BI	615	307565	.42*	.22	.40	.43	.14	.70	11817*	7195179	3085	>.999	.048	.050	3.9%
Attitude → BI	334	119041	.65*	.23	.62	.67	.35	.94	4932*	3880808	1680	>.999	.054	.055	3.2%
Facilitating conditions (UTAUT) → BI	322	195406	.39*	.20	.36	.41	.13	.64	5921*	1808181	1620	>.999	.039	.041	4.3%
Hedonic motivation (UTAUT) → BI	210	101706	.53*	.22	.50	.56	.25	.81	3927*	1479877	1060	>.999	.049	.050	3.3%
Self-efficacy → BI	191	137310	.50*	.18	.47	.53	.27	.73	3567*	693569	965	>.999	.032	.033	3.5%
Satisfaction → BI	166	63145	.46*	.29	.41	.50	.08	.83	4045*	480406	840	>.999	.084	.087	2.9%
Trust → BI	148	56016	.52*	.23	.48	.55	.23	.80	2234*	516447	750	>.999	.051	.053	4.2%
General risk → BI	139	101094	-.06*	.24	-.10	-.02	-.36	.25	4867*	8822	705	>.999	.056	.057	2.9%
Personal innovativeness → BI	100	29204	.30*	.32	.23	.36	-.11	.70	2252*	71999	510	>.999	.102	.106	3.9%
PBC → BI	96	39099	.52*	.23	.47	.56	.22	.81	1519*	163840	490	>.999	.054	.056	4.2%
Price value (UTAUT) → BI	91	35358	.48*	.27	.42	.54	.13	.83	2032*	180505	465	>.999	.074	.077	3.1%
Competence → BI	89	42556	.37*	.21	.33	.42	.10	.64	1440*	111918	455	>.999	.044	.046	5.0%
Compatibility → BI	87	86334	.65*	.12	.63	.68	.50	.80	1065*	348390	445	>.999	.014	.014	3.4%
Experience → BI	82	37064	.29*	.23	.24	.34	-.01	.59	1549*	52090	420	>.999	.055	.057	4.7%
Costs → BI	80	38281	-.12*	.32	-.19	-.05	-.53	.29	2778*	14010	410	>.999	.102	.105	2.8%
Output quality → BI	72	28906	.48*	.30	.41	.55	.09	.87	1985*	103505	370	>.999	.092	.094	2.5%
Anxiety → BI	70	25342	-.16*	.25	-.22	-.10	-.48	.16	1213*	9729	360	>.999	.062	.066	5.6%
Information quality → BI	68	32784	.42*	.25	.36	.48	.10	.74	1459*	76121	350	>.999	.061	.064	3.6%
Image → BI	61	18930	.39*	.17	.35	.44	.17	.62	457*	40740	315	>.999	.030	.034	10.6%
Privacy risk → BI	57	26219	-.23*	.32	-.31	-.14	-.64	.19	2070*	14032	295	>.999	.105	.108	2.6%
Age → BI	53	28264	.00	.12	-.03	.04	-.15	.15	384*	—	—	.050	.067	.070	3.6%
Security risk → BI	52	36997	-.29*	.26	-.36	-.22	-.62	.04	1875*	41883	270	>.999	.083	.085	2.5%
Habit (UTAUT) → BI	47	21012	.60*	.31	.51	.69	.21	.99	1526*	78057	245	>.999	.094	.095	1.6%
Innovativeness of IT → BI	43	12205	.39*	.16	.34	.44	.19	.60	264*	19399	225	>.999	.026	.030	12.9%
Task relevance → BI	41	9724	.46*	.29	.37	.55	.09	.83	622*	18739	215	>.999	.084	.088	4.7%
Playfulness → BI	38	9855	.41*	.24	.33	.48	.11	.71	418*	16907	200	>.999	.055	.060	7.1%
Locus of control → BI	37	13223	.41*	.25	.33	.50	.10	.73	606*	19628	195	>.999	.061	.064	4.7%
Service quality → BI	36	13313	.41*	.35	.30	.53	-.03	.86	1217*	18489	190	>.999	.120	.123	2.3%
Voluntariness → BI	28	10496	.12	.35	-.01	.25	-.33	.57	964*	—	—	>.999	.121	.125	2.9%
Education → BI	24	10217	.23*	.28	.12	.35	-.13	.60	616*	3828	130	>.999	.080	.083	3.6%
Alternative attractiveness → BI	21	4577	.14	.37	-.02	.30	-.34	.62	493*	—	—	>.999	.140	.146	4.2%
Convenience → BI	21	6551	.55*	.16	.48	.62	.34	.76	135*	9444	115	>.999	.026	.029	9.6%
Identification → BI	17	4524	.56*	.23	.45	.68	.26	.86	194*	6137	95	>.999	.055	.058	5.2%
Openness → BI	16	5082	.20*	.23	.08	.32	-.09	.49	207*	894	90	>.999	.051	.055	7.3%

Relationship	k	N	rc	SD	$_{-95\%}$CI	$_{+95\%}$CI	$_{-80\%}$CR	$_{+80\%}$CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PVA
Demonstrability → BI	16	3713	.53*	.26	.40	.66	.20	.86	185*	3454	90	>.999	.066	.070	5.6%
Reliability → BI	14	5381	.50*	.19	.40	.60	.26	.74	158*	4267	80	>.999	.035	.038	5.8%
Accessibility → BI	14	13179	.39*	.19	.29	.49	.15	.64	357*	2982	80	>.999	.036	.038	3.1%
Trialability → BI	13	2861	.32*	.23	.19	.45	.03	.61	121*	866	75	>.999	.053	.058	9.3%
Management support → BI	12	2904	.32*	.33	.13	.52	-.10	.75	237*	1046	70	>.999	.111	.116	4.4%
Customization → BI	12	4015	.47*	.20	.35	.59	.21	.73	135*	3017	70	>.999	.041	.044	6.2%
Interactivity → BI	12	8529	.49*	.19	.38	.60	.24	.73	234*	4224	70	>.999	.036	.037	3.5%
Relationship quality → BI	12	2310	.46*	.15	.37	.55	.27	.65	44*	1513	70	>.999	.021	.027	19.9%
Involvement → BI	10	3048	.45*	.14	.36	.55	.28	.63	51*	1645	60	>.999	.019	.022	14.3%
Observability → BI	10	1828	.52*	.14	.42	.62	.34	.70	31*	996	60	>.999	.020	.026	22.0%
Responsiveness → BI	10	4429	.39*	.18	.28	.51	.16	.62	115*	1811	60	>.999	.032	.034	6.8%
Incentive structures → BI	9	2872	.40*	.26	.23	.58	.07	.73	145*	1257	55	>.999	.067	.071	4.9%
Extraversion → BI	8	2888	.22*	.18	.09	.35	-.01	.45	78*	266	50	>.999	.033	.037	9.6%
Neuroticism → BI	8	1882	.08	.20	-.07	.23	-.18	.34	65*	—	—	.967	.041	.047	12.3%
Income → BI	8	3044	.21*	.07	.15	.28	.12	.31	20*	328	50	>.999	.005	.008	36.2%
Agreeableness → BI	7	2936	.11	.16	-.02	.24	-.10	.32	60*	—	—	>.999	.026	.029	11.5%
Conscientiousness → BI	7	2936	.02	.13	-.09	.13	-.15	.19	45*	—	—	.287	.018	.021	15.7%
Social identity → BI	7	2730	.57*	.11	.48	.66	.43	.71	28*	1476	45	>.999	.012	.014	14.6%
Other needs → BI	7	7212	.29*	.26	.09	.48	-.05	.62	356*	1174	45	>.999	.068	.069	1.8%
Need for interaction → BI	7	2720	.12	.29	-.10	.34	-.25	.49	180*	—	—	2720	.084	.087	3.8%
Optimism → BI	7	2176	.56*	.18	.43	.70	.34	.79	55*	1194	45	>.999	.032	.034	7.5%
Organizational climate → BI	6	2068	.31*	.20	.15	.48	.06	.57	66*	316	40	>.999	.039	.043	7.8%
Social status → BI	6	3875	.21*	.05	.16	.26	.15	.26	11*	264	40	>.999	.002	.004	50.0%
Visibility → BI	5	1650	.49*	.17	.33	.65	.27	.71	38*	484	35	>.999	.030	.033	9.0%
Mood → BI	5	1067	.49*	.13	.37	.62	.33	.66	17*	284	35	>.999	.017	.021	20.5%
Market complexity → BI	4	1374	.56*	.14	.41	.71	.38	.74	22*	389	30	>.999	.020	.022	10.9%
Altruism → BI	4	884	.48*	.17	.30	.66	.26	.70	21*	205	30	>.999	.029	.034	13.5%
Tenure → BI	2	878	-.09*	.00	-.10	-.07	-.09	-.09	0	2	20	.848	.000	.000	100.0%
Loyalty → BI	2	597	.28*	.00	.25	.31	.28	.28	0	24	20	>.999	.000	.001	100.0%
Escapism → BI	2	4495	.59*	.05	.51	.66	.52	.65	11*	835	20	>.999	.003	.003	9.5%
Fairness → BI	2	521	.35*	.00	.34	.37	.35	.35	0	29	20	>.999	.000	.000	100.0%
Marital status → BI	2	1015	-.06	.16	-.29	.16	-.27	.14	23*	—	—	.605	.025	.027	8.6%
Network externalities → BI	2	460	.59*	.00	.52	.66	.59	.59	1	79	20	>.999	.000	.002	100.0%
Data quality → BI	1	455	.37	.00	—	—	—	—	—	—	—	—	—	—	—
Impulsiveness → BI	1	329	.17	.00	—	—	—	—	—	—	—	—	—	—	—
Use (U)															
Performance expectancy (UTAUT) → U	304	110935	.46*	.23	.43	.48	.17	.75	4368*	1597549	1530	>.999	.051	.054	5.0%

Relationship	k	N	rc	SD	$_{-95\%}$CI	$_{+95\%}$CI	$_{-80\%}$CR	$_{+80\%}$CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PVA
Effort expectancy (UTAUT) → U	260	97399	.34*	.25	.31	.37	.01	.66	4752*	720236	1310	>.999	.064	.067	4.6%
Social influence (UTAUT) → U	200	74140	.31*	.21	.28	.34	.04	.59	2636*	355148	1010	>.999	.046	.049	6.6%
Behavioral intention (UTAUT) → U	192	67497	.50*	.26	.46	.54	.17	.83	3385*	740408	970	>.999	.065	.068	3.8%
Facilitating conditions (UTAUT) → U	160	62021	.37*	.21	.34	.40	.10	.63	1992*	284794	810	>.999	.043	.046	6.6%
Hedonic motivation (UTAUT) → U	70	29057	.40*	.22	.35	.46	.13	.68	1055*	82260	360	>.999	.047	.049	5.2%
Attitude → U	65	21684	.46*	.26	.40	.52	.13	.79	1058*	74806	335	>.999	.065	.069	4.5%
Satisfaction → U	62	20328	.45*	.26	.38	.51	.12	.78	1024*	58670	320	>.999	.066	.070	4.5%
Self-efficacy → U	59	16831	.31*	.26	.25	.38	-.02	.65	843*	20432	305	>.999	.067	.071	6.1%
Output quality → U	42	12824	.44*	.26	.36	.52	.11	.77	635*	22672	220	>.999	.067	.070	5.0%
Competence → U	37	14265	.41*	.27	.32	.50	.06	.75	807*	16563	195	>.999	.073	.076	3.5%
Information quality → U	36	15102	.41*	.29	.31	.50	.04	.78	941*	21945	190	>.999	.084	.087	3.0%
Compatibility → U	36	10591	.44*	.25	.36	.52	.12	.76	501*	18332	190	>.999	.062	.065	5.3%
Trust → U	34	13962	.37*	.23	.29	.45	.07	.67	589*	15511	180	>.999	.055	.057	4.7%
Experience → U	34	13895	.42*	.22	.34	.50	.13	.71	520*	10307	180	>.999	.050	.053	5.0%
Age → U	30	11369	-.02	.11	-.07	.02	-.16	.11	138*	—	—	.687	.011	.014	21.9%
Anxiety → U	25	12334	-.01	.24	-.11	.08	-.32	.29	537*	—	—	.297	.057	.060	4.7%
Habit (UTAUT) → U	25	10518	.56*	.20	.48	.63	.30	.81	320*	19414	135	>.999	.040	.041	4.7%
General risk → U	25	10691	.08	.33	-.05	.22	-.34	.51	860*	—	—	>.999	.111	.114	2.9%
Price value (UTAUT) → U	23	9492	.34*	.17	.27	.42	.12	.57	223*	6537	125	>.999	.030	.033	8.6%
Task relevance → U	23	5509	.56*	.34	.42	.70	.13	.99	461*	6617	125	>.999	.113	.117	3.0%
Personal innovativeness → U	21	5856	.48*	.33	.33	.62	.06	.89	459*	5050	115	>.999	.106	.109	3.2%
Image → U	20	8801	.33*	.13	.27	.39	.16	.50	128*	3473	110	>.999	.018	.020	13.4%
Costs → U	19	8615	-.23*	.28	-.36	-.10	-.59	.14	521*	2489	105	>.999	.081	.084	3.4%
PBC → U	18	5295	.37*	.18	.28	.46	.14	.61	127*	2932	100	>.999	.033	.037	11.9%
Education → U	16	6701	.11*	.15	.03	.18	-.08	.29	117*	325	90	>.999	.022	.025	13.5%
Voluntariness → U	14	5708	.13*	.14	.05	.20	-.05	.30	90*	310	80	>.999	.019	.022	15.3%
Security risk → U	13	6469	-.27*	.27	-.42	-.13	-.61	.07	346*	1710	75	>.999	.211	.214	1.4%
Service quality → U	13	4340	.44*	.46	.19	.69	-.15	1.03	685*	2334	75	>.999	.070	.073	3.4%
Playfulness → U	11	2493	.32*	.19	.21	.44	.09	.56	68*	541	65	>.999	.034	.040	14.0%
Innovativeness of IT → U	10	3617	.34*	.20	.21	.46	.08	.59	117*	753	60	>.999	.039	.042	7.2%
Organizational climate → U	9	2833	.20*	.20	.07	.34	-.05	.46	94*	287	55	>.999	.041	.045	9.1%
Openness → U	8	2214	.17*	.12	.08	.27	.02	.33	32*	122	50	>.999	.015	.020	23.9%
Trialability → U	8	2605	.16*	.19	.03	.30	-.08	.40	72*	140	50	>.999	.035	.039	10.7%
Management support → U	8	2120	.50*	.18	.37	.63	.27	.73	55*	961	50	>.999	.032	.036	9.9%
Privacy risk → U	7	3519	-.26	.37	-.54	.02	-.74	.22	410*	—	—	>.999	.140	.142	1.5%
Demonstrability → U	7	1320	.39*	.17	.25	.53	.17	.61	31*	241	45	>.999	.029	.036	18.8%
Locus of control → U	6	2364	.21*	.23	.02	.40	-.09	.51	93*	146	40	>.999	.054	.057	6.1%
Involvement → U	6	2523	.33*	.21	.15	.50	.06	.59	82*	452	40	>.999	.044	.047	6.3%

Relationship	k	N	rc	SD	$_{-95\%}$CI	$_{+95\%}$CI	$_{-80\%}$CR	$_{+80\%}$CR	Q	FSN	Tolerance	Power	V_{rho}	V_r	PVA
Observability → U	6	2005	.45*	.17	.31	.59	.24	.66	42*	535	40	>.999	.028	.031	10.8%
Extraversion → U	6	1522	.06	.17	-.08	.21	-.15	.27	35*	—	—	.757	.028	.033	17.0%
Alternative attractiveness → U	5	1616	.19*	.00	.14	.24	.19	.19	4	49	35	>.999	.000	.004	100.0%
Neuroticism → U	5	1227	-.06	.00	-.12	.00	-.06	-.06	4	—	—	.676	.000	.005	100.0%
Agreeableness → U	5	1322	.06	.15	-.09	.20	-.14	.25	26*	—	—	.705	.023	.028	19.4%
Conscientiousness → U	5	1322	.09	.18	-.08	.26	-.14	.31	33*	—	—	.949	.031	.037	15.2%
Visibility → U	5	786	.16*	.15	.00	.32	-.03	.36	17*	15	35	.998	.023	.033	29.6%
Reliability → U	4	1538	.37*	.00	.33	.42	.37	.37	2	202	30	>.999	.000	.002	100.0%
Customization → U	4	1208	.23	.27	-.04	.50	-.12	.57	69*	—	—	>.999	.072	.076	5.4%
Interactivity → U	4	2219	.49*	.27	.22	.76	.14	.84	129*	338	30	>.999	.075	.077	2.1%
Convenience → U	3	363	.37*	.09	.22	.51	.26	.48	4	32	25	>.999	.008	.017	54.8%
Identification → U	3	769	.39*	.18	.17	.60	.16	.62	19*	78	25	>.999	.032	.036	12.5%
Accessibility → U	3	1946	.08	.08	-.03	.19	-.03	.19	12*	—	—	>.999	.007	.010	25.5%
Relationship quality → U	3	605	.27	.23	-.01	.54	-.03	.56	26*	—	—	.989	.053	.059	10.7%
Income → U	3	1905	.09*	.00	.05	.13	.09	.09	2	14	25	>.999	.000	.002	100.0%
Social Identity → U	3	970	.60*	.12	.44	.75	.44	.76	12*	262	25	>.999	.016	.018	14.2%
Social status → U	3	2388	.21	.25	-.08	.50	-.11	.53	109*	—	—	>.999	.062	.064	2.6%
Market complexity → U	3	684	.23	.26	-.08	.53	-.10	.55	36*	—	—	>.999	.066	.071	7.7%
Tenure → U	3	1302	-.10*	.00	-.14	-.06	-.10	-.10	1	7	25	.976	.000	.001	100.0%
Responsiveness → U	2	1386	.17*	.10	.02	.33	.04	.30	13*	26	20	>.999	.011	.013	15.2%
Other needs → U	2	1242	.37*	.09	.23	.51	.25	.49	9*	75	20	>.999	.008	.010	18.1%
Loyalty → U	2	597	.04	.00	-.05	.13	.04	.04	2	—	—	.252	.000	.004	100.0%
Incentive structures → U	1	275	.72	.00	—	—	—	—	—	—	—	—	—	—	—
Need for interaction → U	1	1273	.13	.00	—	—	—	—	—	—	—	—	—	—	—
Optimism → U	1	44	.47	.00	—	—	—	—	—	—	—	—	—	—	—
Altruism → U	1	1076	.19	.00	—	—	—	—	—	—	—	—	—	—	—
Escapism → U	1	428	.59	.00	—	—	—	—	—	—	—	—	—	—	—
Fairness → U	1	109	.17	.00	—	—	—	—	—	—	—	—	—	—	—
Marital status → U	1	855	-.02	.00	—	—	—	—	—	—	—	—	—	—	—
Network externalities → U	1	262	.46	.00	—	—	—	—	—	—	—	—	—	—	—

BI= behavioral intention; U= use; PBC=Perceived behavioral control. k=number of effect sizes; N=cumulative sample size; rc=sample-sized weighted-reliability adjusted correlation; CI=95%-confidence interval; CR=80% credibility interval; Q=Q statistic; FSN=fail-safe N; Power=power statistics; V_{rho}=variance of population correlation; V_r=variance of observed correlation; PVA= percent of variance in observed correlations due to sampling error and other artifacts; * $p<.05$. The table is based on the full data set.

APPENDIX G. UNIVARIATE RESULTS

Relationship	*k*	*N*	*Rc*	*SD*	$_{-95\%}CI$	$_{+95\%}CI$	$_{-80\%}CR$	$_{+80\%}CR$	*Q*	*FSN*	*Tolerance*	*Power*	V_{rho}	V_r	*PVA*
Behavioral Intention (BI)															
Performance expectancy → BI	925	417994	.62*	.23	.61	.64	.33	.92	17074*	26487305	4635	>.999	.052	.054	2.7%
Effort expectancy → BI	795	365756	.50*	.24	.48	.52	.20	.80	16068*	12583653	3985	>.999	.056	.058	3.3%
Social influence → BI	615	307565	.42*	.22	.40	.43	.14	.70	11817*	7195179	3085	>.999	.048	.050	3.9%
Facilitating conditions → BI	322	195406	.39*	.20	.36	.41	.13	.64	5921*	1808181	1620	>.999	.039	.041	4.3%
Hedonic motivation → BI	210	101706	.53*	.22	.50	.56	.25	.81	3927*	1479877	1060	>.999	.049	.050	3.3%
Personal innovativeness → BI	100	29204	.30*	.32	.23	.36	-.11	.70	2252*	71999	510	>.999	.102	.106	3.9%
Price value → BI	91	35358	.48*	.27	.42	.54	.13	.83	2032*	180505	465	>.999	.074	.077	3.1%
Compatibility → BI	87	86334	.65*	.12	.63	.68	.50	.80	1065*	348390	445	>.999	.014	.014	3.4%
Costs → BI	80	38281	-.12*	.32	-.19	-.05	-.53	.29	2778*	14010	410	>.999	.102	.105	2.8%
Habit → BI	47	21012	.60*	.31	.51	.69	.21	.99	1526*	78057	245	>.999	.094	.095	1.6%
Education → BI	24	10217	.23*	.28	.12	.35	-.13	.60	616*	3828	130	>.999	.080	.083	3.6%
Use (U)															
Performance expectancy → U	304	110935	.46*	.23	.43	.48	.17	.75	4368*	1597549	1530	>.999	.051	.054	5.0%
Effort expectancy → U	260	97399	.34*	.25	.31	.37	.01	.66	4752*	720236	1310	>.999	.064	.067	4.6%
Social influence → U	200	74140	.31*	.21	.28	.34	.04	.59	2636*	355148	1010	>.999	.046	.049	6.6%
Behavioral intention → U	192	67497	.50*	.26	.46	.54	.17	.83	3385*	740408	970	>.999	.065	.068	3.8%
Facilitating conditions → U	160	62021	.37*	.21	.34	.40	.10	.63	1992*	284794	810	>.999	.043	.046	6.6%
Hedonic motivation → U	70	29057	.40*	.22	.35	.46	.13	.68	1055*	82260	360	>.999	.047	.049	5.2%
Compatibility → U	36	10591	.44*	.25	.36	.52	.12	.76	501*	18332	190	>.999	.062	.065	5.3%
Habit → U	25	10518	.56*	.20	.48	.63	.30	.81	320*	19414	135	>.999	.040	.041	4.7%
Price value → U	23	9492	.34*	.17	.27	.42	.12	.57	223*	6537	125	>.999	.030	.033	8.6%
Personal innovativeness → U	21	5856	.48*	.33	.33	.62	.06	.89	459*	5050	115	>.999	.106	.109	3.2%
Costs → U	19	8615	-.23*	.28	-.36	-.10	-.59	.14	521*	2489	105	>.999	.081	.084	3.4%
Education → U	16	6701	.11*	.15	.03	.18	-.08	.29	117*	325	90	>.999	.022	.025	13.5%

k=number of effect sizes; N=cumulative sample size; rc=sample-sized weighted-reliability adjusted correlation; SD = sample size weighted observed standard deviation of correlations; CI=95%-confidence interval; CR=80% credibility interval; Q=Q statistic; FSN=fail-safe N; Power=power statistics; V_{rho}=variance of population correlation; V_r=variance of observed correlation; PVA= percent of variance in observed correlations due to sampling error and other artifacts; * p<.05. The table is based on the full data set.

APPENDIX H. TESTING OF DIFFERENCES ACROSS MEASUREMENTS

IV	DV	k	rc	SD	-95%CI	+95%CI	-80%CR	+80%CR	Q	FSN	F	p
Performance expectancy	Use	303	.46	.23	.43	.48	.17	.75	4364*	1593168	2.44	.12
	Narrow definition	91	.48	.22	.43	.52	.20	.76	1456*	182503		
	Alias	212	.45	.23	.42	.48	.15	.74	2894*	697042		
Effort expectancy	Use	258	.36	.21	.34	.39	.09	.64	3332*	749490	.44	.51
	Narrow definition	91	.38	.19	.34	.42	.14	.63	1083*	110189		
	Alias	167	.35	.23	.32	.39	.06	.64	2235*	284771		
Social influence	Use	196	.32	.20	.29	.35	.06	.57	2275*	351390	2.32	.13
	Narrow definition	109	.35	.21	.31	.39	.08	.61	1356*	130743		
	Alias	87	.32	.17	.28	.36	.10	.54	603*	50505		
Price value	Use	23	.34	.17	.27	.42	.12	.57	223*	6537	.79	.39
	Narrow definition	9	.38	.17	.26	.49	.16	.59	95*	1405		
	Alias	14	.32	.17	.22	.41	.10	.54	123*	1869		
Hedonic motivation	Use	70	.40	.22	.35	.46	.13	.68	1055*	82260	1.27	.26
	Narrow definition	14	.48	.14	.40	.55	.30	.65	123*	6388		
	Alias	56	.37	.23	.31	.44	.07	.67	884*	42760		
Facilitating conditions	Use	158	.37	.20	.34	.40	.11	.63	1911*	289470	3.66	.06
	Narrow definition	116	.39	.20	.35	.43	.14	.64	1394*	183005		
	Alias	41	.31	.21	.24	.37	.03	.58	465*	12113		
Habit	Use	24	.56	.19	.48	.64	.32	.81	295*	19538	.39	.54
	Narrow definition	22	.57	.20	.48	.65	.31	.82	292*	17110		
	Alias	2	.49	.00	.45	.52	.49	.49	0	78		
Compatibility	Use	36	.44	.25	.36	.52	.12	.76	501*	18332	1.15	.29
	Narrow definition	34	.43	.25	.35	.52	.11	.75	487*	15834		
	Alias	2	.65	.00	.62	.68	.65	.65	0	89		
Education	Use	15	.09	.10	.04	.15	-.04	.22	63	169	—	—
	Narrow definition	15	.09	.10	.04	.15	-.04	.22	63	169		
	Alias	—	—	—	—	—	—	—	—	—		
Personal innovativeness	Use	20	.36	.23	.26	.47	.07	.66	200*	2949	.05	.82
	Narrow definition	16	.37	.24	.24	.49	.06	.67	180*	1964		
	Alias	4	.33	.17	.15	.52	.12	.55	19*	96		
Costs	Use	17	-.26	.17	-.35	-.18	-.48	-.04	167*	1885	3.79	.07
	Narrow definition	7	-.16	.06	-.22	-.10	-.24	-.08	16*	142		
	Alias	10	-.35	.19	-.47	-.23	-.59	-.11	105*	977		
Performance expectancy	Behavioral intention	907	.64	.20	.63	.65	.39	.89	12694*	26868467	.09	.77
	Narrow definition	217	.59	.20	.56	.62	.33	.85	2731*	1462088		

IV	DV	k	rc	SD	-95%CI	+95%CI	-80%CR	+80%CR	Q	FSN	F	p
	Alias	690	.65	.19	.64	.67	.40	.90	9752*	15794446		
Effort expectancy	Behavioral intention	781	.51	.21	.50	.53	.24	.78	12820*	12797262	.09	.76
	Narrow definition	246	.42	.25	.39	.46	.11	.74	5029*	1183852		
	Alias	535	.55	.18	.53	.57	.31	.79	6920*	6195943		
Social influence	Behavioral intention	603	.43	.20	.41	.44	.17	.68	9941*	7326087	1.79	.18
	Narrow definition	313	.46	.23	.43	.49	.16	.76	5552*	1968175		
	Alias	290	.40	.17	.38	.42	.18	.62	4193*	1699495		
Price value	Behavioral intention	88	.52	.18	.48	.56	.29	.75	860*	196045	.35	.55
	Narrow definition	32	.54	.19	.48	.61	.30	.78	455*	35335		
	Alias	56	.50	.16	.45	.54	.29	.71	392*	64871		
Hedonic motivation	Behavioral intention	208	.53	.22	.50	.56	.26	.81	3747*	1486817	.00	.98
	Narrow definition	30	.44	.22	.36	.52	.16	.72	1042*	43941		
	Alias	178	.57	.20	.54	.60	.31	.83	2436*	1019405		
Facilitating conditions	Behavioral intention	320	.39	.19	.37	.41	.14	.64	5715*	1821910	2.55	.11
	Narrow definition	240	.38	.19	.36	.41	.14	.62	4423*	1153089		
	Alias	80	.43	.20	.39	.48	.18	.69	981*	78296		
Habit	Behavioral intention	43	.66	.18	.61	.72	.43	.89	509*	85638	1.46	.23
	Narrow definition	40	.67	.18	.61	.73	.44	.90	463*	77514		
	Alias	3	.52	.20	.28	.75	.26	.78	30*	199		
Compatibility	Behavioral intention	82	.66	.09	.64	.68	.55	.77	584*	340416	.05	.82
	Narrow definition	75	.66	.09	.64	.68	.55	.77	573*	298212		
	Alias	7	.66	.08	.59	.72	.56	.75	11	1389		
Education	Behavioral intention	22	.18	.19	.10	.26	-.06	.42	269	1933	—	—
	Narrow definition	22	.18	.19	.10	.26	-.06	.42	269	1933		
	Alias	—	—	—	—	—	—	—	—	—		
Personal innovativeness	Behavioral intention	96	.35	.25	.30	.40	.03	.67	1332*	84425	1.32	.25
	Narrow definition	61	.37	.25	.31	.44	.05	.69	884*	40630		
	Alias	35	.31	.24	.22	.39	-.01	.62	428*	7887		
Costs	Behavioral intention	80	-.12	.32	-.19	-.05	-.53	.29	2778*	14010	.00	1.00
	Narrow definition	34	-.11	.25	-.20	-.03	-.43	.21	796*	2482		
	Alias	46	-.12	.37	-.23	-.02	-.59	.34	1981*	4652		

k=number of effect sizes; N=cumulative sample size; rc=sample-sized weighted-reliability adjusted correlation; SD = sample size weighted observed standard deviation of correlations; CI=95%-confidence interval; CR=80% credibility interval; Q=Q statistic; FSN=fail-safe N; F=F-test; * p<.05. a. The confidence intervals and the F-test display similar results for moderator test. We did not consider education in this analysis since this predictor was measured similarly across all studies.

APPENDIX I. CORRELATION MATRIX

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.	29.	30.	31.	32.
1. Age	1.00																															
2. Anxiety	.08	1.00																														
3. Attitude	.05	-.06	1.00																													
4. Use	-.02	-.01	.46	1.00																												
5. Behavioral intention	.00	-.16	.65	.50	1.00																											
6. Compatibility	.21	-.06	.65	.44	.65	1.00																										
7. Competence	.03	.15	.40	.41	.37	.40	1.00																									
8. Costs	-.03	.13	-.07	-.23	-.12	-.02	-.05	1.00																								
9. Effort expectancy	-.03	-.11	.50	.34	.50	.70	.42	-.07	1.00																							
10. Education	.14	-.09	.07	.11	.23	.21	.31	-.04	.15	1.00																						
11. Hedonic motivation	-.08	.05	.58	.40	.53	.57	.35	-.04	.50	-.04	1.00																					
12. Experience	.03	-.17	.30	.42	.29	.65	.28	-.38	.26	.22	.21	1.00																				
13. Facilitating conditions	-.03	-.07	.43	.37	.39	.37	.32	-.29	.46	.31	.52	.30	1.00																			
14. Habit	-.11	-.07	.55	.56	.60	.21	.21	-.17	.39	.09	.42	.35	.39	1.00																		
15. Image	-.02	-.04	.37	.33	.39	.34	.21	-.13	.34	.00	.43	.49	.38	.21	1.00																	
16. Information quality	.02	.01	.50	.41	.42	.42	.36	-.18	.43	.10	.40	.05	.50	.46	.35	1.00																
17. Innovativeness of IT	-.22	-.09	.34	.34	.39	.36	.27	-.26	.41	.05	.37	.41	.33	.50	.46	.43	1.00															
18. Social influence	.06	.04	.43	.31	.42	.37	.30	-.08	.36	.21	.43	.16	.28	.48	.44	.46	.27	1.00														
19. Output quality	.04	.03	.60	.44	.48	.48	.46	.04	.35	-.07	.43	.18	.42	.28	.44	.65	.41	.42	1.00													
20. PBC	-.03	-.08	.39	.37	.52	.53	.59	-.07	.71	.21	.39	.33	.41	.66	.19	.39	.29	.40	.17	1.00												
21. Personal innovativeness	-.10	-.13	.30	.48	.30	.51	.33	-.31	.37	.15	.40	.34	.30	.11	.21	.36	.34	.27	.26	.41	1.00											
22. Playfulness	.02	-.10	.53	.32	.41	.57	.74	.22	.41	.21	.45	.42	.26	.38	.31	.49	.00	.35	.15	.46	.51	1.00										
23. Risk	-.01	.02	-.11	.08	-.06	-.09	.15	.26	-.05	.21	-.16	-.06	-.17	.20	.21	.02	-.06	.02	-.02	-.19	-.11	-.08	1.00									
24. Satisfaction	.11	.17	.55	.45	.46	.49	.27	-.04	.44	.04	.53	.20	.36	.32	.60	.56	.37	.36	.57	.30	.12	.42	.01	1.00								
25. Security risk	.12	-.18	-.20	-.27	-.29	-.23	-.19	.23	-.28	-.10	-.42	-.15	-.20	-.48	-.41	-.56	-.34	-.35	-.05	-.28	-.22	-.44	.30	-.30	1.00							
26. Self-efficacy	-.07	-.13	.44	.31	.50	.66	.55	.00	.61	.10	.38	.31	.46	.54	.23	.32	.35	.28	.35	.56	.39	.38	-.13	.23	-.21	1.00						
27. Service quality	.21	-.08	.36	.44	.41	.21	.30	.07	.48	.12	.43	.24	.51	.21	.15	.57	.72	.40	.53	.08	.49	.42	.05	.50	-.59	.29	1.00					
28. Task relevance	.21	-.04	.56	.56	.46	.38	.20	.01	.39	-.04	.49	.49	.49	.69	.47	.69	.47	.28	.40	.21	.32	.36	.20	.28	-.08	.28	.35	1.00				
29. Trust	-.06	-.23	.51	.37	.52	.54	.41	-.30	.47	.01	.54	.66	.51	.47	.41	.52	.32	.39	.51	.49	.13	.42	-.04	.55	-.36	.39	.50	.42	1.00			
30. Performance expectancy	.01	-.05	.60	.46	.62	.70	.39	-.07	.60	.17	.58	.24	.41	.45	.43	.47	.34	.44	.50	.49	.33	.43	-.07	.49	-.31	.51	.50	.51	.50	1.00		
31. Price value	.09	.00	.48	.34	.48	.50	.24	.00	.30	.06	.43	.10	.33	.40	.23	.34	.40	.41	.53	.36	.36	.45	.03	.58	-.15	.23	.50	.46	.25	.37	1.00	
32. Voluntariness	-.01	-.22	-.04	.13	.12	.37	.00	.26	.14	.02	-.03	.15	.20	.21	.03	-.22	-.01	.04	.07	.52	-.37	.52	-.24	.14	.23	.01	.21	-.25	-.53	.10	.30	1.00

Note. PBC=Perceived behavioral control. Harmonic mean across all collected effects is 1,665. The table is based on the full data set.

APPENDIX J. TEST OF POTENTIAL BI-EXTENSIONS (SEM)

DV: Behavioral Intention	UTAUT (R^2=55.9%)	Test of different extensions	
		Estimate	ΔR^2
Performance Expectancy	.30*		
Effort Expectancy	.10*		
Social Influence	-.02		
Facilitating conditions	-.02		
Hedonic motivation	.11*		
Price value	.17*		
Habit	.33*		
Compatibility		.62*	10.3%
Attitude		.23*	2.6%
Education		.18*	2.5%
Task relevance		-.20*	1.6%
Anxiety		-.12*	1.5%
Image		.13*	1.1%
Output quality		.14*	1.1%
Trust		.15*	1.2%
General risk		-.10*	.9%
Competence		.10*	.7%
Security risk		.07*	.4%
Self-efficacy		.08*	.4%
Experience		.05*	.3%
Personal innovativeness		.04*	.2%
Voluntariness		-.05*	.2%
Costs		-.04*	.2%
Age		.03	.1%
Innovativeness of IT		-.02	.1%
Satisfaction		.03	.1%
Service quality		.05*	.1%
Information quality		.00	.0%
Playfulness		.00	.0%
Perceived behavioral control		-.01	.0%

* $p < .05$. The table is based on the full data set. Using the data set without outliers, we find strong effects for compatibility (β=.64; ΔR^2=10.7%), education (β=.11; ΔR^2=1.0%), and personal innovativeness (β=.11; ΔR^2=.9%).

APPENDIX K. TEST OF POTENTIAL UB-EXTENSIONS (SEM)

DV: Use	UTAUT (R^2=37.1%)	Test of different extensions: Estimate	ΔR^2
Behavioral Intention	.22*		
Facilitating Conditions	.14*		
Habit	.37*		
Personal innovativeness		.39*	12.8%
Compatibility		.34*	5.6%
Service quality		.30*	6.0%
Competence		.25*	5.1%
Satisfaction		.24*	4.3%
Output quality		.24*	4.2%
Experience		.22*	4.0%
Task relevance		.29*	3.8%
Performance expectancy		.17*	1.7%
Image		.14*	1.6%
Costs		-.11*	1.1%
Information quality		.12*	.9%
Self-efficacy		-.11*	.7%
Attitude		.10*	.5%
Hedonic motivation		.09*	.5%
Anxiety		.06*	.4%
Perceived behavioral control		-.09*	.4%
Playfulness		.06*	.3%
General risk		.05*	.2%
Price value		.05*	.2%
Age		.03	.1%
Effort expectancy		.03	.1%
Innovativeness of IT		.03	.1%
Security risk		.00	.0%
Voluntariness		.00	.0%
Social influence		.00	.0%
Trust		.01	.0%
Education		.02	.0%

* $p < .05$. The table is based on the full data set. Using the data set without outliers, we find strong effects for compatibility (β=.40; ΔR^2=7.1%), personal innovativeness (β=.26; ΔR^2=5.2%), and costs (β=-.14; ΔR^2=1.8%).

APPENDIX L. RESULTS OF STRUCTURAL EQUATION MODELING

		Individual Models					Integrated Models		
	UTAUT2 (Venkatesh et al. 2012)	Model 1: UTAUT2 Replication	Model 2: Compatibility Extension	Model 3: Education Extension	Model 4: Innovativeness Extension	Model 5: Costs Extension	Model 6: Integrated Model (2)	Model 7: Integrated Model (3)	Model 8: Integrated Model (4)
Behavioral intention (R^2)	**44%**	**55.9%**	**66.2%**	**58.4%**	**56.1%**	**56.1%**	**66.9%**	**67.0%**	**67.4%**
Performance Expectancy	.21*	.30*	.05*	.27*	.30*	.30*	.05*	.05*	.05*
Effort Expectancy	.16*	.10*	-.17*	.10*	.09*	.10*	-.16*	-.16*	-.15*
Social Influence	.14*	-.02	-.03	-.06*	-.02	-.02	-.05*	-.05*	-.05*
Facilitating conditions	.16*	-.02	.02	-.09*	-.02	-.03	-.03	-.03	-.05*
Hedonic motivation	.23*	.11*	.02	.19*	.10*	.12*	.07*	.08*	.10*
Price value	.14*	.17*	-.01	.18*	.16*	.18*	.01	.01	.03
Habit	.32*	.33*	.51*	.34*	.34*	.32*	.51*	.51*	.49*
Compatibility	—	—	.62*	—	—	—	.58*	.60*	.60*
Education	—	—	—	.18*	—	—	.10*	.10*	.11*
Personal innovativeness	—	—	—	—	.04*	—	—	-.05*	-.08*
Costs	—	—	—	—	—	-.04*	—	—	-.07*
Use (R^2)	**35%**	**37.1%**	**42.7%**	**37.1%**	**49.9%**	**38.2%**	**42.7%**	**51.1%**	**51.2%**
Behavioral Intention	.33*	.22*	-.04	.23*	.10*	.23*	-.03	.00	-.00
Facilitating Conditions	.15*	.14*	.07*	.14*	.04*	.11*	.08*	.03	.02
Habit	.24*	.37*	.48*	.37*	.44*	.36*	.48*	.48*	.48*
Compatibility	—	—	.34*	—	—	—	.34*	.16*	.17*
Education	—	—	—	-.02	—	—	-.02	-.03	-.03
Personal innovativeness	—	—	—	—	.39*	—	—	.34*	.33*
Costs	—	—	—	—	—	-.11*	—	—	-.04*
Chi^2(df)	—	56.53(5)	94.64(5)	55.65(5)	74.16(5)	70.65(5)	96.72(5)	164.66(5)	160.31(5)
CFI	—	.991	.990	.992	.990	.990	.990	.985	.986
GFI	—	.993	.989	.993	.991	.992	.990	.985	.986
SRMR	—	.018	.016	.016	.014	.018	.014	.016	.015

* $p < .05$. The analyses are based on the full data set.

APPENDIX M. SUBGROUP ANALYSIS FOR DICHOTOMOUS MODERATORS

IV	DV	k	N	rc	SD	-95%CI	+95%CI	-80%CR	+80%CR	Q	FSN	F	Sig.
Performance expectancy	Use	304	110935	.46	.23	.43	.48	.17	.75	4368	1597549		
	Consumer	201	83387	.47	.22	.44	.50	.19	.75	3117	805393	1.54	.22
	Employee	103	27548	.43	.24	.38	.48	.12	.73	1226	134229		
	Transaction	44	16749	.57	.20	.51	.63	.31	.83	520	56177	12.40	.00[a]
	Non-transaction	260	94186	.44	.23	.41	.47	.15	.73	3664	1054370		
	Internet	201	75487	.47	.23	.44	.50	.18	.76	2958	735519	.83	.36
	Non-Internet	103	35448	.44	.23	.39	.48	.15	.73	1396	164993		
	Mobile	61	19241	.51	.20	.46	.56	.26	.76	581	78917	4.15	.04
	Non-mobile	243	91694	.45	.23	.42	.48	.15	.74	3742	966108		
	Student	96	33984	.44	.20	.40	.48	.18	.70	1065	141374	.29	.59
	Non-student	208	76951	.47	.24	.43	.50	.16	.77	3294	788224		
Effort expectancy	Use	260	97399	.34	.25	.31	.37	.01	.66	4752	720236		
	Consumer	179	75884	.34	.26	.30	.38	.01	.67	3807	393558	.00	.98
	Employee	81	21515	.33	.24	.28	.39	.03	.64	945	48908		
	Transaction	33	12357	.46	.22	.39	.54	.18	.74	454	21564	8.16	.00[a]
	Non-transaction	227	85042	.32	.25	.29	.35	.00	.64	4137	492383		
	Internet	168	62394	.37	.23	.34	.41	.09	.66	2457	338874	9.55	.00[a]
	Non-Internet	92	35005	.27	.28	.21	.33	-.09	.64	2123	70956		
	Mobile	53	17901	.44	.24	.37	.50	.14	.74	765	45424	9.03	.00[a]
	Non-mobile	207	79498	.32	.25	.28	.35	-.01	.64	3828	403738		
	Student	86	29589	.29	.31	.23	.36	-.10	.69	2053	67332	2.39	.12
	Non-student	174	67810	.36	.22	.32	.39	.07	.64	2640	346949		
Social influence	Use	200	74140	.31	.21	.28	.34	.04	.59	2636	355148		
	Consumer	135	54260	.32	.22	.28	.36	.04	.60	1968	179294	.28	.60
	Employee	65	19880	.30	.21	.25	.35	.03	.56	663	29698		
	Transaction	26	9946	.45	.21	.37	.53	.18	.71	335	12003	12.03	.00[a]
	Non-transaction	174	64194	.29	.21	.26	.32	.03	.56	2145	236444		
	Internet	131	45713	.35	.24	.30	.39	.04	.65	1959	165708	5.96	.02[a]
	Non-Internet	69	28427	.26	.16	.22	.30	.06	.47	591	35606		
	Mobile	47	15990	.39	.23	.33	.46	.10	.69	642	28306	7.35	.01[a]
	Non-mobile	153	58150	.29	.20	.26	.33	.03	.55	1900	182799		
	Student	65	22745	.32	.22	.27	.38	.05	.60	783	36451	.37	.54
	Non-student	135	51395	.31	.21	.27	.35	.04	.58	1851	163907		
Price value	Use	23	9492	.34	.17	.27	.42	.12	.57	223	6537		
	Consumer	19	8092	.37	.17	.29	.45	.15	.59	179	5380	2.40	.14

IV	DV	k	N	rc	SD	-95%CI	+95%CI	-80%CR	+80%CR	Q	FSN	F	Sig.
	Employee	4	1400	.20	.12	.07	.33	.05	.35	19	53		
	Transaction	10	3200	.38	.23	.23	.53	.08	.68	135	1140	.56	.46
	Non-transaction	13	6292	.33	.13	.25	.40	.16	.49	85	2204		
	Internet	18	6959	.35	.19	.25	.44	.10	.59	203	3793	.03	.87
	Non-Internet	5	2533	.34	.10	.25	.43	.22	.46	21	366		
	Mobile	12	5024	.35	.17	.24	.45	.13	.57	119	1806	.00	.96
	Non-mobile	11	4468	.34	.17	.23	.45	.12	.57	105	1461		
	Student	8	2478	.44	.16	.32	.55	.23	.64	50	989	2.61	.12
	Non-student	15	7014	.31	.17	.22	.40	.10	.53	153	2427		
Hedonic motivation	Use	70	29057	.40	.22	.35	.46	.13	.68	1055	82260		
	Consumer	63	27038	.41	.22	.35	.46	.13	.69	1004	71022	.25	.62
	Employee	7	2019	.35	.17	.22	.49	.13	.57	47	406		
	Transaction	19	8960	.51	.17	.43	.58	.29	.72	193	10144	7.75	.01[a]
	Non-transaction	51	20097	.36	.22	.30	.42	.08	.64	761	34590		
	Internet	59	23848	.42	.22	.37	.48	.15	.70	871	61334	2.38	.13
	Non-Internet	11	5209	.31	.19	.20	.43	.07	.56	147	1522		
	Mobile	22	8362	.45	.24	.34	.55	.14	.75	371	8721	.90	.35
	Non-mobile	48	20695	.39	.20	.33	.45	.13	.65	670	37366		
	Student	23	7403	.47	.21	.38	.56	.20	.75	272	9684	2.71	.10
	Non-student	47	21654	.38	.21	.32	.44	.11	.65	748	35451		
Facilitating conditions	Use	160	62021	.37	.21	.34	.40	.10	.63	1992	284794		
	Consumer	103	44788	.37	.21	.33	.42	.11	.64	1430	133705	.40	.53
	Employee	56	17233	.36	.20	.30	.41	.09	.62	559	28173		
	Transaction	22	8812	.43	.20	.34	.51	.17	.68	279	7176	1.58	.21
	Non-transaction	137	53209	.36	.21	.32	.40	.10	.62	1689	201435		
	Internet	100	37217	.37	.20	.33	.42	.12	.63	1142	108894	.14	.71
	Non-Internet	59	24804	.36	.22	.30	.42	.09	.64	847	41422		
	Mobile	27	9557	.38	.19	.30	.45	.14	.61	253	8052	.03	.86
	Non-mobile	132	52464	.37	.21	.33	.41	.10	.64	1739	196937		
	Student	47	18031	.43	.24	.36	.50	.12	.73	734	30053	5.31	.02
	Non-student	112	43990	.35	.19	.31	.38	.11	.59	1203	129716		
Habit	Use	25	10518	.56	.20	.48	.63	.30	.81	320	19414		
	Consumer	21	9238	.55	.21	.46	.64	.28	.81	308	13809	.35	.56
	Employee	4	1280	.61	.09	.51	.71	.50	.73	10	472		
	Transaction	8	3851	.58	.12	.49	.67	.42	.74	49	2401	.10	.75
	Non-transaction	17	6667	.54	.23	.43	.65	.24	.84	269	8145		

IV	DV	k	N	rc	SD	-95%CI	+95%CI	-80%CR	+80%CR	Q	FSN	F	Sig.
	Internet	23	9137	.59	.16	.52	.66	.38	.80	196	16990	4.97	.04
	Non-Internet	2	1381	.31	.25	-.05	.66	-.02	.63	60	–		
	Mobile	10	4883	.56	.15	.46	.65	.37	.75	82	3592	.01	.92
	Non-mobile	15	5635	.55	.23	.43	.67	.25	.85	238	6291		
	Student	10	2717	.55	.22	.41	.69	.27	.83	98	1929	.00	.96
	Non-student	15	7801	.56	.19	.46	.66	.31	.80	222	9084		
Compatibility	Use	36	10591	.44	.25	.36	.52	.12	.76	501	18332		
	Consumer	22	7294	.42	.25	.31	.53	.09	.74	359	7027	.45	.51
	Employee	14	3297	.49	.23	.37	.61	.20	.78	133	2646		
	Transaction	5	2197	.41	.23	.20	.61	.11	.70	89	556	.12	.74
	Non-transaction	31	8394	.45	.25	.36	.54	.13	.77	410	12479		
	Internet	21	6655	.44	.26	.33	.55	.11	.77	335	6911	.01	.91
	Non-Internet	15	3936	.44	.23	.32	.56	.14	.74	166	2717		
	Mobile	12	4231	.43	.23	.30	.56	.14	.72	172	2329	.02	.90
	Non-mobile	24	6360	.45	.26	.34	.55	.11	.78	328	7570		
	Student	12	3329	.44	.22	.31	.57	.16	.72	121	1772	.00	.98
	Non-student	24	7262	.44	.26	.33	.55	.11	.77	380	8678		
Education	Use	16	6701	.11	.15	.03	.18	-.08	.29	117	325		
	Consumer	10	3831	.14	.18	.02	.26	-.09	.37	99	221	1.14	.30
	Employee	6	2870	.06	.05	.00	.12	.00	.12	10	5		
	Transaction	3	2334	.13	.00	.09	.17	.13	.13	2	29	.13	.72
	Non-transaction	13	4367	.09	.18	-.01	.20	-.14	.33	114	–		
	Internet	12	5450	.10	.14	.02	.19	-.08	.29	90	183	.03	.87
	Non-Internet	4	1251	.11	.17	-.07	.28	-.11	.32	27	–		
	Mobile	1	976	.10	.00	–	–	–	–	–	–	.00	.95
	Non-mobile	15	5725	.11	.16	.02	.19	-.10	.31	117	269		
	Student	4	463	.36	.44	-.08	.81	-.20	.93	61	–	3.68	.08
	Non-student	12	6238	.09	.07	.04	.14	-.01	.18	35	123		
Personal innovativeness	Use	21	5856	.48	.33	.33	.62	.06	.89	459	5050		
	Consumer	13	3969	.58	.34	.39	.76	.14	1.01	336	3115	4.93	.04[a]
	Employee	8	1887	.26	.12	.15	.36	.10	.41	28	226		
	Transaction	3	1046	.65	.22	.40	.91	.37	.94	40	369	1.23	.28
	Non-transaction	18	4810	.43	.33	.28	.59	.01	.86	389	2678		
	Internet	15	4601	.51	.36	.32	.69	.05	.96	428	3125	.65	.43
	Non-Internet	6	1255	.36	.11	.25	.47	.22	.50	16	224		
	Mobile	5	1620	.32	.14	.18	.45	.14	.49	27	250	1.76	.20

IV	DV	k	N	rc	SD	-95%CI	+95%CI	-80%CR	+80%CR	Q	FSN	F	Sig.
	Non-mobile	16	4236	.54	.35	.36	.71	.08	.99	391	3035		
	Student	4	1140	.24	.00	.18	.30	.24	.24	3	60	2.51	.13
	Non-student	17	4716	.53	.34	.37	.70	.10	.97	400	3978		
Costs	Use	19	8615	-.23	.28	-.36	-.10	-.59	.14	521	2489		
	Consumer	18	8479	-.22	.28	-.36	-.09	-.59	.14	511	2165	.33	.58
	Employee	1	136	-.54	.00	–	–	–	–	–	–		
	Transaction	6	2532	-.50	.26	-.72	-.29	-.84	-.16	134	772	10.30	.01[a]
	Non-transaction	13	6083	-.11	.20	-.22	.00	-.37	.15	189	–		
	Internet	13	5391	-.35	.25	-.49	-.21	-.67	-.02	261	1995	7.14	.02[a]
	Non-Internet	6	3224	-.02	.21	-.20	.15	-.29	.24	107	–		
	Mobile	10	3462	-.28	.29	-.47	-.10	-.65	.09	218	749	.49	.49
	Non-mobile	9	5153	-.19	.28	-.37	-.01	-.54	.16	290	498		
	Student	5	1343	-.49	.38	-.83	-.15	-.98	.00	145	399	3.11	.10
	Non-student	14	7272	-.18	.23	-.30	-.05	-.48	.12	298	885		
Behavioral intention	Use	192	67497	.50	.26	.46	.54	.17	.83	3385	740408		
	Consumer	133	51872	.51	.27	.46	.56	.17	.85	2827	402323	.78	.38
	Employee	58	15625	.47	.21	.42	.53	.20	.74	546	51103		
	Transaction	25	9453	.63	.26	.53	.74	.29	.97	522	22244	9.31	.00[a]
	Non-transaction	166	58044	.48	.25	.44	.52	.16	.79	2712	505858		
	Internet	121	45124	.55	.26	.51	.60	.22	.88	2331	366087	15.94	.00[a]
	Non-Internet	70	22373	.39	.21	.34	.44	.12	.66	776	65175		
	Mobile	37	12913	.54	.20	.47	.60	.28	.80	411	33503	1.25	.27
	Non-mobile	154	54584	.49	.27	.45	.53	.15	.83	2959	458774		
	Student	66	20812	.44	.26	.38	.51	.11	.77	1040	67657	3.52	.06
	Non-student	125	46685	.52	.25	.48	.57	.20	.85	2274	360288		
Performance expectancy	Behavioral intention	925	417994	.62	.23	.61	.64	.33	.92	17074	26487305		
	Consumer	728	367444	.63	.23	.61	.65	.33	.92	15206	18081210	1.19	.28
	Employee	197	50550	.59	.21	.56	.62	.32	.87	1826	799729		
	Transaction	138	48863	.61	.20	.57	.64	.35	.86	1565	601472	.33	.57
	Non-transaction	787	369131	.63	.23	.61	.64	.33	.92	15495	19105175		
	Internet	676	333086	.63	.24	.61	.64	.32	.93	15117	14924066	.01	.94
	Non-Internet	249	84908	.62	.17	.59	.64	.40	.84	1951	1646909		
	Mobile	259	105536	.58	.24	.55	.61	.28	.89	4580	2048062	5.06	.02[a]
	Non-mobile	666	312458	.64	.22	.62	.65	.35	.92	12330	13804097		
	Student	345	109984	.61	.19	.59	.63	.37	.85	3019	3181158	.25	.62
	Non-student	580	308010	.63	.24	.61	.65	.32	.94	14032	11309155		

IV	DV	k	N	rc	SD	-95%CI	+95%CI	-80%CR	+80%CR	Q	FSN	F	Sig.
Effort expectancy	Behavioral intention	795	365756	.50	.24	.48	.52	.20	.80	16068	12583653		
	Consumer	627	323038	.51	.24	.49	.53	.21	.81	14038	8924163	3.40	.07[a]
	Employee	168	42718	.45	.24	.42	.49	.15	.76	1944	313452		
	Transaction	111	39344	.50	.21	.46	.54	.24	.76	1313	262596	.00	.97
	Non-transaction	684	326412	.50	.24	.48	.52	.19	.81	14755	9209979		
	Internet	577	290478	.51	.22	.49	.53	.23	.79	11241	7353399	3.22	.07
	Non-Internet	218	75278	.46	.29	.42	.50	.09	.83	4725	698068		
	Mobile	224	88426	.53	.22	.50	.56	.25	.81	3160	1086244	6.07	.01
	Non-mobile	571	277330	.49	.24	.47	.51	.18	.80	12832	6275050		
	Student	299	96826	.49	.28	.46	.52	.13	.84	5689	1498146	.37	.54
	Non-student	496	268930	.51	.22	.49	.53	.22	.79	10363	5397445		
Social influence	Behavioral intention	615	307565	.42	.22	.40	.43	.14	.70	11817	7195179		
	Consumer	492	277142	.41	.22	.39	.43	.13	.70	10781	5159895	.15	.70
	Employee	123	30423	.43	.21	.39	.47	.17	.70	1030	168674		
	Transaction	91	33855	.47	.27	.42	.53	.13	.82	1949	175850	3.53	.06
	Non-transaction	524	273710	.41	.21	.39	.43	.14	.68	9773	5120846		
	Internet	450	246480	.41	.22	.39	.43	.13	.70	9953	4346103	.15	.70
	Non-Internet	165	61085	.43	.20	.40	.46	.17	.68	1858	357031		
	Mobile	195	84373	.51	.20	.48	.54	.26	.77	2542	876808	37.97	.00[a]
	Non-mobile	420	223192	.38	.22	.36	.40	.11	.66	8535	3048143		
	Student	231	73986	.46	.21	.43	.48	.18	.73	2648	841114	5.42	.02[a]
	Non-student	384	233579	.40	.22	.38	.43	.12	.69	9060	3115720		
Price value	Behavioral intention	91	35358	.48	.27	.42	.54	.13	.83	2032	180505		
	Consumer	85	33950	.48	.26	.43	.54	.15	.82	1831	167045	.01	.90
	Employee	6	1408	.41	.43	.06	.76	-.14	.96	196	255		
	Transaction	19	6294	.39	.48	.17	.61	-.23	1.01	1089	6099	1.92	.17
	Non-transaction	72	29064	.50	.20	.45	.55	.25	.75	898	120164		
	Internet	77	30907	.48	.27	.41	.54	.13	.82	1759	129871	.40	.53
	Non-Internet	14	4451	.52	.28	.37	.67	.16	.88	268	4144		
	Mobile	52	20253	.53	.15	.49	.58	.34	.73	392	69144	4.18	.04
	Non-mobile	39	15105	.40	.37	.29	.52	-.07	.88	1536	26178		
	Student	27	7674	.45	.42	.29	.60	-.09	.98	1002	12662	.37	.54
	Non-student	64	27684	.49	.22	.44	.54	.21	.77	1021	97480		
Hedonic motivation	Behavioral intention	210	101706	.53	.22	.50	.56	.25	.81	3927	1479877		
	Consumer	198	98855	.53	.22	.50	.56	.25	.82	3880	1364045	.05	.82
	Employee	12	2851	.53	.14	.45	.62	.35	.71	47	2348		

IV	DV	k	N	rc	SD	-95%CI	+95%CI	-80%CR	+80%CR	Q	FSN	F	Sig.
	Transaction	30	14692	.62	.20	.55	.69	.37	.88	475	43239	5.20	.02[a]
	Non-transaction	180	87014	.52	.22	.48	.55	.23	.80	3345	1017044		
	Internet	178	93749	.53	.22	.50	.56	.25	.81	3597	1171229	.39	.53
	Non-Internet	32	7957	.56	.22	.48	.65	.28	.85	323	17997		
	Mobile	87	34368	.57	.20	.53	.61	.32	.82	1054	243069	3.69	.06
	Non-mobile	123	67338	.51	.23	.47	.55	.22	.81	2819	523299		
	Student	90	24958	.61	.22	.56	.65	.33	.88	932	199868	7.81	.01[a]
	Non-student	120	76748	.51	.22	.47	.55	.23	.78	2846	591890		
Facilitating conditions	Behavioral intention	322	195406	.39	.20	.36	.41	.13	.64	5921	1808181		
	Consumer	236	175155	.38	.19	.36	.41	.14	.63	4935	1193022	.63	.43
	Employee	86	20251	.41	.25	.36	.47	.09	.73	975	63641		
	Transaction	48	21065	.50	.23	.43	.56	.20	.79	850	53869	10.56	.00[a]
	Non-transaction	274	174341	.37	.19	.35	.40	.13	.61	4865	1237617		
	Internet	215	162297	.39	.19	.36	.41	.15	.63	4495	996228	.05	.83
	Non-Internet	107	33109	.38	.24	.34	.43	.08	.69	1425	120015		
	Mobile	69	29557	.53	.21	.48	.58	.25	.80	1010	127601	28.03	.00[a]
	Non-mobile	253	165849	.36	.18	.34	.39	.13	.60	4413	974898		
	Student	104	40796	.50	.19	.46	.54	.26	.75	1148	206633	27.73	.00[a]
	Non-student	218	154610	.36	.19	.33	.38	.12	.60	4272	792100		
Habit	Behavioral intention	47	21012	.60	.31	.51	.69	.21	.99	1526	78057		
	Consumer	41	19161	.59	.31	.50	.69	.20	.99	1438	60043	.19	.66
	Employee	6	1851	.63	.26	.43	.84	.31	.96	87	1174		
	Transaction	10	4448	.73	.11	.66	.80	.59	.87	44	6176	2.27	.14
	Non-transaction	37	16564	.56	.33	.46	.67	.14	.99	1411	40292		
	Internet	39	18454	.61	.30	.52	.71	.23	.99	1287	59349	.57	.46
	Non-Internet	8	2558	.48	.34	.24	.72	.04	.92	211	1272		
	Mobile	16	10788	.62	.27	.49	.75	.28	.96	630	15125	.24	.62
	Non-mobile	31	10224	.57	.34	.45	.69	.13	1.01	887	24437		
	Student	21	6493	.53	.40	.36	.70	.02	1.04	773	8906	1.07	.31
	Non-student	26	14519	.63	.25	.53	.72	.30	.95	722	34196		
Compatibility	Behavioral intention	87	86334	.65	.12	.63	.68	.50	.80	1065	348390		
	Consumer	69	83258	.66	.11	.63	.68	.52	.79	862	283855	7.52	.01[a]
	Employee	18	3076	.46	.23	.35	.57	.17	.75	124	3285		
	Transaction	17	6251	.70	.12	.64	.76	.55	.86	77	12252	1.10	.30
	Non-transaction	70	80083	.65	.12	.62	.68	.50	.80	975	229901		
	Internet	67	80668	.65	.12	.62	.68	.50	.80	948	236423	.14	.71

IV	DV	k	N	rc	SD	-95%CI	+95%CI	-80%CR	+80%CR	Q	FSN	F	Sig.
	Non-Internet	20	5666	.64	.16	.57	.71	.44	.84	116	10799		
	Mobile	35	9930	.60	.18	.53	.66	.36	.83	269	33480	1.93	.17
	Non-mobile	52	76404	.66	.11	.63	.69	.52	.79	771	165799		
	Student	29	11557	.66	.25	.57	.75	.34	.98	530	31399	.21	.65
	Non-student	58	74777	.65	.09	.63	.67	.54	.76	534	170545		
Education	Behavioral intention	24	10217	.23	.28	.12	.35	-.13	.60	616	3828		
	Consumer	18	9505	.24	.29	.10	.37	-.14	.61	605	3082	.05	.83
	Employee	6	712	.18	.08	.08	.29	.08	.28	9	35		
	Transaction	1	503	1	.00	–	–	–	–	–	–	22.19	.00
	Non-transaction	23	9714	.19	.20	.10	.27	-.07	.45	316	2389		
	Internet	18	9535	.24	.29	.10	.38	-.13	.61	607	3279	.18	.67
	Non-Internet	6	682	.13	.00	.07	.20	.13	.13	4	16		
	Mobile	2	4450	.09	.05	.02	.17	.03	.15	9	24	4.74	.04[a]
	Non-mobile	22	5767	.34	.34	.20	.48	-.09	.77	496	3221		
	Student	6	1341	.49	.28	.26	.73	.13	.86	87	383	3.15	.09
	Non-student	18	8876	.19	.26	.07	.31	-.14	.52	446	1775		
Personal innovativeness	Behavioral intention	100	29204	.30	.32	.23	.36	-.11	.70	2252	71999		
	Consumer	80	24727	.29	.33	.22	.36	-.14	.72	2096	48475	.27	.60
	Employee	20	4477	.34	.20	.24	.43	.08	.60	150	2300		
	Transaction	14	4721	.25	.52	-.03	.52	-.42	.92	934	–	.68	.41
	Non-transaction	86	24483	.31	.26	.25	.36	-.03	.64	1308	54195		
	Internet	74	22388	.28	.35	.20	.36	-.16	.73	2055	38414	.58	.45
	Non-Internet	26	6816	.34	.18	.27	.41	.11	.57	185	5205		
	Mobile	38	13011	.38	.30	.28	.47	-.01	.76	884	18405	5.77	.02
	Non-mobile	62	16193	.23	.32	.15	.31	-.17	.64	1261	17550		
	Student	30	8888	.42	.17	.36	.48	.21	.63	196	10538	6.01	.02[a]
	Non-student	70	20316	.24	.35	.16	.33	-.21	.69	1915	27390		
Costs	Behavioral intention	80	38281	-.12	.32	-.19	-.05	-.53	.29	2778	14010		
	Consumer	76	37598	-.12	.32	-.19	-.05	-.53	.29	2717	13254	.02	.89
	Employee	4	683	-.14	.34	-.49	.20	-.58	.29	61	–		
	Transaction	16	5652	-.47	.29	-.61	-.32	-.83	-.10	355	3593	21.43	.00[a]
	Non-transaction	64	32629	-.05	.28	-.12	.02	-.41	.31	1821	–		
	Internet	66	25358	-.16	.37	-.25	-.07	-.62	.31	2503	11982	2.80	.10
	Non-Internet	14	12923	-.03	.15	-.11	.05	-.22	.15	187	–		
	Mobile	45	27331	-.05	.29	-.14	.03	-.42	.31	1584	–	8.41	.00[a]
	Non-mobile	35	10950	-.28	.34	-.39	-.16	-.71	.16	922	5119		

IV	DV	k	N	rc	SD	-95%CI	+95%CI	-80%CR	+80%CR	Q	FSN	F	Sig.
	Student	20	5182	-.31	.28	-.44	-.19	-.67	.04	317	2329	4.41	.04[a]
	Non-student	60	33099	-.09	.31	-.17	-.01	-.49	.32	2290	4872		

k=number of effect sizes; N=cumulative sample size; rc=sample-sized weighted-reliability adjusted correlation; CI=95%-confidence interval; CR=80% credibility interval; Q=Q statistic; FSN=fail-safe N; F=F-test; * p<.05. a. The confidence intervals and the F-test display similar results for moderator test. The analyses are based on the full data set.

APPENDIX N. RESULTS OF SUBGROUP ANALYSIS FOR CONTINUOUS MODERATORS

			FULL DATA SET						
IV	**DV**		**Age**	**Female**	**PDI**	**IND-COL**	**MAS-FEM**	**UA**	**Year**
Performance expectancy	Use	r	-.06	.00	.15	-.17	-.09	.00	.11
		Sig.	.16	.49	.00	.00	.07	.49	.03
		k	304	304	304	304	304	304	304
Effort expectancy	Use	r	.06	.06	.15	-.21	-.08	-.04	.13
		Sig.	.19	.16	.01	.00	.10	.28	.02
		k	260	260	260	260	260	260	260
Social influence	Use	r	-.08	-.03	.08	-.15	-.06	-.02	.28
		Sig.	.14	.33	.14	.02	.19	.40	.00
		k	200	200	200	200	200	200	200
Price value	Use	r	-.17	-.04	.33	-.29	-.30	.05	.36
		Sig.	.22	.43	.05	.09	.09	.40	.05
		k	23	23	23	23	23	23	23
Hedonic motivation	Use	r	-.10	.09	.16	-.15	-.04	-.16	.04
		Sig.	.20	.23	.09	.12	.38	.10	.36
		k	70	70	70	70	70	70	70
Facilitating conditions	Use	r	.06	-.16	.09	-.15	-.02	.00	.13
		Sig.	.23	.02	.14	.03	.41	.48	.05
		k	159	159	159	159	159	159	159
Habit	Use	r	-.06	-.12	.43	-.45	-.07	-.35	.29
		Sig.	.39	.28	.02	.01	.37	.04	.08
		k	25	25	25	25	25	25	25
Compatibility	Use	r	.05	-.02	.23	-.44	-.04	.10	.08
		Sig.	.38	.45	.09	.00	.42	.28	.33
		k	36	36	36	36	36	36	36
Education	Use	r	.05	.39	-.02	-.33	.27	-.02	.12
		Sig.	.43	.07	.47	.11	.16	.46	.33
		k	16	16	16	16	16	16	16
Personal innovativeness	Use	r	-.37	.16	.12	-.47	-.46	.43	-.05
		Sig.	.05	.25	.30	.02	.02	.03	.42
		k	21	21	21	21	21	21	21
Costs	Use	r	-.13	.03	-.20	.22	-.03	-.04	-.44
		Sig.	.30	.45	.21	.19	.46	.44	.03
		k	19	19	19	19	19	19	19
Behavioral intention	Use	r	-.01	.06	.02	-.09	.02	.03	.05
		Sig.	.43	.21	.41	.12	.41	.32	.25
		k	191	191	191	191	191	191	191
Performance expectancy	Behavioral intention	r	.00	.03	-.04	.07	-.02	.03	.04
		Sig.	.49	.15	.09	.02	.22	.21	.13
		k	925	925	925	925	925	925	925
Effort expectancy	Behavioral intention	r	.04	.01	.03	-.04	-.08	.02	.08
		Sig.	.11	.37	.20	.12	.01	.30	.01
		k	795	794	795	795	795	795	795
Social influence	Behavioral intention	r	.01	.01	.07	-.12	-.04	.05	.17
		Sig.	.42	.43	.05	.00	.19	.10	.00
		k	615	615	615	615	615	615	615
Price value	Behavioral intention	r	-.17	-.08	.11	-.17	-.14	.10	-.03
		Sig.	.06	.21	.14	.06	.10	.18	.40
		k	91	91	91	91	91	91	91
Hedonic motivation	Behavioral intention	r	.06	.04	.03	.08	.05	-.03	.09
		Sig.	.21	.27	.35	.14	.24	.32	.09
		k	210	210	210	210	210	210	210
Facilitating conditions	Behavioral intention	r	-.03	-.02	.14	-.12	-.14	.01	.14
		Sig.	.31	.36	.01	.01	.01	.42	.00
		k	322	322	322	322	322	322	322

Habit	Behavioral intention	r	.07	-.03	.34	-.23	-.02	-.33	-.02
		Sig.	.32	.41	.01	.06	.43	.01	.46
		k	47	47	47	47	47	47	47
Compatibility	Behavioral intention	r	-.12	.11	-.01	.12	-.06	.05	.19
		Sig.	.14	.15	.46	.13	.30	.34	.04
		k	87	87	87	87	87	87	87
Education	Behavioral intention	r	.07	.32	-.02	-.28	.24	.14	-.22
		Sig.	.38	.06	.46	.09	.13	.25	.15
		k	24	24	24	24	24	24	24
Personal innovativeness	Behavioral intention	r	-.13	-.10	-.13	.09	-.11	.00	.05
		Sig.	.10	.15	.10	.18	.13	.50	.31
		k	100	100	100	100	100	100	100
Costs	Behavioral intention	r	-.10	-.05	.20	-.09	.23	-.28	.03
		Sig.	.18	.34	.04	.20	.02	.01	.41
		k	80	80	80	80	80	80	80

r=correlation between continuous moderator and effect size; k=number of effect sizes. PDI = power distance of country culture; IND-COL=individualism versus collectivism of culture; MAS-FEM=masculinity versus femininity of culture; UA=uncertainty avoidance of culture. The analyses are based on the full data set.

APPENDIX O. COMPARISON OF SUBGROUP ANALYSIS FOR DICHOTOMOUS MODERATORS (WITH AND WITHOUT EFFECT SIZE OUTLIERS)

		WITHOUT EFFECT SIZE OUTLIERS				FULL DATA SET			
IV	**DV**	**k**	**rc**	**F**	**Sig.**	**k**	**rc**	**F**	**Sig.**
Performance expectancy	Use	303	.46			304	.46		
	Consumer	201	.47	1.76	.19	201	.47	1.54	.22
	Employee	102	.43			103	.43		
	Transaction	44	.57	12.63	.00[a]	44	.57	12.40	.00[a]
	Non-transaction	259	.44			260	.44		
	Internet	201	.47	.97	.33	201	.47	.83	.36
	Non-Internet	102	.44			103	.44		
	Mobile	60	.51	3.78	.05	61	.51	4.15	.04
	Non-mobile	243	.45			243	.45		
	Student	96	.44	.26	.61	96	.44	.29	.59
	Non-student	207	.47			208	.47		
Effort expectancy	Use	258	.36			260	.34		
	Consumer	178	.37	.09	.77	179	.34	.00	.98
	Employee	80	.35			81	.33		
	Transaction	33	.46	6.96	.01[a]	33	.46	8.16	.00[a]
	Non-transaction	225	.35			227	.32		
	Internet	167	.38	2.92	.09	168	.37	9.55	.00[a]
	Non-Internet	91	.33			92	.27		
	Mobile	53	.44	6.89	.01	53	.44	9.03	.00[a]
	Non-mobile	205	.35			207	.32		
	Student	85	.37	.23	.63	86	.29	2.39	.12
	Non-student	173	.36			174	.36		
Social influence	Use	196	.32			200	.31		
	Consumer	133	.32	.00	.96	135	.32	.28	.60
	Employee	63	.32			65	.30		
	Transaction	25	.42	8.28	.00[a]	26	.45	12.03	.00[a]
	Non-transaction	171	.30			174	.29		
	Internet	128	.34	5.60	.02[a]	131	.35	5.96	.02[a]
	Non-Internet	68	.27			69	.26		
	Mobile	46	.38	4.77	.03	47	.39	7.35	.01[a]
	Non-mobile	150	.30			153	.29		
	Student	64	.31	.00	.99	65	.32	.37	.54
	Non-student	132	.32			135	.31		

		WITHOUT EFFECT SIZE OUTLIERS				FULL DATA SET			
IV	**DV**	**k**	**rc**	**F**	**Sig.**	**k**	**rc**	**F**	**Sig.**
Price value	Use	23	.34			23	.34		
	Consumer	19	.37	2.40	.14	19	.37	2.40	.14
	Employee	4	.20			4	.20		
	Transaction	10	.38	.56	.46	10	.38	.56	.46
	Non-transaction	13	.33			13	.33		
	Internet	18	.35	.03	.87	18	.35	.03	.87
	Non-Internet	5	.34			5	.34		
	Mobile	12	.35	.00	.96	12	.35	.00	.96
	Non-mobile	11	.34			11	.34		
	Student	8	.44	2.61	.12	8	.44	2.61	.12
	Non-student	15	.31			15	.31		
Hedonic motivation	Use	70	.40			70	.40		
	Consumer	63	.41	.25	.62	63	.41	.25	.62
	Employee	7	.35			7	.35		
	Transaction	19	.51	7.75	.01[a]	19	.51	7.75	.01[a]
	Non-transaction	51	.36			51	.36		
	Internet	59	.42	2.38	.13	59	.42	2.38	.13
	Non-Internet	11	.31			11	.31		
	Mobile	22	.45	.90	.35	22	.45	.90	.35
	Non-mobile	48	.39			48	.39		
	Student	23	.47	2.71	.10	23	.47	2.71	.10
	Non-student	47	.38			47	.38		
Facilitating conditions	Use	158	.37			160	.37		
	Consumer	101	.38	.52	.47	103	.37	.40	.53
	Employee	56	.36			56	.36		
	Transaction	21	.44	2.33	.13	22	.43	1.58	.21
	Non-transaction	136	.36			137	.36		
	Internet	98	.38	.22	.64	100	.37	.14	.71
	Non-Internet	59	.36			59	.36		
	Mobile	26	.39	.17	.68	27	.38	.03	.86
	Non-mobile	131	.37			132	.37		
	Student	46	.43	5.32	.02	47	.43	5.31	.02
	Non-student	111	.35			112	.35		
Habit	Use	24	.56			25	.56		
	Consumer	20	.55	.31	.58	21	.55	.35	.56

		WITHOUT EFFECT SIZE OUTLIERS				FULL DATA SET			
IV	**DV**	**k**	**rc**	**F**	**Sig.**	**k**	**rc**	**F**	**Sig.**
	Employee	4	.61			4	.61		
	Transaction	8	.58	.06	.82	8	.58	.10	.75
	Non-transaction	16	.55			17	.54		
	Internet	22	.59	5.56	.03	23	.59	4.97	.04
	Non-Internet	2	.31			2	.31		
	Mobile	10	.56	.00	1.00	10	.56	.01	.92
	Non-mobile	14	.56			15	.55		
	Student	9	.57	.02	.88	10	.55	.00	.96
	Non-student	15	.56			15	.56		
Compatibility	Use	36	.44			36	.44		
	Consumer	22	.42	.45	.51	22	.42	.45	.51
	Employee	14	.49			14	.49		
	Transaction	5	.41	.12	.74	5	.41	.12	.74
	Non-transaction	31	.45			31	.45		
	Internet	21	.44	.01	.91	21	.44	.01	.91
	Non-Internet	15	.44			15	.44		
	Mobile	12	.43	.02	.90	12	.43	.02	.90
	Non-mobile	24	.45			24	.45		
	Student	12	.44	.00	.98	12	.44	.00	.98
	Non-student	24	.44			24	.44		
Education	Use	15	.09			16	.11		
	Consumer	9	.12	1.21	.29	10	.14	1.14	.30
	Employee	6	.06			6	.06		
	Transaction	3	.13	.50	.49	3	.13	.13	.72
	Non-transaction	12	.08			13	.09		
	Internet	11	.09	.13	.72	12	.10	.03	.87
	Non-Internet	4	.11			4	.11		
	Mobile	1	.10	.00	.96	1	.10	.00	.95
	Non-mobile	14	.09			15	.11		
	Student	3	.21	1.37	.26	4	.36	3.68	.08
	Non-student	12	.09			12	.09		
Personal innovativeness	Use	20	.36			21	.48		
	Consumer	12	.43	2.42	.14	13	.58	4.93	.04[a]
	Employee	8	.26			8	.26		
	Transaction	3	.65	12.77	.00[a]	3	.65	1.23	.28

		WITHOUT EFFECT SIZE OUTLIERS				FULL DATA SET			
IV	**DV**	**k**	**rc**	**F**	**Sig.**	**k**	**rc**	**F**	**Sig.**
	Non-transaction	17	.28			18	.43		
	Internet	14	.36	.00	1.00	15	.51	.65	.43
	Non-Internet	6	.36			6	.36		
	Mobile	5	.32	.26	.62	5	.32	1.76	.20
	Non-mobile	15	.38			16	.54		
	Student	4	.24	1.38	.25	4	.24	2.51	.13
	Non-student	16	.40			17	.53		
Costs	Use	17	-.26			19	-.23		
	Consumer	16	-.26	.75	.40	18	-.22	.33	.58
	Employee	1	-.54			1	-.54		
	Transaction	5	-.41	6.41	.02[a]	6	-.50	10.30	.01[a]
	Non-transaction	12	-.19			13	-.11		
	Internet	12	-.30	1.65	.22	13	-.35	7.14	.02[a]
	Non-Internet	5	-.17			6	-.02		
	Mobile	9	-.19	1.83	.20	10	-.28	.49	.49
	Non-mobile	8	-.32			9	-.19		
	Student	4	-.28	.02	.88	5	-.49	3.11	.10
	Non-student	13	-.26			14	-.18		
Behavioral intention	Use	192	.50			192	.50		
	Consumer	133	.51	.78	.38	133	.51	.78	.38
	Employee	58	.47			58	.47		
	Transaction	25	.63	9.31	.00[a]	25	.63	9.31	.00[a]
	Non-transaction	166	.48			166	.48		
	Internet	121	.55	15.94	.00[a]	121	.55	15.94	.00[a]
	Non-Internet	70	.39			70	.39		
	Mobile	37	.54	1.25	.27	37	.54	1.25	.27
	Non-mobile	154	.49			154	.49		
	Student	66	.44	3.52	.06	66	.44	3.52	.06
	Non-student	125	.52			125	.52		
Performance expectancy	Behavioral intention	907	.64			925	.62		
	Consumer	715	.64	1.58	.21	728	.63	1.19	.28
	Employee	192	.61			197	.59		
	Transaction	136	.62	.55	.46	138	.61	.33	.57
	Non-transaction	771	.64			787	.63		
	Internet	661	.64	1.06	.30	676	.63	.01	.94

		WITHOUT EFFECT SIZE OUTLIERS				FULL DATA SET			
IV	**DV**	**k**	**rc**	**F**	**Sig.**	**k**	**rc**	**F**	**Sig.**
	Non-Internet	246	.62			249	.62		
	Mobile	253	.61	3.01	.08	259	.58	5.06	.02[a]
	Non-mobile	654	.65			666	.64		
	Student	342	.61	2.33	.13	345	.61	.25	.62
	Non-student	565	.65			580	.63		
Effort expectancy	Behavioral intention	781	.51			795	.50		
	Consumer	617	.52	3.11	.08[a]	627	.51	3.40	.07[a]
	Employee	164	.47			168	.45		
	Transaction	110	.50	.16	.69	111	.50	.00	.97
	Non-transaction	671	.51			684	.50		
	Internet	567	.51	.01	.94	577	.51	3.22	.07
	Non-Internet	214	.51			218	.46		
	Mobile	221	.53	4.07	.04	224	.53	6.07	.01
	Non-mobile	560	.51			571	.49		
	Student	290	.52	1.53	.22	299	.49	.37	.54
	Non-student	491	.51			496	.51		
Social influence	Behavioral intention	603	.43			615	.42		
	Consumer	480	.43	.00	.98	492	.41	.15	.70
	Employee	123	.43			123	.43		
	Transaction	89	.51	9.61	.00[a]	91	.47	3.53	.06
	Non-transaction	514	.42			524	.41		
	Internet	441	.42	.00	.96	450	.41	.15	.70
	Non-Internet	162	.43			165	.43		
	Mobile	194	.52	40.29	.00[a]	195	.51	37.97	.00[a]
	Non-mobile	409	.39			420	.38		
	Student	226	.47	8.90	.00[a]	231	.46	5.42	.02[a]
	Non-student	377	.41			384	.40		
Price value	Behavioral intention	88	.52			91	.48		
	Consumer	83	.52	.15	.70	85	.48	.01	.90
	Employee	5	.52			6	.41		
	Transaction	18	.54	.43	.51	19	.39	1.92	.17
	Non-transaction	70	.51			72	.50		
	Internet	75	.51	.62	.43	77	.48	.40	.53
	Non-Internet	13	.55			14	.52		
	Mobile	52	.53	.68	.41	52	.53	4.18	.04

		WITHOUT EFFECT SIZE OUTLIERS				FULL DATA SET			
IV	**DV**	**k**	**rc**	**F**	**Sig.**	**k**	**rc**	**F**	**Sig.**
	Non-mobile	36	.50			39	.40		
	Student	26	.57	2.16	.15	27	.45	.37	.54
	Non-student	62	.50			64	.49		
Hedonic motivation	Behavioral intention	208	.53			210	.53		
	Consumer	196	.53	.04	.85	198	.53	.05	.82
	Employee	12	.53			12	.53		
	Transaction	30	.62	5.03	.03[a]	30	.62	5.20	.02[a]
	Non-transaction	178	.52			180	.52		
	Internet	176	.53	.34	.56	178	.53	.39	.53
	Non-Internet	32	.56			32	.56		
	Mobile	86	.57	3.37	.07	87	.57	3.69	.06
	Non-mobile	122	.52			123	.51		
	Student	88	.62	10.53	.00[a]	90	.61	7.81	.01[a]
	Non-student	120	.51			120	.51		
Facilitating conditions	Behavioral intention	320	.39			322	.39		
	Consumer	234	.39	.56	.46	236	.38	.63	.43
	Employee	86	.41			86	.41		
	Transaction	48	.50	10.43	.00[a]	48	.50	10.56	.00[a]
	Non-transaction	272	.38			274	.37		
	Internet	214	.39	.02	.87	215	.39	.05	.83
	Non-Internet	106	.40			107	.38		
	Mobile	69	.53	27.98	.00[a]	69	.53	28.03	.00[a]
	Non-mobile	251	.36			253	.36		
	Student	103	.50	27.80	.00[a]	104	.50	27.73	.00[a]
	Non-student	217	.36			218	.36		
Habit	Behavioral intention	43	.66			47	.60		
	Consumer	37	.67	.00	.99	41	.59	.19	.66
	Employee	6	.63			6	.63		
	Transaction	10	.73	1.55	.22	10	.73	2.27	.14
	Non-transaction	33	.64			37	.56		
	Internet	36	.68	2.88	.10	39	.61	.57	.46
	Non-Internet	7	.50			8	.48		
	Mobile	15	.68	.37	.55	16	.62	.24	.62
	Non-mobile	28	.64			31	.57		
	Student	18	.64	.37	.55	21	.53	1.07	.31

		WITHOUT EFFECT SIZE OUTLIERS				FULL DATA SET			
IV	**DV**	**k**	**rc**	**F**	**Sig.**	**k**	**rc**	**F**	**Sig.**
	Non-student	25	.67			26	.63		
Compatibility	Behavioral intention	82	.66			87	.65		
	Consumer	67	.67	3.77	.06[a]	69	.66	7.52	.01[a]
	Employee	15	.55			18	.46		
	Transaction	17	.70	1.02	.32	17	.70	1.10	.30
	Non-transaction	65	.66			70	.65		
	Internet	62	.66	.71	.40	67	.65	.14	.71
	Non-Internet	20	.64			20	.64		
	Mobile	34	.62	2.56	.11	35	.60	1.93	.17
	Non-mobile	48	.67			52	.66		
	Student	27	.73	7.27	.01[a]	29	.66	.21	.65
	Non-student	55	.65			58	.65		
Education	Behavioral intention	22	.18			24	.23		
	Consumer	16	.18	.00	.98	18	.24	.05	.83
	Employee	6	.18			6	.18		
	Transaction	0	–	–	–	1	1.00	22.19	.00
	Non-transaction	22	.18			23	.19		
	Internet	16	.18	.08	.78	18	.24	.18	.67
	Non-Internet	6	.13			6	.13		
	Mobile	2	.09	4.01	.06	2	.09	4.74	.04[a]
	Non-mobile	20	.25			22	.34		
	Student	5	.46	9.59	.01[a]	6	.49	3.15	.09
	Non-student	17	.13			18	.19		
Personal innovativeness	Behavioral intention	96	.35			100	.30		
	Consumer	76	.35	.04	.84	80	.29	.27	.60
	Employee	20	.34			20	.34		
	Transaction	12	.37	.17	.68	14	.25	.68	.41
	Non-transaction	84	.35			86	.31		
	Internet	70	.35	.02	.88	74	.28	.58	.45
	Non-Internet	26	.34			26	.34		
	Mobile	37	.43	8.44	.00[a]	38	.38	5.77	.02
	Non-mobile	59	.28			62	.23		
	Student	30	.42	3.04	.08	30	.42	6.01	.02[a]
	Non-student	66	.32			70	.24		
Costs	Behavioral intention	80	-.12			80	-.12		

		WITHOUT EFFECT SIZE OUTLIERS				FULL DATA SET			
IV	**DV**	**k**	**rc**	**F**	**Sig.**	**k**	**rc**	**F**	**Sig.**
	Consumer	76	-.12	.02	.89	76	-.12	.02	.89
	Employee	4	-.14			4	-.14		
	Transaction	16	-.47	21.43	.00[a]	16	-.47	21.43	.00[a]
	Non-transaction	64	-.05			64	-.05		
	Internet	66	-.16	2.80	.10[a]	66	-.16	2.80	.10
	Non-Internet	14	-.03			14	-.03		
	Mobile	45	-.05	8.41	.00[a]	45	-.05	8.41	.00[a]
	Non-mobile	35	-.28			35	-.28		
	Student	20	-.31	4.41	.04[a]	20	-.31	4.41	.04[a]
	Non-student	60	-.09			60	-.09		

k=number of effect sizes; rc=sample-sized weighted-reliability adjusted correlation F=F-test. a. The confidence intervals and the F-test display similar results for moderator test.

APPENDIX P. COMPARISON OF CONTINUOUS MODERATOR RESULTS (WITH AND WITHOUT EFFECT SIZE OUTLIERS)

			WITHOUT EFFECT SIZE OUTLIRS							FULL DATA SET						
IV	DV		Age	Female	PDI	IND-COL	MAS-FEM	UA	Year	Age	Female	PDI	IND-COL	MAS-FEM	UA	Year
Performance expectancy	Use	r	-.06	.00	.14	-.17	-.10	.02	.12	-.06	.00	.15	-.17	-.09	.00	.11
		Sig.	.16	.48	.01	.00	.04	.39	.02	.16	.49	.00	.00	.07	.49	.03
		k	303	303	303	303	303	303	303	304	304	304	304	304	304	304
Effort expectancy	Use	r	.06	.08	.16	-.22	-.08	-.04	.14	.06	.06	.15	-.21	-.08	-.04	.13
		Sig.	.16	.10	.01	.00	.09	.28	.01	.19	.16	.01	.00	.10	.28	.02
		k	258	258	258	258	258	258	258	260	260	260	260	260	260	260
Social influence	Use	r	-.05	-.06	.05	-.12	-.05	-.04	.29	-.08	-.03	.08	-.15	-.06	-.02	.28
		Sig.	.24	.21	.23	.04	.25	.31	.00	.14	.33	.14	.02	.19	.40	.00
		k	196	196	196	196	196	196	196	200	200	200	200	200	200	200
Price value	Use	r	-.17	-.04	.33	-.29	-.30	.05	.36	-.17	-.04	.33	-.29	-.30	.05	.36
		Sig.	.22	.43	.05	.09	.09	.40	.05	.22	.43	.05	.09	.09	.40	.05
		k	23	23	23	23	23	23	23	23	23	23	23	23	23	23
Hedonic motivation	Use	r	-.10	.09	.16	-.15	-.04	-.16	.04	-.10	.09	.16	-.15	-.04	-.16	.04
		Sig.	.20	.23	.09	.12	.38	.10	.36	.20	.23	.09	.12	.38	.10	.36
		k	70	70	70	70	70	70	70	70	70	70	70	70	70	70
Facilitating conditions	Use	r	.03	-.19	.10	-.17	-.03	.02	.12	.06	-.16	.09	-.15	-.02	.00	.13
		Sig.	.35	.01	.11	.02	.34	.38	.07	.23	.02	.14	.03	.41	.48	.05
		k	157	157	157	157	157	157	157	159	159	159	159	159	159	159
Habit	Use	r	-.09	.06	.51	-.55	-.18	-.26	.39	-.06	-.12	.43	-.45	-.07	-.35	.29
		Sig.	.34	.39	.01	.00	.20	.11	.03	.39	.28	.02	.01	.37	.04	.08
		k	24	24	24	24	24	24	24	25	25	25	25	25	25	25
Compatibility	Use	r	.05	-.02	.23	-.44	-.04	.10	.08	.05	-.02	.23	-.44	-.04	.10	.08
		Sig.	.38	.45	.09	.00	.42	.28	.33	.38	.45	.09	.00	.42	.28	.33
		k	36	36	36	36	36	36	36	36	36	36	36	36	36	36
Education	Use	r	.23	.64	-.14	-.33	.29	-.71	.45	.05	.39	-.02	-.33	.27	-.02	.12
		Sig.	.20	.01	.31	.11	.14	.00	.05	.43	.07	.47	.11	.16	.46	.33
		k	15	15	15	15	15	15	15	16	16	16	16	16	16	16
Personal innovativeness	Use	r	-.37	.18	.00	-.42	-.26	.31	.02	-.37	.16	.12	-.47	-.46	.43	-.05
		Sig.	.05	.22	.49	.03	.13	.09	.47	.05	.25	.30	.02	.02	.03	.42
		k	20	20	20	20	20	20	20	21	21	21	21	21	21	21
Costs	Use	r	-.18	.09	.31	-.10	.12	-.32	-.35	-.13	.03	-.20	.22	-.03	-.04	-.44
		Sig.	.25	.37	.11	.35	.33	.11	.09	.30	.45	.21	.19	.46	.44	.03
		k	17	17	17	17	17	17	17	19	19	19	19	19	19	19
Behavioral intention	Use	r	-.01	.06	.02	-.09	.02	.03	.05	-.01	.06	.02	-.09	.02	.03	.05

		Sig.	.43	.21	.41	.12	.41	.32	.25	.43	.21	.41	.12	.41	.32	.25
		k	191	191	191	191	191	191	191	191	191	191	191	191	191	191
Performance expectancy	Behavioral intention	r	.05	.05	-.05	.08	-.01	.01	.07	.00	.03	-.04	.07	-.02	.03	.04
		Sig.	.06	.08	.05	.01	.36	.33	.02	.49	.15	.09	.02	.22	.21	.13
		k	907	907	907	907	907	907	907	925	925	925	925	925	925	925
Effort expectancy	Behavioral intention	r	.05	.02	.02	-.04	-.09	.05	.09	.04	.01	.03	-.04	-.08	.02	.08
		Sig.	.07	.26	.32	.13	.01	.06	.00	.11	.37	.20	.12	.01	.30	.01
		k	781	780	781	781	781	781	781	795	794	795	795	795	795	795
Social influence	Behavioral intention	r	.00	-.01	.06	-.12	-.02	.05	.18	.01	.01	.07	-.12	-.04	.05	.17
		Sig.	.46	.43	.06	.00	.29	.13	.00	.42	.43	.05	.00	.19	.10	.00
		k	603	603	603	603	603	603	603	615	615	615	615	615	615	615
Price value	Behavioral intention	r	-.15	.07	.00	-.07	-.13	.11	.02	-.17	-.08	.11	-.17	-.14	.10	-.03
		Sig.	.08	.25	.50	.27	.12	.15	.41	.06	.21	.14	.06	.10	.18	.40
		k	88	88	88	88	88	88	88	91	91	91	91	91	91	91
Hedonic motivation	Behavioral intention	r	.05	.01	.02	.07	.05	-.02	.10	.06	.04	.03	.08	.05	-.03	.09
		Sig.	.23	.43	.37	.17	.23	.37	.08	.21	.27	.35	.14	.24	.32	.09
		k	208	208	208	208	208	208	208	210	210	210	210	210	210	210
Facilitating conditions	Behavioral intention	r	-.03	-.02	.14	-.14	-.15	.02	.11	-.03	-.02	.14	-.12	-.14	.01	.14
		Sig.	.29	.34	.01	.01	.00	.37	.03	.31	.36	.01	.01	.01	.42	.00
		k	320	320	320	320	320	320	320	322	322	322	322	322	322	322
Habit	Behavioral intention	r	.06	-.04	.36	-.25	-.06	-.36	.13	.07	-.03	.34	-.23	-.02	-.33	-.02
		Sig.	.35	.41	.01	.05	.36	.01	.20	.32	.41	.01	.06	.43	.01	.46
		k	43	43	43	43	43	43	43	47	47	47	47	47	47	47
Compatibility	Behavioral intention	r	-.08	.18	-.02	.10	-.14	.09	.27	-.12	.11	-.01	.12	-.06	.05	.19
		Sig.	.25	.05	.43	.18	.10	.22	.01	.14	.15	.46	.13	.30	.34	.04
		k	82	82	82	82	82	82	82	87	87	87	87	87	87	87
Education	Behavioral intention	r	.13	.26	.16	-.51	.06	-.19	-.18	.07	.32	-.02	-.28	.24	.14	-.22
		Sig.	.29	.12	.24	.01	.39	.20	.21	.38	.06	.46	.09	.13	.25	.15
		k	22	22	22	22	22	22	22	24	24	24	24	24	24	24
Personal innovativeness	Behavioral intention	r	-.03	-.08	-.06	.03	-.14	.10	.07	-.13	-.10	-.13	.09	-.11	.00	.05
		Sig.	.40	.21	.28	.38	.09	.17	.26	.10	.15	.10	.18	.13	.50	.31
		k	96	96	96	96	96	96	96	100	100	100	100	100	100	100
Costs	Behavioral intention	r	-.10	-.05	.20	-.09	.23	-.28	.03	-.10	-.05	.20	-.09	.23	-.28	.03
		Sig.	.18	.34	.04	.20	.02	.01	.41	.18	.34	.04	.20	.02	.01	.41
		k	80	80	80	80	80	80	80	80	80	80	80	80	80	80

r=correlation between continuous moderator and effect size; k=number of effect sizes. PDI = power distance of country culture; IND-COL=individualism versus collectivism of culture; MAS-FEM=masculinity versus femininity of culture; UA=uncertainty avoidance of culture.

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