# The Effects of Digital Nativity on Non-Volitional Routine and Innovative IS Usage


| | |
|---|---|
| Journal: | *Information Technology & People* |
| Manuscript ID | ITP-12-2021-0971.R3 |
| Manuscript Type: | Article |
| Keywords: | Digital divide < Phenomenon, Continuance < Theoretical concept, Technology adoption < Theory, Survey < Methodology, Structural equation modeling < Quantitative method < Method, Survey data < Data, User satisfaction < Individual attribute < Unit attribute, Perception < Individual attribute < Unit attribute, Behavior < Theoretical concept, Task-technology fit < Theory |
| | |

# The Effects of Digital Nativity on Non-Volitional Routine and Innovative IS Usage



## Abstract

**Purpose** – This study explores the differences between digital immigrants and digital natives in continuance of routine and innovative information system use.

**Design/methodology/approach** – A quantitative survey was conducted with two different samples comprising 100 digital immigrants and 152 digital natives in mandatory information system use contexts. Data were analyzed with structural equation modelling to examine the hypothesized relationships in the research model.

**Findings** – Results revealed differences among digital nativity groups. The effect of confirmation of expectations about system use on satisfaction is stronger for digital natives whereas the effect on task-technology fit is similar in both digital groups. Interestingly, significant differences between digital nativity groups occur in routine use. For digital immigrants, task-technology fit and habit are significant while for digital natives, satisfaction significantly affects routine use. The results show no difference between digital native groups regarding innovative use.

**Originality/value** – This study extends the concept of digital nativity to routine and innovative system use, contributing to an enhanced understanding about the differences in IS continuance based on digital nativity. It also provides a fine-grained discussion of how to classify digital nativity and its impact in working contexts and extends the IS continuance model by considering two types of IS usage.

**Keywords** - digital native, digital immigrants, routine use, innovative use, IS continuance

**Paper type** - Research Paper

## 1. Introduction

Today, organizations' workforces are composed of workers with different digital nativity, including digital immigrants (DI) and digital natives (DN). DN are individuals born in the digital age that grew up acquainted with and surrounded by technology (Prensky, 2001a). DI were born before the digital age and started using technology later in life (Prensky, 2001a). Exposure to digital environments affects how individuals think, pay attention, and interact (Prensky, 2001b), both in their daily lives and at work (Colbert et al., 2016). Research suggests that new generations have different expectations regarding information systems (IS) use at work (Ghobadi & Mathiassen, 2020), and digital nativity differences in employees manifest in several work practices. For example, to communicate with colleagues, DN use social networks while DI use traditional communication modes (e.g., email, phone).

During the COVID-19 pandemic, organizations increased their remote workforces, and now employees depend heavily on technology to collaborate with colleagues, access organizational facilities, or manage team tasks. Therefore, employees must use IS to their full potential because technology use influences individuals' competencies, self-awareness, control, and expectations (Colbert et al., 2016). Since different digital workforces have different approaches to system use (Colbert et al., 2016), it is important to understand the role that digital nativity plays in employee IS usage when organizations require employees to use IS to perform their work. Research shows that the long-term viability of an IS depends on its effective continued usage (Bhattacherjee, 2001). Adoption and continuance research is grounded in the assumption that users are resistant to technology (Venkatesh et al., 2003). However, while that may be true for DI, as their system use experiences are often in mandatory use settings, DN experiences with technology occur in personal volitional contexts from an early age, making them more open and receptive to technology. Consequently, what we know about IS Continuance (ISC) and use behaviors (Appendix A) may not incorporate the digital workforce's variance of use patterns across the different types of employee digital nativity. Additionally, there are two frequent use behaviors in organizations: routine and innovative. Routine usage can be defined as the standardized and regular form of IS use to support work tasks (Li et al., 2013; Schwarz, 2003). Innovative usage occurs when users take novel or innovative approaches to work task resolution, which occurs when users find new ways to use the IS to perform work, explore more features, and consequently produce novel practices of system usage (Li et al., 2013). However, there is still limited knowledge of how digitally enabled workforces apply both use behaviors at work and what drives those behaviors across generations. In this research, we seek to understand DN and DI routine and innovative continued use behaviors and their antecedents, guided by the question: *What is the influence of digital nativity on IS continuance factors and their effects on routine and innovative use behaviors?*

We extend Bhattacherjee (2001)'s ISC to include both routine and innovative use, considering the user's digital nativity. Following Vodanovich et al. (2010), we define digital nativity by considering a user's age and task experience. The model is tested with 252 users in two non-volitional use settings. The results show that confirmation of IS expectations strongly influences satisfaction in DN. Habit and task-technology fit (TTF) have a stronger effect on routine use for DI, while for DN it is satisfaction that affects routine use. Routine use and satisfaction similarly affect innovative use in both digital nativity groups.

This research contributes to the extension of ISC models by differentiating the effects of routine and innovative use. While previous research advances ISC with some form of extended use (Hsieh & Wang, 2007), we investigate two types of use behaviors that users simultaneously engage in while using a system in a non-volitional setting. This is particularly important in the context of our main (second) extension, which is to explore the role of user's digital nativity in ISC. While DI's ISC behaviors are grounded on usefulness-related factors like habit and TTF, DN rely only on affect factors like satisfaction with the system. Additionally, experience and age influence use behaviors differently. While routine use is positively affected by both, age negatively affects innovative use revealing that as employees age they exhibit lower levels of explorative behavior and settle on routines. These results can guide managers to foster a more effective IS usage when dealing with a mixed workforce.

This paper is organized as follows. First, the theoretical foundations and hypotheses are presented, followed by the methods, analyses, and results. We then provide a discussion of the results and their implications, followed by concluding comments.

## 2. Theoretical Foundations and Hypotheses

### *2.1 Digital Nativity*

Digital users can be classified based on their level of comfort within the digital world (Vodanovich et al., 2010). The literature often classifies the digital nativity of a person based on the time of life at which they started to use technology (Prensky, 2001a). Early access and exposure to technology shape the way technology users think, learn, operate, behave, and act (Prensky, 2001b), making age a determining element in digital nativity. While much is known from that literature, the relationship with technology cannot be defined exclusively based on users' generational cohort given the high variation in use amongst individuals belonging to the same generation (Ghobadi & Mathiassen, 2020; Vodanovich et al., 2010).

Previous research suggested alternative ways to classify users' digital nativity beyond the age-based perspective. For example, digital users can be considered on a continuum representing their levels of technological fluency (Wang et al., 2012). Other studies classify digital nativity based on user digital literacy (Nikou et al., 2019; Wang et al., 2012), or computer engagement, "the degree to which an individual is affectively and cognitively involved with computer usage behavior" (Kesharwani, 2020, p. 4). While those dimensions are important to classify users in general, system use is a rich concept lying in the interaction of three dimensions: user, task, and system (Burton-Jones & Straub, 2006) that should be considered when defining an individual's digital nativity.

Thus, Vodanovich et al. (2010) propose a multidimensional approach to define digital nativity, including user, system, activity, and context. DN are users that started using IS earlier in life developing their digital nativity at home in personal activities with ubiquitous IS (Vodanovich et al., 2010). These IT skills reflect embedded use practices matured through ongoing use of technology while growing up. DN tend to be more active experiential learners, skilled multitaskers, and highly dependent on technology to communicate with others and access information (Bennett et al., 2008). DI are individuals born earlier that reached adulthood with limited access to technology and developed their digital nativity in professional activities with more traditional IS (Vodanovich et al., 2010). Research shows that as users become older their information processing capacity in IT-enabled tasks diminishes, but IT experience and IT self-efficacy mitigate this decrease (Tams, 2022). Consequently, we consider digital nativity in non-volitional usage by combining age, reflecting the digital environment that users were exposed to (Vokic & Vidovic, 2015), and experience to reflect the degree of instrumental use of an IS (Ghobadi & Mathiassen, 2020).

*2.2 ISC Model*

Bhattacherjee (2001) proposed the ISC based on the assumption that the users' cognitive beliefs about system use continue to change during usage, turning into personal affect in ISC. ISC states that continuance intention is driven by the user's satisfaction and perceived usefulness with previous use. Satisfaction with an IS results from the confirmation of prior expectations of the system performance and its perceived usefulness. Confirmation of prior expectations not only influences satisfaction but also perceived usefulness, the other determinant of continuance intentions (Bhattacherjee, 2001).

Adoption and continuance theories are grounded in the premise that users resist technology (Venkatesh et al., 2003). Those theories and models explain what drives intention to use and continue to use an IS for users like DI, that were mandated throughout life to use a certain technology at work. However, DI and DN differ in their resistance to technology. While DI usually resist new technology, DN are more receptive and open to them (Vodanovich et al., 2010), which may affect ISC. For example, studies of digital nativity (age-based) in social media use show that ISC differs between DN and DI (Metallo & Agrifoglio, 2015). Building on these, four premises affect our hypotheses' development. First, the environment and culture to which users were exposed to while growing up shaped their thinking processes and use behaviors (Prensky, 2001b), affecting their resistance to technology. Second, the information processing capacity of users in IT-enabled tasks (i.e., instrumental uses of technology) decreases as time passes, but it can be mitigated by experience and self-efficacy (Li et al., 2013; Tams, 2022). Third, ISC goes beyond intention, and users can show multiple use behaviors, such as routine and innovative use (Li et al., 2013; Prensky, 2001b). Finally, for innovative use to occur in non-volitional settings, users need extra motivation (Karahanna & Agarwal, 2006).

*2.2.1 ISC Determinants*

Expectations are key in determining the way people perceive their surroundings, biasing their perceptions and their accuracy (De Lange et al., 2018). The confirmation of prior expectations about an IS determines user satisfaction about the IS and their behavioral intentions (Bhattacherjee, 2001; Venkatesh & Goyal, 2010). Expectations determine the baseline level for satisfaction (Oliver, 1980). Users with different digital nativity build different expectations about the IS and respond differently in light of those expectations. For example, growing up in an environment in which technologies are ubiquitous creates expectations that all technologies should be designed to be ubiquitous and intuitive (Ghobadi & Mathiassen, 2020; Vodanovich et al., 2010). Although technology for professional uses has become more user-friendly over the years, DI acquire their digital nativity via instrumental uses in work contexts, developing lower expectations about the IS. Conversely, for DN that developed higher expectations about technology and use, confirmation of those expectations results in higher satisfaction.

*H1a.* The positive relationship between confirmation and satisfaction will be stronger for DN.

The perceived usefulness of an IS is a well-established determinant of ISC that "captures the instrumentality of IS use" (Bhattacherjee, 2001, p. 356). In instrumental uses of IS, perceived task-technology fit (TTF), the degree to which individuals perceive a match between systems' features, task requirements, and their needs towards completing a task (Fuller & Dennis, 2009) is an antecedent of perceived usefulness and continuance intentions (Larsen et al., 2009; Lin, 2012). By adding TTF to ISC, Larsen et al. (2009) incorporated the task dimension of system use into the ISC. TTF can be considered a surrogate for perceived usefulness reflecting the users' perceptions of the benefits of IS usage in the context of a task. In mandatory contexts, usefulness represents users' assessment of the benefits of use and fit of the IS to the task.

Previous research shows that DN devaluate the perceived usefulness of technology (Agosto, 2004; Metallo & Agrifoglio, 2015). Although low initial perceptions may be more easily confirmed, confirmation of low levels of usefulness results in lower behavioral intentions and satisfaction (Venkatesh & Goyal, 2010). DN are experienced users in technology for personal use and can assess TTF in such contexts, but not in non-volitional IT-enabled tasks. On the other hand, DI that developed their user skills in professional environments can better assess TTF in such contexts developing higher expectations about the TTF. Additionally, for experienced users, ease of use concerns are replaced by instrumental considerations about use to increase job performance (Karahanna et al., 1999), positively impacting the user's satisfaction.

*H1b.* The positive relationship between confirmation and TTF will be stronger for DI.

*H1c.* The positive relationship between TTF and satisfaction will be stronger for DI.

While learning to use the system, users develop automatic use behaviors. IS habit, "the extent to which people tend to perform behaviors (use IS) automatically because of learning" (Limayem et al., 2007, p. 709), is an important antecedent of ISC. Since IS use is instrumental in task performance, IS habits may not develop only because of the IS itself but also by the context of the task (Burton-Jones & Straub, 2006). While performing an IT-enabled task, users unconsciously refine their use behaviors by developing IS habits to better solve the task (De Guinea & Markus, 2009). Habit reduces the cognitive and behavioral efforts of using the system, limiting the power of intention on ISC (Limayem et al., 2007). Moreover, satisfaction is the primary determinant of continuance intention in ISC, but it is also a key element for habit formation because it motivates the repetition of use behaviors (Limayem et al., 2007). When users are satisfied with their system use, they achieve higher symbolic adoption of the system (Wang & Hsieh, 2006). As such, users are more committed towards system use and more willing to use it to increase task performance, which should be similar for DN and DI users.

*H1d.* The relationship between satisfaction and habit will be equal for DN and DI.

### *2.3 ISC and Use Behaviors*

In non-volitional use settings, users must use the system regardless of their intentions to continue to use it or not. Prior research shows that ISC explains IS use in volitional and non-volitional use contexts beyond continuance intentions, as extended forms of system use (Hsieh & Wang, 2007).

After IS acceptance, in the routinization stage (Hsieh & Zmud, 2006), routine use behavior helps support work tasks and is integrated into work routines (Li et al., 2013; Schwarz, 2003). IS usage transcends conscious behavior because it is part of normal routines (Bhattacherjee, 2001), and is perceived as regular and repetitive (Li et al., 2013; Schwarz, 2003). Research shows that perceived usefulness and satisfaction are important determinants of routine use (Li et al., 2013; Wang et al., 2014). Additionally, when using the IS becomes a habit, the same usage pattern is performed as an unconscious automatic behavior (Limayem et al., 2007). Routines are a consequence of habits, so habit is a strong antecedent of routine usage. The extent of interaction and familiarity with technology is especially relevant to the establishment of habit (Limayem et al., 2007). Triandis (1980) argues that until a behavior becomes routinized, it is influenced by behavioral intentions; however, after routinization it is influenced by habit. DN are experienced users with general technology easily adapting to unfamiliar technologies; however, for them IS usage for instrumental purposes like in non-volitional IT-enabled tasks, it must be accompanied with an explicit opportunity to use the IS (Ng, 2012). Kesharwani (2020)'s study on ISC intentions found no differences in the habit mechanism of digital nativity groups. However, both groups were composed by young users with different computer engagement levels in a university setting. They found that engaging with technology is not related with the development of habit mechanisms, but experience is. Based on the roots of digital nativity, in performing IT-enabled tasks, it is expected that DI that have higher levels of experience and time of instrumental uses of IS will develop stronger usage habits, and consequently higher routine usage.

*H2a.* The positive relationship between habit and routine usage will be stronger for DI.

Experience guides the formation of expectations about TTF and routine use. While habits take time to fully develop, the perception of TTF depends on the assessment of how a system matches the task to complete and if it can improve performance (Staples & Seddon, 2004). If users perceive a fit between the IS and the task to accomplish, the user will repeat these use practices for similar tasks. As aforementioned, DN have less experience in task-related usage and may not perceive the same level of fit, especially for repeated tasks in non-volitional settings. As such, we expect that for DN who have less task-related experience with the IS, TTF will have less effect on their routine use.

*H2b.* The positive relationship between TTF and routine usage will be stronger for DI.

If users are satisfied with their IS usage in task resolution, they confirm their own perceptions about the system, typically as an appreciation of the support the system provides for their task accomplishment. This positively influences their intention to continue using the IS, which leads to the development of more comprehensive methods of IS usage. Therefore, users with higher satisfaction with IS usage are more likely to adopt routine and extended usage behaviors (Wang et al., 2014). For less experienced users in instrumental uses, such as DN, with non-repetitive, regularized, or habitual use practices, their routines are influenced by behavioral intentions such as satisfaction (Triandis, 1980). On the other hand, DI routine use is mainly driven by habit. Therefore, behavioral intentions have little influence on their routines. However, satisfaction may induce higher symbolic adoption in DI (Karahanna & Agarwal, 2006), motivating them to use the system beyond their routinized practices to increase task performance, and that negatively affects the continuance of routine use.

> *H2c.* For DN, satisfaction is positively related to routine use. For DI, satisfaction is negatively related to routine use.

The IT implementation model establishes routine use as an antecedent of extended use behaviors such as innovative use (Hsieh & Zmud, 2006). Extended usage precedes the infusion stage of IT, in which IS use is deeply embedded in the individuals′ behaviors and organizational work systems. In the infusion stage, emergent use includes exploration of new features and attempts to innovate with the IS (Hsieh & Zmud, 2006). Previous research shows that in mandatory use contexts, extended use is a determinant of emergent use (Wang & Hsieh, 2006).

Innovative use is an exploratory use behavior in which users search for new ways of usage by exploring new features and creating novel forms to perform their work tasks (Li et al., 2013), which involves experimentation, change, and risk-taking (March, 1991). While routine use is affected by usefulness-related factors, innovative use determinants are motivation and satisfaction (Li et al., 2013; Wang et al., 2014). Previous research shows contradictory results about the effect of satisfaction on extended use. In models with both extended and emergent use, having symbolic adoption instead of perceived ease of use, satisfaction is a determinant of extended use but not of emergent use (Wang & Hsieh, 2006). In another study, perceived ease of use is a determinant of extended use; however, satisfaction is not related to extended use (Hsieh & Wang, 2007).

As early adopters of IS, DN are better prepared to experiment, search for new ways to use the IS, and consider innovative technologies instead of traditional ones. They are more enthusiastic and curious about trying and experiencing new technologies and continuing to use them if they acknowledge that they add value to their personal and work lives (Kesharwani, 2020). Thus, DN may be more motivated to innovate (Karahanna et al., 2006), being more open to discovering new forms of IS usage. Therefore, DN's satisfaction should increase their innovative use. Furthermore, confirmation of expectations created by exploratory usage will increase their system satisfaction and motivate them to continue to explore innovative IS uses. As such, the effect of satisfaction on innovative use is stronger for DN.

*H3a*. The positive relationship between satisfaction and innovative usage will be stronger for DN.

The IT implementation model places routine use as a previous stage of extended and emergent forms of using an IS (Hsieh & Zmud, 2006). Routine use, as a previous stage of extended use, provides users a solid base to start exploring new features of the IS (Wang et al., 2014). When users can combine routine and innovative use, they develop capacities that allow them to use the IS to its fullest potential (Hsieh & Zmud, 2006; Li et al., 2013). Research shows that routine use is insufficient to achieve the maximum value from IT (Karahanna et al., 2006). Therefore, to increase task performance, DI will search and explore newer innovative uses of the IS. Conversely, DN with fewer instrumental use experiences may not have the ability to evaluate how much value IT can provide in task resolution.

*H3b.* The positive relationship between routine and innovative use will be stronger for DI.

Based on the literature about digital nativity and the continuance model, Figure I depicts our research model.

[Figure I]

## 3. Method

To test our hypotheses, we surveyed employees and students and analyzed the data with Structural Equation Modeling.

### *3.1 Measures*

All scales were adapted from prior research (Table BI – Appendix B). The English version of the questionnaire was reviewed for content validity and translated into the primary language of the participants applying the back-translation technique (Sekaran & Bougie, 2016). A professional translator and an academic independently translated the original items from English into the native language of the respondents. Both translated versions were analyzed, and an agreed version was translated back into English by another academic to confirm translation equivalence. Then, the questionnaire was pre-tested and pilot tested. Tests revealed the scales were reliable and valid (Appendix C).

*3.2 Participants*

We collected data from a European organization where the use of an IS was mandatory to complete a work task. Employees in this organization were mandated to use an IT service management tool to accomplish most work tasks. We sent an email to 176 employees that the organization allowed to voluntarily participate. We received 116 responses, however, seven were removed due to missing data. The final sample size was of 109 employee responses for a response rate of 61.9% comprising 53.0% females and a mean age of 42.7 years. However, the sample only had seven employees younger than 30 years old. To increase our sample of young users, we collected data from students in a western European university. The students were mandated to use an IS to accomplish a task for a mandatory project of a system development prototype (e.g., hotel booking, restaurant ordering software) in MS Access (taught in previous classes; knowledge was expected). All students were invited but participation was voluntary. The survey took place before the project's final presentations. Of the 216 surveys distributed, 147 were returned. After removing two responses with substantial missing data, 145 valid responses remained, representing a response rate of 67.1%. The final student sample comprised 53.0% females and a mean age of 20.8 years.

To ensure the appropriateness of merging the employee and student samples, and to test for nonresponse bias, we followed the procedures in Ma and Agarwal (2007). We conducted a series of independent t-tests on all variables in the research model. The results revealed no differences between the student and employee samples except for routine use and habit in employees, and innovative use for students. As expected, students reported higher innovative use, which can be related to more exploratory behaviors, while employees were more constrained to use the system to perform work tasks. Overall, however, our results suggest that we could merge the samples for multi-group hypothesis testing. The combined final sample was comprised of 254 participants with an age range of 19 to 65 years with mean age of 30.2 years and 53.0% female respondents.

*3.3 Digital Nativity Groups*

To assign the study's participants into their digital nativity group, we performed a cluster analysis with age and task experience as classifiers. Based on these variables, we obtained two clusters corresponding each to the defined digital nativity groups. The results of an outlier analysis revealed two data points in the DI group as outliers that were removed . Our final digital nativity groups were comprised by 152 DN and 100 DI. Table I shows group characteristics.

[Table I]

Following Westland (2010), we computed the minimum sample size for our model. Considering a small to medium effect (0.2 to 0.5) (Cohen, 1992) for a desired statistical power level of 0.8 with a probability level of 0.05, the minimum sample size for model structure was 110, which suggested our sample of 252 was sufficient. Additionally, for multi-group analysis, we computed anticipated effect sizes for each sample size. Both, DN and DI sample sizes allowed us to achieve medium effect sizes (0.31 to 0.36).

*3.4 Data Validation and Analyses*

Before testing the model, we conducted several validation tests (Appendix C). There were no issues with normality, multi-collinearity, or common method bias, and the measurement model exhibited good psychometric characteristics, as shown in Tables BI and CI. The CFA results indicated good model fit ($\chi^2/df$ =2.002; CFI=0.959; SRMR=0.062; RMSEA=0.063) (Hu & Bentler, 1999).

To ensure that the factor structure and loadings were equivalent across digital nativity groups before estimating the structural equation model with multi-group analysis, we assessed the measurement model invariance. We first tested for configural invariance (the constructs in the model have the same pattern of unconstrained and fixed loadings across groups (Putnick & Bornstein, 2016)). The model estimating the two groups with unconstrained loadings presented good goodness-of-fit values ($\chi^2/df$ =1.681; CFI=0.947; SRMR=0.069; RMSEA=0.052) (Hu & Bentler, 1999), revealing configural invariance across digital nativity groups. The overall factor structure of the measurement model fitted well for both digital nativity groups. Second, we tested for metric invariance, i.e., each item contributing to the construct similarly across digital nativity groups (Putnick & Bornstein, 2016), by comparing the unconstrained model with the constrained model with fixed factorial weights and variances of the groups. We obtained good multi-group model fit indicating metric invariance ($\chi^2/df$ =1.634; CFI=0.948; SRMR=0.092; RMSEA=0.050). Finally, we tested scalar invariance to assess whether the item intercepts were equivalent across digital nativity groups by constraining the item intercepts in the model to be equivalent in the two groups (Putnick & Bornstein, 2016). The results revealed partial invariance ($\chi^2$=245.68, df =40; p-value = 0.000); however, the model fit of the scalar invariant model was not significantly worse than the metric invariant model ($\chi^2/df$ =1.676; CFI=0.947; SRMR=0.067; RMSEA=0.052). This indicates that constraining the intercepts across digital nativity groups did not significantly affect model fit, and scalar invariance was supported (Putnick & Bornstein, 2016).

## 4. Analyses and Results

To assess the effects of digital nativity on the ISC, we performed multi-group analysis to compare the structural models of the digital nativity groups (McLean & Wilson, 2019). The results of the structural model invariance test indicated that the model was not invariant across the two digital nativity groups ($\chi^2$=290.20, df =49; p-value = 0.000< 0.05), revealing differences in some paths. However, since our goal is to explore the effect of digital nativity groups in ISC, we considered both differences: significance, and the strength of the associations in the model.

The structural model revealed good model fit ($\chi^2/df$ =1.675; CFI=0.947; SRMR=0.096; RMSEA=0.052) (Hu & Bentler, 1999). Overall, the model can explain a large percentage of variance of the endogenous variables in the two digital nativity groups. For DI, the explained variance in satisfaction is 71.1%, 55.3% in TTF, 37.0% in habit, 76.8% in routine use, and 54.2% in innovative use. For DN, explained variance is 67.2% in satisfaction, 62.9% in TTF, 32.8% in habit, 29.8% in routine use, and 47.9% in innovative use. Table II and Figure II present the results for the multi-group tests.

[Table II; Figure II]

Results show a strong effect of confirmation on both satisfaction and perceived TTF for both digital nativity groups. The differences between DN and DI coefficients are significant for the relationship between confirmation and satisfaction, as this relationship is stronger for DN, thus supporting H1a. Even though the paths are significant, results show no significant differences in betas in the relationship between confirmation and perceived TTF, thus H1b is not supported. H1c predicted a stronger positive effect of TTF on satisfaction for DI. Results show that this relationship is different in the model across DN and DI; the relationship is only significantly positive for DI, partially supporting H1c. Results show no differences between DI and DN in the relationship between satisfaction and habit, supporting H1d. The results indicate a positive significant effect of habit on routine usage for DI, but nonsignificant for DN, partially supporting H2a. Similarly, the effect of TTF on routine usage is only positively significant for DI, partially supporting H2b. H2c predicted that the effect of satisfaction on routine usage would be positive for DN and negative for DI. Since this relationship is only positively significant for DN, H2c is partially supported. H3a predicted a stronger effect of satisfaction on innovative usage for DN. Even though the paths are significant, results show no significant difference in betas, thus H3a is not supported. Similarly, for H3b there are no differences in betas for routine to innovative use between DI and DN, so H3b is not supported.

### *4.1 Post Hoc Analyses*

To validate our findings and gain additional insights, we tested the effects of digital nativity variables on routine and innovative use behaviors. The results show that age has a positive effect on routine use but a negative effect on innovative use. Additionally, task experience positively influences routine use. Figure III shows these results.

[Figure III]

## 5. Discussion

In this study, we incorporate routine and innovative use in the ISC for non-volitional use contexts across two groups of digital users: DN and DI. One major difference between DN and DI is the key role of confirmation of expectations for DN. While confirmation is positively related to satisfaction for both, the relationship is stronger for DN. It is the strongest relationship in DN's ISC model. Because satisfaction is the only determinant of habit, routine, and innovative use, this highlights the importance of confirmation's influence on satisfaction for DN. Confirmation was also positively related to TTF, but there were no differences between digital nativity groups.

The findings enhance our understanding of digital worker expectations in instrumental uses of IS. Our results highlight differences in the factors that affect routine use across digital nativity groups. While DI's routine use is predicted by habit and TTF, for DN it is predicted by satisfaction. Routines are "sequential patterns of action that are based in the interconnected, reciprocally-triggering habits of routine participants" (Turner & Cacciatori, 2016, p. 2). In other words, routines are interlinked habits developing from a process of incremental learning. Habit is an automatic behavior developed gradually through learning. Our findings indicate that satisfaction is a determinant of habit regardless user's digital nativity. When users are satisfied with system use, they will be motivated to continue to learn and develop use habits throughout their lives. Additionally, our results confirm previous research showing that DN devaluate the usefulness of technology (Metallo & Agrifoglio, 2015). Relationships associating utility-related variables are not significant in ISC for DN. Experience increases the usefulness considerations of an IS (Karahanna et al., 1999), and consequently, the development of routine use is associated with short-term task performance (Sun et al., 2019). Further research should investigate at which point experience overturns digital nativity, and when technology utility value in instrumental uses emerges.

Age is negatively related to innovative use, but together with task experience is positively related to routine use. However, routine use and satisfaction are similarly related to innovative use in DN and DI. Despite the negative age effect on innovative use, ISC determinants of innovative use are consistent across digital nativity groups. Innovative use at work can be stimulated by: (i) user personal characteristics, where a user's innovative nature enables them to explore new usage behaviors and adopt new ideas (Rogers, 1995); (ii) system use practices that are not sufficient to support users to achieve work goals, thus demanding new forms of use (Li et al. 2013); and, (iii) when the work system triggers changes in usage routines (Jasperson et al., 2005). Innovative use can help achieve additional IS value (Jasperson et al. 2005; Li et al. 2013), however to explore creative ways to use the system, users must first be familiar with and knowledgeable about technology. Both experience and beliefs are relevant to innovative usage, contributing to the debate about the impact of age on employee innovation (Parsons, 2015). Aging workforces are innovative at work if they have the necessary accumulated experiences with the IS.

*5.1 Theoretical Implications*

The study's results have important implications for the ISC literature and research on digital nativity. Our main theoretical contribution is an extension of the ISC model by adding two use behaviors (routine and innovative), considering the instrumental use of an IS in non-volitional settings. Users can simultaneously perform multiple behaviors while using a system (Li et al., 2013). The proposed extended ISC model allows researchers to focus beyond continuance intentions to usage behaviors, identifying what variables affect innovative and routine usage behaviors.

We also extend ISC by exploring the role of the digital nativity of users on IS continuance. Challenging the assumption of users' resistance to technology, our work demonstrates that this premise does not apply to all users. In fact, DN usage relies on receptiveness to technology, devaluating the usefulness component of technology. This has important implications on ISC relationships, which are different for DN and DI. For DI, ISC relationships are consistent with previous research. For DN, our empirical results show that satisfaction is more important. These differences found between DN and DI highlight the importance of digital nativity for future works theorizing about IS continuance.

Prior continuance literature reveals inconsistent results about the effect of satisfaction on post-acceptance behaviors. By adding digital nativity into ISC, we contribute with different insights on the effect of satisfaction on routine and innovative use. Traditionally, satisfaction influences routine use in ISC (Wang et al., 2014); however, we found that for DI this relationship is outweighed by adoption stage variables (e.g., TTF, habit). Additionally, previous research shows that in extended, emergent, and innovative behaviors, the relationship is dampened in the presence of usefulness-related variables (Wang et al., 2014; Hsieh & Wang, 2007). In our study, satisfaction is always related to innovative use for both digital nativity groups. This may indicate a change in the users profiles that may impact the way we categorize use behaviors, with more innovative users driven by satisfaction.

Finally, another theoretical contribution is the operationalization of digital nativity. By considering experience as a component of digital nativity in addition to age, we explain how experience increases usefulness perceptions, changing the digital nativity of users and their ISC. This contribution is important for future research that studies impacts of digital nativity on innovation.

*5.2 Practical Implications*

This research provides insights on how to deal with distinct digital nativity groups, highlighting the gap between employees coexisting in the workplace, with implications for how to onboard employees. The management of post-adoption system use in distinct generational groups is important as it impacts work performance. In operational activities, routine use is fundamental;

however, to achieve long-term benefits, managers may encourage innovative use to improve employees' work processes, and consequently their performance. Less experienced users have difficulty in regulating work processes and performance with innovative use; however, their system use enables them to be more creative and to experiment with new ideas (Sun et al., 2019). Managers should take advantage of these innovative practices to improve and innovate work processes. Finally, this research provides system developers and designers clues on how to conceptualize new technologies. Since DN's ISC behaviors are influenced by satisfaction, systems should offer flexibility for new generations. DN enter the workforce acquainted with more pervasive and ubiquitous technologies, changing working and communication paradigms in organizations (Vodanovich et al., 2010).

## 6. Conclusions, Limitations and Further Research

This research has some limitations. First, participants came from different settings. However, we needed representative samples of DN and DI with sufficiently comparable sample sizes. The statistical tests indicate measurement model invariance, reducing this concern. Future research should focus on different organizations with equivalent digital nativity groups in their workforces. Another limitation is the possible bias due to using self-reported questionnaires as data collection method. To ensure this was not a concern in our dataset, we tested for common method variance and found no issues.

Even with the noted limitations, our work provides substantial contributions. Our findings indicate that although some similarities exist for digital nativity in ISC use, important differences are present in the post-adoptive behaviors of those groups. Future research should explore the tensions between these distinct groups of employees and use behaviors in organizations that could represent enriching learning opportunities for both groups. To further understand how innovative usage differs between digital groups, research should explore other contextual factors that may constrain or enable DN's innovative use, employing different theoretical backgrounds since in our study, ISC did not capture such differences. Previous research shows the bilateral nature of satisfaction: cognitive and emotional, in affecting continuance intentions (Mamun et al., 2020) of young users. Further research should study this connection considering both types of satisfaction for each digital nativity group. The need to achieve goals requiring more routinized use conflicts with innovative practices that provide long-term benefits. Our work opens an avenue to explore routines development considering sociological aspects of system use. Moreover, the distinct digital nativity of employees may cause some tensions in the way users approach work tasks resolution and IS use; our work provides an insight into the effects of the digital transformation of work and its actors.

## 7 References

Agosto, D. E. (2004). Design vs. content: A study of adolescent girls' website design preferences. *International Journal of Technology and Design Education*, *14*(3), 245-260.

Bennett, S., Maton, K., & Kervin, L. (2008). The ‘digital natives’ debate: A critical review of the evidence. *British Journal of Educational Technology*, *39*(5), 775-786.

Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly*, *25*, 351-370.

Burton-Jones, A., & Straub, D. W. (2006). Reconceptualizing System Usage: An Approach and Empirical Test. *Information Systems Research*, *17*, 228-246.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155-159.

Colbert, A., Yee, N., & George, G. (2016). The digital workforce and the workplace of the future. *Academy of Management Journal*, *59*(3), 731-739.

De Guinea, A. O., & Markus, M. L. (2009). Why break the habit of a lifetime? Rethinking the roles of intention, habit, and emotion in continuing information technology use. *MIS Qarterly*, *33*(3), 433-444.

De Lange, F. P., Heilbron, M., & Kok, P. (2018). How do expectations shape perception? *Trends in Cognitive Sciences*, *22*(9), 764-779.

Fuller, R. M., & Dennis, A. R. (2009). Does Fit Matter? The Impact of Task-Technology Fit and Appropriation on Team Performance in Repeated Tasks. *Information Systems Research*, *20*, 2-17.

Ghobadi, S., & Mathiassen, L. (2020). A Generational Perspective on the Software Workforce: Precocious Users of Social Networking in Software Development. *Journal of Management Information Systems*, *37*(1), 96-128.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate Data Analysis*. NJ: Pearson Prentice Hall.

Hsieh, J., & Zmud, R. W. (2006). Understanding post-adoptive usage behaviors: A two-dimensional view. *DIGIT 2006 Proceedings*, *Paper 3*.

Hsieh, J. J. P.-A., & Wang, W. (2007). Explaining employees' Extended Use of complex information systems. *European Journal of Information Systems*, *16*(3), 216-227.

Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1-55.

Jasperson, J. S., Carter, P. E., & Zmud, R. W. (2005). A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quarterly*, *29*, 525-557.

Karahanna, E., & Agarwal, R. (2006). When the spirit is willing: Symbolic adoption and technology exploration. *Working Paper, University of Georgia, Athens, GA*.

Karahanna, E., Agarwal, R., & Angst, C. M. (2006). Reconceptualizing compatibility beliefs in technology acceptance research. *MIS Quarterly*, 781-804.
Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly*, *23*(2), 183-213.
Kesharwani, A. (2020). Do (how) digital natives adopt a new technology differently than digital immigrants? A longitudinal study. *Information & Management*, *57*(2), 103170.
Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159-174.
Larose, D. T., & Larose, C. D. (2015). *Data Mining and Predictive Analytics, 2nd Edition*. NJ: Wiley.
Larsen, T. J., Sørebø, A. M., & Sørebø, Ø. (2009). The role of task-technology fit as users' motivation to continue information system use. *Computers in Human Behavior*, *25*(3), 778-784.
Li, X., Hsieh, J. J. P.-A., & Rai, A. (2013). Motivational differences across post-acceptance information system usage behaviors: An investigation in the business intelligence systems context. *Information Systems Research*, *24*, 659-682.
Limayem , M., Hirt, S. G., & Cheung, C. M. K. (2007). How Habit Limits the Predictive Power of Intention: the Case of Information Systems Continuance. *MIS Quarterly*, *31*, 705-737.
Lin, W.-S. (2012). Perceived fit and satisfaction on web learning performance: IS continuance intention and task-technology fit perspectives. *International Journal of Human-Computer Studies*, *70*(7), 498-507.
Ma, M., & Agarwal, R. (2007). Through a glass darkly: Information technology design, identity verification, and knowledge contribution in online communities. *Information Systems Research*, *18*(1), 42-67.
Mamun, M. R. A., Senn, W. D., Peak, D. A., Prybutok, V. R., & Torres, R. A. (2020). Emotional satisfaction and IS continuance behavior: reshaping the expectation-confirmation model. *International Journal of Human–Computer Interaction*, *36*(15), 1437-1446.
March, J. G. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science*, *2*, 71-87.
McLean, G., & Wilson, A. (2019). Shopping in the digital world: Examining customer engagement through augmented reality mobile applications. *Computers in Human Behavior*, *101*, 210-224.
Metallo, C., & Agrifoglio, R. (2015). The effects of generational differences on use continuance of Twitter: an investigation of digital natives and digital immigrants. *Behaviour & Information Technology*, *34*(9), 869-881.
Ng, W. (2012). Can we teach digital natives digital literacy? *Computers & Education*, *59*(3), 1065-1078.
Nikou, S., Brännback, M., & Widén, G. (2019). The impact of digitalization on literacy: Digital immigrants vs digital natives. 27th European Conference on Information Systems (ECIS), Stockholm & Uppsala, Sweden.
Oliver, R. L. (1980). A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. *Journal of Marketing Research*, *17*, 460-469.
Parsons, R. A. (2015). The impact of age on innovation. *Management Research Review*.

Podsakoff, P., MacKenzie, S., Lee, J., & Podsakoff, N. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *Journal of Applied Psychology*, *88*(5), 879-903.
Prensky, M. (2001a). Digital Natives, Digital Immigrants Part 1. *On the Horizon*, *9*(5), 1-6.
Prensky, M. (2001b). Digital Natives, Digital Immigrants Part 2: Do They Really Think Differently? *On the Horizon*, *9*(6), 1-6.
Putnick, D. L., & Bornstein, M. H. (2016). Measurement invariance conventions and reporting: The state of the art and future directions for psychological research. *Developmental Review*, *41*, 71-90.
Rogers, E. M. (1995). *Diffusion of innovations*. New York.
Schwarz, A. H. (2003). *Defining information technology acceptance A human-centered, management-oriented perspective*
Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach*. John Wiley & Sons.
Staples, D. S., & Seddon, P. (2004). Testing the Technology-to-Performance Chain Model. *Journal of Organizational and End User Computing*, *16*, 17-36.
Straub, D., Boudreau, M.-C., & Gefen, D. (2004). Validation Guidelines for IS Positivist Research. *Communications of the Association for Information Systems*, *13*(1), 380-426.
Sun, H., Wright, R. T., & Thatcher, J. (2019). Revisiting the Impact of System Use on Task Performance: An Exploitative-Explorative System Use Framework. *Journal of the Association for Information Systems*, *20*(4), 3.
Tams, S. (2022). Helping older workers realize their full organizational potential: a moderated mediation model of age and IT-enabled task performance. *MIS Quarterly*, *46*(1), 1-33.
Triandis, H. C. (1980). Values, attitudes, and interpersonal behavior. *Nebraska Symposium on Motivation, 1979: Beliefs, Attitudes, and Values*, 195-259.
Turner, S. F., & Cacciatori, E. (2016). *Implications for Routines Research*.
Venkatesh, V., & Goyal, S. (2010). Expectation disconfirmation and technology adoption: polynomial modeling and response surface analysis. *MIS Quarterly*, 281-303.
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*, 533-556.
Vodanovich, S., Sundaram, D., & Myers, M. (2010). Research commentary—digital natives and ubiquitous information systems. *Information Systems Research*, *21*(4), 711-723.
Vokic, N. P., & Vidovic, M. (2015). Managing internal digital publics: What matters is digital age not digital nativity. *Public Relations Review*, *41*(2), 232-241.
Wang, E., Myers, M. D., & Sundaram, D. (2012). *Digital natives and digital immigrants: towards a model of digital fluency* ECIS 2012,
Wang, W., & Hsieh, J. (2006). Beyond routine: Symbolic adoption, extended use, and emergent use of complex information systems in the mandatory organizational context. ECIS 2012,
Wang , W., Zhang, Y., Song, B., & Ren, J. (2014). How to understand Post-Acceptance Information System Usage Behaviors: Perspective from IS Success Model. PACIS (2014),
Westland, J. C. (2010). Lower bounds on sample size in structural equation modeling. *Electronic Commerce Research and Applications*, *9*(6), 476-487.

## 8 Appendices

### Appendix A. Sample participant digital nativity in ISC studies

To classify digital nativity of ISC papers, we used the reported age and occupation information in the studies, with occupation as a proxy for experience since most studies do not measure or report actual experience (e.g., Staples & Seddon, 2004). When an article specifically indicated they focused on DI or DN, we used their classification. To ensure the process was reliable, two coders independently classified a set of papers and calculated inter-rater reliability using Cohen's Kappa. We achieved Kappa's of 0.7 to 1, which are considered substantial to perfect agreement (Landis & Koch, 1977). Thus, our classification scheme was reliable. Table AI presents the digital nativity in ISC studies.

[Table AI]

### Appendix B. Scales

[Table BI]

### Appendix C. Data Validation

Data were checked for skewness with results lower than the absolute value of 1, meeting the rule of +/-2.2. Multicollinearity tests show variance inflation factors were all below 5 (low multicollinearity) except for PTTF1, PTTF2, HAB1, and HAB2 that were between 5.0 and 6.8, indicative of moderate multicollinearity (Larose & Larose, 2015).

Measurement model was tested with confirmatory factor analyses for both samples. For convergent validity, we examined factor loadings based on the confirmatory model specifications that include all items for all constructs. The standardized regression weights for each model are in Table BI with their significance levels. All loadings were significant at $p < .001$ or better. The CFA analyses resulted in an acceptable to excellent model fit (Straub et al., 2004). We also examined the AVEs of our scales and all are greater than 0.5. (Hair et al., 2006) (Table CI). For discriminant validity, we compared the square root of each construct's AVE with the inter-construct correlations (diagonals in Table CI).

[Table CI]

Common method bias was evaluated with several procedures. We computed the marker variable test adding a theoretically uncorrelated latent variable (team collaboration) which produced a value of 0.27, corresponding to a low common method variance of 0.07. We also ran the common latent factor test yielding a value of 0.70, corresponding to a common method variance of 0.49. Finally, Harman's single factor test (Podsakoff et al., 2003) yielded no single factor able to explain at least 50% of total variance (largest variance explained by one factor is 33.9%). Accordingly, it is unlikely that common method bias influenced the results.

# The Effects of Digital Nativity on Non-Volitional Routine and Innovative IS Usage

## Tables

| **Study** | | **Digital Natives n=152** | **Digital Immigrants n= 100** |
|---|---|---|---|
| Age | | 23.29 (s.d. 6.59) (19-46) | 44.00 (s.d. 8.13) (33-65) |
| Task Experience | | 1.74 (s.d. 0.47) (1-3) | 2.76 (s.d. 0.65) (1-4) |
| Sample | Employees | n: 10<br>Age: 31 (s.d. 3.89) 27-38<br>Task Exp.: 1.50 (s.d. 0.53) 1-2 | n: 97<br>Age: 44.30 (s.d. 8.07) 33-65<br>Task Exp.: 2.81 (s.d. 0.65) 1-4 |
| | Students | n: 142<br>Age: 20.52 (s.d. 2.13) 19-30<br>Task Exp.: 1.73 (s.d. 0.47) 1-3 | n: 3<br>Age: 34.33 (s.d. 1.15) 33-35<br>Task Exp.: 2 (s.d. 0.00) 2-2 |
| **Constructs** | | **Descriptive Statistics (mean (s.d.))** | |
| Confirmation | | 3.89 (1.16) | 3.74 (1.37) |
| Satisfaction | | 2.99 (0.77) | 2.95 (0.74) |
| Perceived Task-Technology Fit | | 4.23 (1.11) | 4.23 (1.31) |
| Habit | | 3.60 (1.32) | 4.31 (1.60) |
| Routine Use | | 3.06 (1.36) | 4.64 (1.62) |
| Innovative Use | | 3.81 (1.59) | 3.30 (1.60) |

**Table I.** Digital nativity groups characteristics and descriptive statistics

| Paths | SEM Regression Estimates | | Multi-group Testing (DI vs DN) | | Supported? |
|---|---|---|---|---|---|
| | **DI** | **DN** | **Difference in Paths** | **Difference in Betas \|DI-DN\|** | |
| CONF → SAT (H1a: DN>DI) | β=0.640*** | β=0.904*** | No | 0.264*** - Yes | Yes |
| CONF → PTTF (H1b: DI >DN) | β=0.744*** | β=0.793*** | No | 0.049 ns – No | No |
| PTTF -> SAT (H1c: DI > DN) | β=0.250* | β= -0.109 ns (p=0.454) | Yes | - | Partial |
| SAT -> HAB (H1d: DI = DN) | β=0.608*** | β=0.572*** | No | 0.036 ns – No | Yes |
| HAB → RUSE (H2a: DI >DN) | β=0.849*** | β=0.185 ns (p=0.054) | Yes | - | Partial |
| PTTF → RUSE (H2b: DI >DN ) | β=0.301** | β= 0.158 ns (p=0.123) | Yes | - | Partial |
| SAT → RUSE (H2c: DN (+); DI (-)) | β=-0.214 ns (p=0.061) | β= 0.308* | Yes | - | Partial |
| SAT → IUSE (H3a: DN>DI) | β=0.434*** | β=0.294*** | No | 0.140 ns – No | No |
| RUSE → IUSE (H3b: DI >DN) | β=0.410** | β=0.494*** | No | 0.084 ns - No | No |

**Note:** CONF-Confirmation; SAT-Satisfaction; PTTF-Perceived Task-Technology Fit; RUSE-Routine Use; HAB-Habit; IUSE-Innovative Use; *** p<0.001; ** p<0.01; * p<0.05.

**Table II.** Summary of hypothesis and multi-group testing results

| Study | Age (years) | Participants and Roles | Technology | Classification |
|---|---|---|---|---|
| Orlikowski and Gash (1994) | NA | Company employees: consultants, managers, and technologists | Notes (Lotus Development Corporation, 1989) | Digital Immigrants (experienced) |
| Goodhue and Thompson (1995) | NA | Employees from two different organizations - administrative/clerical staff; manager/assistant director; director/ assistant superintendent; supervisor/assistant manager; analyst/technical; train-master/roadmaster; professional; superintendent /VP and up | 25 different technologies | Digital Immigrants |
| Orlikowski (2000) | NA | Corporate employees: development team, technology consultants, customer support | Notes (Lotus Development Corporation, 1989) | Digital Immigrants (experienced) |
| Bhattacherjee (2001) | Average: 33.7 yrs (17-63) | Customers of the online banking division (OBD) of a large USA bank: students, professionals, self-employed, academics, executives, retirees | Online Banking | Combined Digital Immigrants and Digital Natives (varied experiences) |
| Schwarz (2003) | NA | University staff with 23.5 years of work experience | ERP system | Digital Immigrants (experienced) |
| Bhattacherjee and Premkumar (2004) | NA | University students | Computer-based training; Rapid application development software | Digital Natives (age-based) |
| Staples and Seddon (2004) | NA | Sample A: Library staff<br>Sample B: ; students | Library's central cataloguing system; Word processors and spreadsheets | Digital Immigrants<br>Digital Natives<br>(experience- and age-based) |
| Burton-Jones and Straub (2006) | NA | University students | MS Excel | Digital Natives (age-based) |
| Limayem  et al. (2007) | NA | University students | World Wide Web (WWW) | Digital Natives (age-based) |
| Saeed and Abdinnour-Helm (2008) | NA | University students | Web-based student IS (mean usage experience 2.6 yrs) | Digital Natives (age-based) |
| Fuller and Dennis (2009) | Average: 21.8 yrs | University students | Spreadsheet add-in to Groove | Digital Natives (age-based) |
| Larsen et al. (2009) | Average: 45 yrs (1% < 30; 23% 31-39; 51% 40-54; 25% >= 55) | University faculty members | E-learning tool | Digital Immigrants (age-based) |
| Turel et al. (2011) | eBay sample: average: 36 yrs (19-58)<br>Student sample: average: 26 yrs (18-36) | eBay users<br>university students | eBay | Separate analyses.<br>Sample 1 – Combined Digital Immigrants and Digital Natives;<br>Sample 2 – Digital Natives (age-based) |
| Lin and Wang (2012) | Average: 19.3yrs<br>Range: 18-22yr | University students | E-learning system | Digital Natives (age-based) |
| Lin (2012) | NA | University students | E-learning system | Digital Natives |

| | | | | |
|---|---|---|---|---|
| | | | | (age-based) |
| Venkatesh et al. (2012) | Average: 30.68yrs | Mobile Internet users | Mobile Internet technology | Digital Immigrants (experienced) |
| Li et al. (2013) | 12.4% <= 25yrs<br>42.0% 26–30yrs<br>25.9% 31–35yrs<br>13.0% 36–40yrs<br>6.7% >=41yrs | Employees from a telecommunication service company - Marketing analysts | Business Intelligence system | Combined Digital Immigrants and Digital Natives (age-based) |
| Qin and Guan (2013) | NA | Employees from a large-scale motor manufacturing company | ERP system | Digital Immigrants (experienced) |
| Baleghi-Zadeh et al. (2014) | 19-24 (94.3%)<br>25-30 (5.7%) | University students | PutraLMS/ iFolio | Digital Natives (age-based) |
| Hoffmann et al. (2014) | Less than 1 year 0.7%<br>1–2 years 2.5%<br>3–4 years 7.0%<br>5–6 years 8.1%<br>7–8 years 6.8%<br>9–10 years 8.8%<br>11–12 years 8.6%<br>13–14 years 9.5%<br>15–16 years 8.1%<br>17 or more years 11.3% | German general population: Students and Employed | Online Services | Combined Digital Immigrants and Digital Natives |
| Tennant et al. (2014) | NA | University faculty members | Learning management system (16% basic, 47% intermediate, 37% advanced users) | Digital Immigrants (experienced) |
| Wang et al. (2014) | 35% 23-29; 43.4% 30-39yrs<br>20.4% 40-49; 1.2% > 50yrs | Employees from a manufacturing company : Knowledge workers from different company departments | ERP system | Digital Immigrants (age-based) |
| Metallo and Agrifoglio (2015) | Average age: DN 25.2yrs / DI 42.72yrs | Twitter users | Twitter | Separate analysis Digital Immigrants Digital Natives (age-based) |
| Ouyang et al. (2017) | NA | University Students | Massive Open Online Courses | Digital Natives (age-based) |
| Jarrahi and Eshraghi (2019) | 43.1% < 30yrs<br>56.9% >= 30yrs | Employees from multiple management consulting firms: Knowledge workers (managerial and non-managerial) | LinkedIn and Twitter | Separate analysis Digital Immigrants Digital Natives (age-based) |

| | | | | |
|---|---|---|---|---|
| Kesharwani (2020) | Average: 22yrs | Post-Graduate students | Quickforce (learning management system) | Specified in study: Digital Immigrants[1] Digital Natives |

**Table AI.** Digital nativity in IS Continuance researc

[1] In Kesharwani (2020), DN/DI are classified by their computer engagement. The author considers DN students above the mean and DI students below the mean.

| Construct | | Items | St. Coef. | S.E. | C.R. | p-value |
|---|---|---|---|---|---|---|
| **Confirmation** (Bhattacherjee (2001)) | CONF1 | My experience with using IS was better than what I expected. | 0.818 | 0.064 | 15.984 | *** |
| | CONF2 | The service level provided by IS was better than what I expected. | 0.888 | 0.067 | 11.626 | *** |
| | CONF3 | Overall, most of my expectations from using IS were confirmed. | 0.690 | 0.059 | 12.626 | *** |
| **Perceived Task-Technology Fit** (Jarupathirun and Zahedi (2007)) | PTTF1 | Functionalities are adequate | 0.870 | 0.035 | 27.222 | *** |
| | PTTF2 | Functionalities are appropriate | 0.910 | 0.048 | 21.516 | *** |
| | PTTF3 | Functionalities are useful | 0.893 | 0.045 | 21.898 | *** |
| | PTTF4 | Functionalities are compatible | 0.884 | 0.045 | 21.555 | *** |
| | PTTF5 | Functionalities are helpful | 0.882 | 0.052 | 19.712 | *** |
| | PTTF6 | Functionalities are sufficient | 0.753 | 0.059 | 15.474 | *** |
| | PTTF7 | Functionalities make the task easy | 0.789 | 0.060 | 16.689 | *** |
| **Satisfaction** (Bhattacherjee (2001)) | SAT1 | How do you feel about your overall experience of *IS* use? Very dissatisfied/Very satisfied. | 0.934 | 0.092 | 12.641 | *** |
| | SAT2 | Very displeased/Very pleased. | 0.820 | 0.057 | 15.411 | *** |
| | SAT3 | Very frustrated/Very contented. | 0.686 | 0.067 | 11.989 | *** |
| | SAT4 | Absolutely terrible/Absolutely delighted | 0.755 | 0.057 | 12.154 | *** |
| **Routine Use** (Li et al. (2013)) | RUSE1 | My use of *IS* has been incorporated into my regular work practices. | 0.812 | 0.048 | 16.189 | *** |
| | RUSE2 | My use of *IS* is pretty much integrated as part of my normal work routine. | 0.880 | 0.046 | 19.226 | *** |
| | RUSE3 | My use of *IS* is now a normal part of my work. | 0.898 | 0.060 | 18.953 | *** |
| **Innovative Use** (Li et al. (2013)) | IUSE1 | I have discovered new uses of IS to enhance my work performance. | 0.873 | 0.052 | 18.610 | *** |
| | IUSE2 | I have used IS in novel ways to support my work. | 0.889 | 0.055 | 18.730 | *** |
| | IUSE3 | I have developed new applications based on IS to support my work. | 0.883 | 0.056 | 18.456 | *** |
| **Habit** (Limayem and Hirt (2003)) | HAB1 | Using the IS has become automatic to me | 0.956 | 0.033 | 30.066 | *** |
| | HAB2 | Using the IS is natural to me (has become) | 0.948 | 0.054 | 15.074 | *** |
| | HAB3 | When faced with the task, using the IS is an obvious choice for me. | 0.733 | 0.053 | 15.486 | *** |
| **Task Experience** (Maynard and Hakel (1997)) | | How much experience do you have in performing the task? | - | - | - | - |

**Note:** All scales are 7-pt Likert-type except for satisfaction which is a differential four-point scale.

**Table BI.** Constructs, item loadings and significance

| | CR | AVE | MSV | CONF | PTTF | SAT | RUSE | IUSE | HAB |
|---|---|---|---|---|---|---|---|---|---|
| **Confirmation (CONF)** | 0.843 | 0.645 | 0.645 | **0.803** | | | | | |
| **Task-Tec. Fit (PTTF)** | 0.950 | 0.733 | 0.599 | 0.774*** | **0.856** | | | | |
| **Satisfaction (SAT)** | 0.878 | 0.647 | 0.631 | 0.794*** | 0.621*** | **0.804** | | | |
| **Routine Use (RUSE)** | 0.899 | 0.747 | 0.448 | 0.460*** | 0.459*** | 0.376*** | **0.864** | | |
| **Innovative Use (IUSE)** | 0.913 | 0.777 | 0.385 | 0.620*** | 0.497*** | 0.563*** | 0.496*** | **0.882** | |
| **Habit (HAB)** | 0.914 | 0.783 | 0.448 | 0.615*** | 0.484*** | 0.489*** | 0.670*** | 0.456*** | **0.885** |

**Note:** AVE- Average Variance Extracted; MSV- Maximum Shared Variance
Significance of Correlations: † $p < 0.100$, * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

**Table CI.** Measurement model quality criteria


Baleghi-Zadeh, S., Ayub, A. F. M., Mahmud, R., & Daud, S. M. (2014). Behaviour Intention to Use the Learning Management : Integrating Technology Acceptance Model with Task-Technology Fit. *Middle-East Journal of Scientific Research*, *19*, 76-84.

Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly*, *25*, 351-370.

Bhattacherjee, A., & Premkumar, G. (2004). Understanding changes in belief and attitude toward information technology usage: a theoretical model and longitudinal test. *MIS Quarterly*, *28*, 229-254.

Burton-Jones, A., & Straub, D. W. (2006). Reconceptualizing System Usage: An Approach and Empirical Test. *Information Systems Research*, *17*, 228-246.

Fuller, R. M., & Dennis, A. R. (2009). Does Fit Matter? The Impact of Task-Technology Fit and Appropriation on Team Performance in Repeated Tasks. *Information Systems Research*, *20*, 2-17.

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *MIS Quarterly*, *19*, 213-236.

Hoffmann, C. P., Lutz, C., & Meckel, M. (2014). Digital natives or digital immigrants? The impact of user characteristics on online trust. *Journal of Management Information Systems*, *31*(3), 138-171.

Jarrahi, M. H., & Eshraghi, A. (2019). Digital Natives vs. Digital Immigrants: A Multidimensional View on Interaction with Social Technologies in Organizations. *Journal of Enterprise Information Management*, *32*(6), 1051-1070.

Jarupathirun, S., & Zahedi, F. M. (2007). Exploring the Influence of Perceptual Factors in the Success of Web-based Spatial DSS. *Decision Support Systems*, *43*, 933-951.

Kesharwani, A. (2020). Do (how) digital natives adopt a new technology differently than digital immigrants? A longitudinal study. *Information & Management*, *57*(2), 103170.

Larsen, T. J., Sørebø, A. M., & Sørebø, Ø. (2009). The role of task-technology fit as users' motivation to continue information system use. *Computers in Human Behavior*, *25*(3), 778-784.

Li, X., Hsieh, J. J. P.-A., & Rai, A. (2013). Motivational differences across post-acceptance information system usage behaviors: An investigation in the business intelligence systems context. *Information Systems Research*, *24*, 659-682.
Limayem, M., & Hirt, S. (2003). Force of Habit and Information Systems Usage: Theory and Initial Validation. *Journal of the Association for Information Systems*, *4*, 65-95.
Limayem , M., Hirt, S. G., & Cheung, C. M. K. (2007). How Habit Limits the Predictive Power of Intention: the Case of Information Systems Continuance. *MIS Quarterly*, *31*, 705-737.
Lin, W.-S. (2012). Perceived fit and satisfaction on web learning performance: IS continuance intention and task-technology fit perspectives. *International Journal of Human-Computer Studies*, *70*(7), 498-507.
Lin, W.-S., & Wang, C.-H. (2012). Antecedences to continued intentions of adopting e-learning system in blended learning instruction: A contingency framework based on models of information system success and task-technology fit. *Computers & Education*, *58*(1), 88-99.
Maynard, D. C., & Hakel, M. D. (1997). Effects of Objective and Subjective Task Complexity on Performance. *Human Performance*, *10*, 303-330.
Metallo, C., & Agrifoglio, R. (2015). The effects of generational differences on use continuance of Twitter: an investigation of digital natives and digital immigrants. *Behaviour & Information Technology*, *34*(9), 869-881.
Orlikowski, W. J. (2000). Using Technology and Constituting Structures: A Practice Lens for Studying Technology in Organizations. *Organization Science*, *11*, 404-428.
Orlikowski, W. J., & Gash, D. C. (1994). Technological frames: making sense of information technology in organizations. *ACM Transactions on Information Systems*, *12*, 174-207.
Ouyang, Y., Tang, C., Rong, W., Zhang, L., Yin, C., & Xiong, Z. (2017). *Task-technology Fit Aware Expectation-confirmation Model towards Understanding of MOOCs Continued Usage Intention*.
Qin, M., & Guan, J. (2013). *Employees Information System Usage Behavior Evolution Based on Social Network Analysis Perspective* Proceedings of the 2013 the International Conference on Education Technology and Information Systems (ICETIS 2013),
Saeed, K. A., & Abdinnour-Helm, S. (2008). Examining the effects of information system characteristics and perceived usefulness on post adoption usage of information systems. *Information & Management*, *45*, 376-386.
Schwarz, A. H. (2003). *Defining information technology acceptance A human-centered, management-oriented perspective*
Staples, D. S., & Seddon, P. (2004). Testing the Technology-to-Performance Chain Model. *Journal of Organizational and End User Computing*, *16*, 17-36.
Tennant, V. M., Mills, A. M., & Chin, W. W. (2014). *Variation in Individuals ' Post-Adoption Behaviors : Use of Information Systems*.
Turel, O., Serenko, A., & Giles, P. (2011). Integrating technology addiction and use: An empirical investigation of online auction users. *MIS Quarterly*, 1043-1061.
Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and user of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*, 157-178.
Wang , W., Zhang, Y., Song, B., & Ren, J. (2014). *How to understand Post-Acceptance Information System Usage Behaviors: Perspective from IS Success Model*.

**The Effects of Digital Nativity on Non-Volitional Routine and Innovative IS Usage**

**Figures**

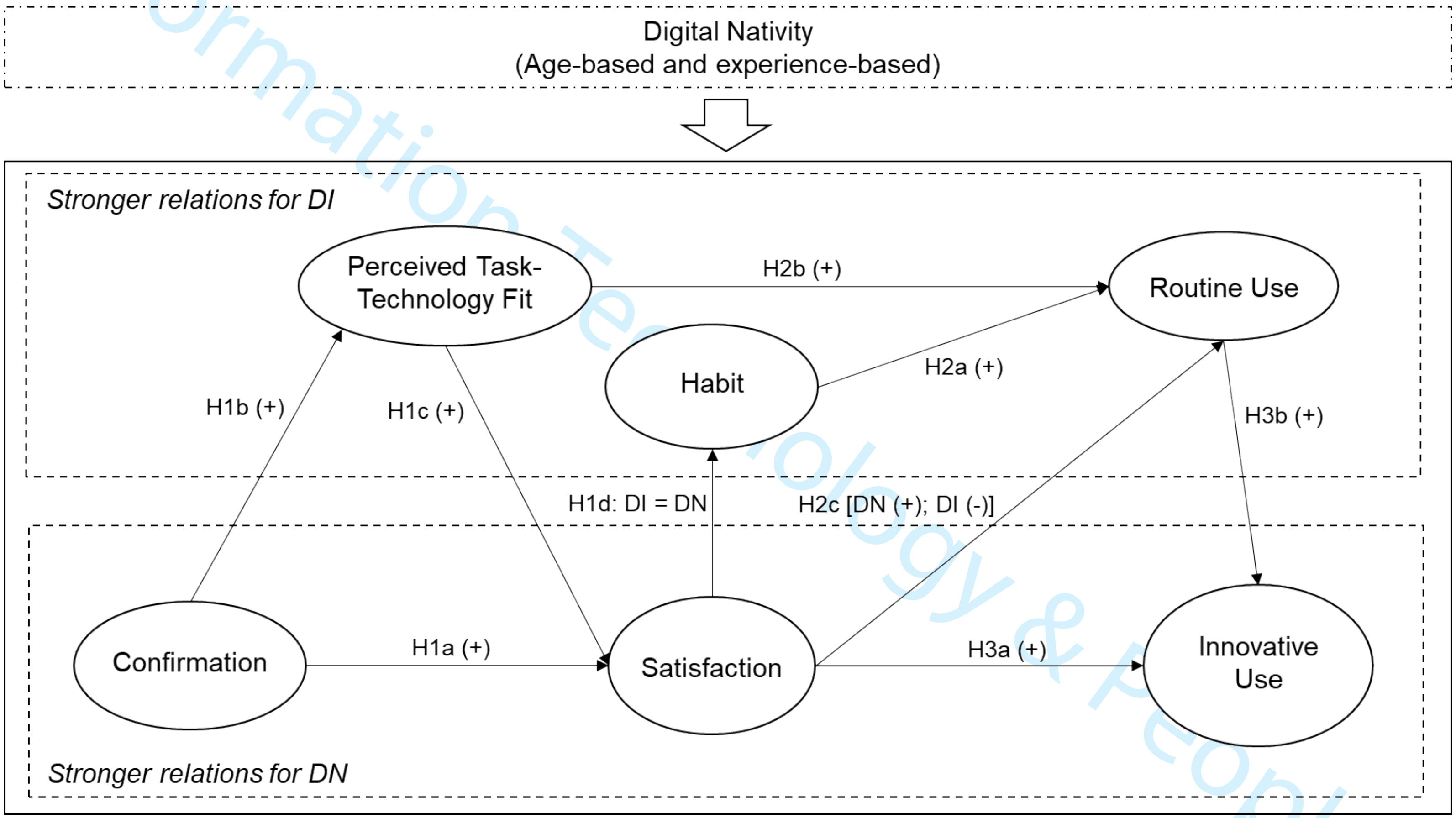


**Figure I.** Research model of IS continuance behaviors in non-volitional use

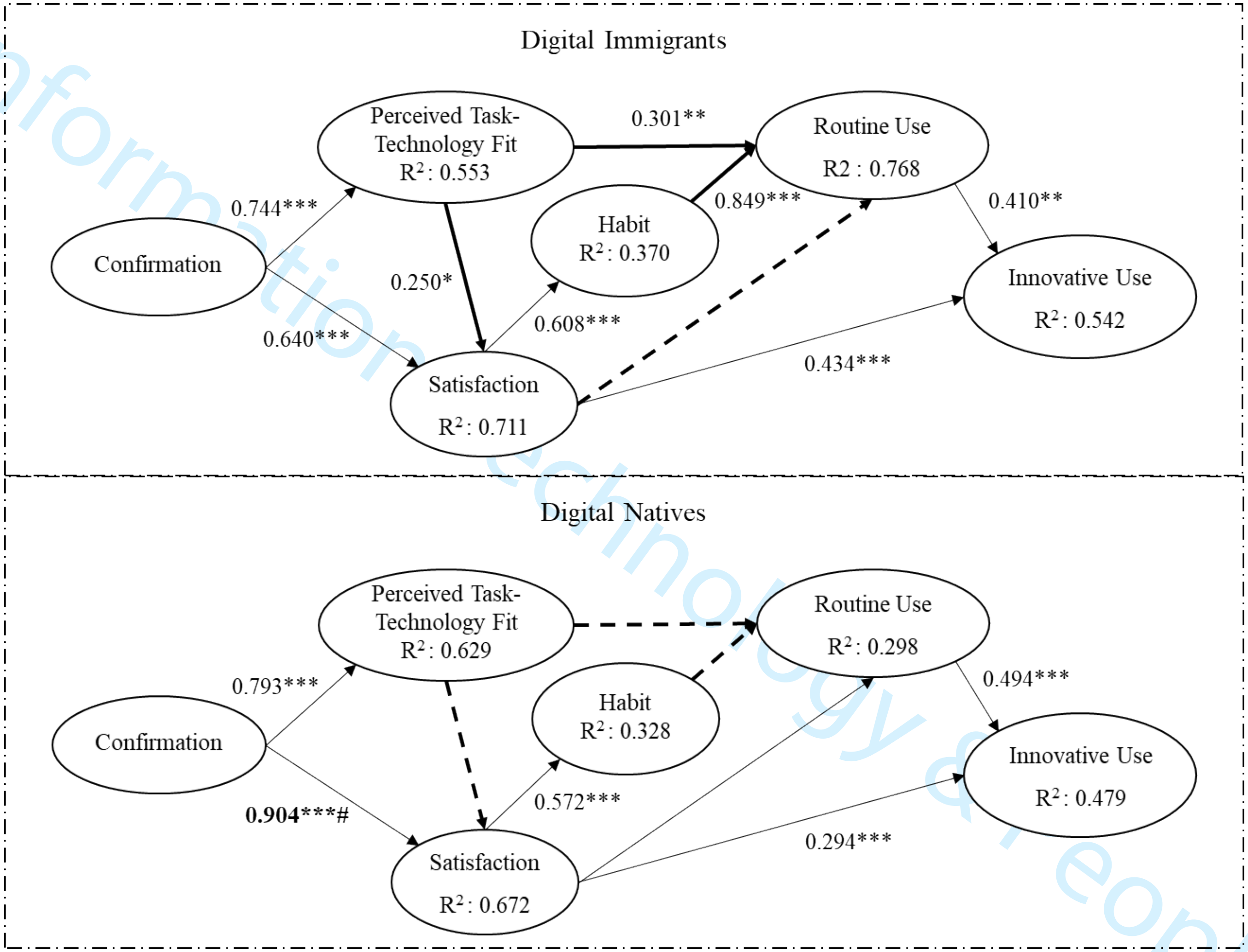


**Figure II.** Research model for digital nativity groups results

**Note:** # DN > DI at 0.05 or better; *** p<0.001; ** p<0.01; * p<0.05

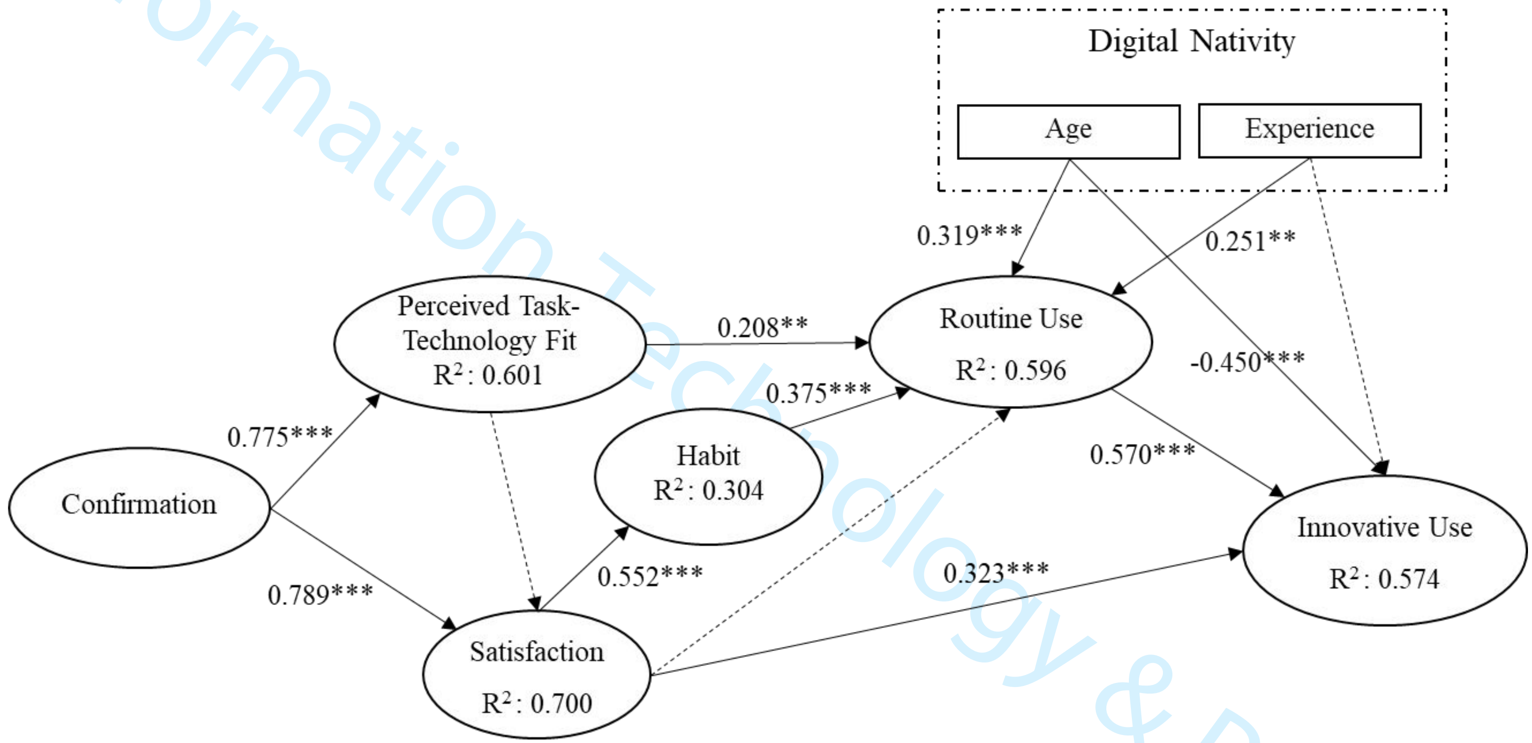


**Figure III.** Post-hoc model results

**Note:** *** p<0.001; ** p<0.01; * p<0.05