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Gender, Age, and Generational Differences in the Use Intention of Mobile Payments and Its Antecedents

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Abstract. Although mobile payments have gained considerable attention in academic research, there still are major gaps in our more in-depth understanding of the antecedents of their acceptance and use. In this study, we aim to address these gaps by examining the potential gender and age differences in the use intention of mobile payments and its antecedents in terms of the effects of the antecedent factors on use intention as well as the antecedent factors and use intention themselves while also considering the critical prerequisite of measurement invariance. Moreover, through a careful selection of the compared age groups, we extend the examination to cover also the potential generational differences between digital natives and digital immigrants. As the data for the study, we use the responses to an online survey that were collected from Finnish consumers in May 2020 and are analysed by using structural equation modelling (SEM). In terms of gender, we find no differences in the effects of the antecedent factors on use intention but find women to perceive the use of mobile payments as both less easy and less secure than men. In turn, in terms of age and generation, we find the effect of social influence on use intention to be stronger for younger users representing digital natives, whereas older users representing digital immigrants were found to perceive the use of mobile payments as less easy. Finally, we discuss these findings in more detail from both theoretical and practical perspectives.

Keywords: Mobile Payments, Use Intention, Antecedents, Gender Differences, Age Differences, Generational Differences, Digital Natives, Digital Immigrants.

1 Introduction

The adoption of mobile payments is progressing very rapidly. For example, whereas the global market of mobile payments was valued at about US$ 1,450 billion in 2020, its value has been forecasted to reach about US$ 5,400 billion by 2026 [1]. Thus, it is not surprising that mobile payments have gained considerable attention also in academic research (cf. [2–7]). However, despite this attention, there are still major gaps in our more in-depth understanding of the acceptance and use of mobile payments, such as the potential gender, age, and generational differences in its antecedents between different user segments. For example, although the potential gender and age differences have already been examined in some prior studies (e.g., [8–15]), these studies have typically suffered from two main methodological shortcomings. First, they have focused either only on the gender and age differences in the effects of various antecedent factors on use intention or only on the gender and age differences in the antecedent factors and use intention themselves, whereas none have examined them both simultaneously under the same study. Second, few of them have focused on establishing an adequate level of measurement invariance between the compared gender or age groups, which has been highlighted as a critical prerequisite for ensuring the meaningfulness of the conducted comparisons in both general [16] and information systems (IS) specific [17] research literature. Thus, our understanding of these differences has remained limited. In contrast, the potential generational differences have been examined only in one prior study that we are aware of [18] and by using a relatively simplistic research model that focused on the effects of perceived usefulness, perceived ease of use, and perceived security on the attitude toward using mobile payment systems instead of use or use intention itself. Thus, more research on also these differences is urgently needed.

In this study, our objective is to address these gaps by examining the potential gender and age differences in the use intention of mobile payments and its antecedents in terms of the effects of the antecedent factors on use intention as well as the antecedent factors and use intention themselves while also considering the critical prerequisite of measurement invariance. Moreover, through a careful selection of the compared age groups, we extend the examination to cover also the potential generational differences between two generations of users that were originally coined by Prensky [19–20] and have since been commonly used IS research (e.g., [18, 21–22]): digital natives and digital immigrants. Of them, *digital natives* (DN) refer to younger users who have grown up using digital technologies, whereas *digital immigrants* (DI) refer to older users who have come to use digital technologies at some later stage of their adult lives. Because of this, these two generations are typically assumed to differ considerably in terms of both their general relationship with (e.g., [19–21]) and their more specific use of (e.g., [23]) these technologies. As the data for the aforementioned examination, we use the responses to an online survey that were collected from Finnish consumers in May 2020 and are analysed by using structural equation modelling (SEM).

After this introduction, we review the prior research on mobile payments and present our research model in Section 2. This is followed by the reporting of the research methodology in Section 3 and the research results in Section 4. The research results are discussed in more detail in Section 5 before concluding the paper with a brief discussion of the limitations of the study and some potential paths for future research in Section 6.

2 Research Model

Throughout the years, various research models for explaining the acceptance and use of mobile payments have been proposed (cf. [2–7]). Most of these models have been based on either IS specific or more general theories for explaining user or human behaviour, such as the technology acceptance model (TAM) [24], the unified theory of acceptance and use of technology (UTAUT) [25], UTAUT2 [26], the theory of reasoned action (TRA) [27–28], and the theory of planned behaviour (TPB) [29–30]. In the models, the use intention or use behaviour of mobile payments has been explained by using numerous different antecedents, of which the six most commonly used antecedents have been (1) perceived ease of use originating from TAM (analogous with effort expectancy originating from UTAUT), (2) perceived usefulness originating from TAM (analogous with performance expectancy originating from UTAUT), (3) social influence originating from UTAUT (analogous with subjective norm originating from TRA and TPB), (4) perceived trust, (5) perceived risk, and (6) perceived security [7]. In addition to the antecedents themselves, there is also considerable variance between the models in terms of how these different antecedents are hypothesised to affect the use intention or use behaviour of mobile payments, with some models hypothesising direct effects and other models hypothesising indirect effects via other antecedents. For example, whereas the study by Khalilzadeh et al. [31] hypothesises perceived security to affect use intention both directly and indirectly via attitude, the study by Liébana-Cabanillas et al. [32] hypothesises only a direct effect, whereas the study by Matemba and Li [33] hypothesises only an indirect effect via privacy concerns. Similar examples for the other aforementioned antecedents are also available.

In this study, we obviously cannot cover all the different antecedents that have been proposed in prior studies or all the different ways in which they have been hypothesised to affect the use intention or use behaviour of mobile payments. Therefore, in order to promote compatibility with prior research as well as to optimise the impact of our study in terms of its findings concerning the potential gender, age, and generational differences being as broadly applicable as possible, our approach is not to aim at any theoretical novelty in our research model but rather the opposite. In other words, we aim our research model to be a parsimonious synthesis of the findings of prior studies in terms of both its constructs and the hypothesised effects between them. We aim to achieve this in three different ways. First, we base the antecedents of the research model on the aforementioned six most commonly used antecedents in prior studies (i.e., perceived usefulness, perceived ease of use, social influence, perceived trust, perceived risk, and perceived security), with the exception that, of the latter three antecedents, we include only perceived security and exclude perceived trust and perceived risk. This avoids the potential conceptual overlaps between these three antecedents and can also be seen to result in a more parsimonious research model because the perceived trust toward mobile payment systems and the perceived risk of using them are typically determined mainly by their perceived security. Second, in terms of the outcome construct of the research model, we focus on use intention instead of actual use behaviour because this construct has more commonly been used as the outcome construct in prior studies [7]. Third, in terms of the hypothesised effects of the antecedents on use intention, we focus only on the most parsimonious alternative, which are the direct effects of the antecedents on use intention. Thus, in our research model, which is illustrated in Figure 1, we hypothesise the use intention (UI) of mobile payments to be affected directly by four antecedent factors: perceived usefulness (PU), perceived ease of use (PEOU), social influence (SI), and perceived security (PS).

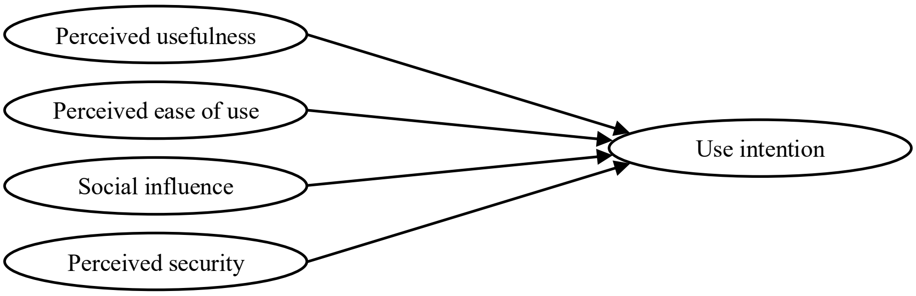

Fig 1. Research model of the study

In terms of gender and age differences, although gender and age have been hypothesised to moderate the effects of various antecedent factors on the acceptance and use of technology in theories like UTAUT and UTAUT2, relatively few prior studies have examined these differences in the context of mobile payments. The most notable exceptions to this are the studies by Liébana-Cabanillas et al. [8–10], which have focused on the gender and age differences in the effects of the antecedent factors on use intention. In addition, the gender differences in the effects of the antecedent factors on use intention have also been examined in the studies by Jaradat and Faqih [11], Lwoga and Lwoga [12], as well as Lee et al. [13]. In turn, only two studies have focused on the gender and age differences in the antecedent factors and use intention themselves, with the study by Hamza and Shah [14] focusing on them only in the case of gender and the study by Acheampong et al. [15] focusing on them in the case of both gender and age. Finally, generational differences in the context of mobile payments have been previously examined only in the study by Fischer et al. [18]. We will discuss the findings of these studies in more detail in Section 5 when reflecting them against those of our study.

3 Methodology

The data for this study was collected in an online survey targeted at Finnish consumers in May 2020. The survey respondents were recruited by sharing the survey link actively via various communication channels, such as the electronic mailing lists of our university and social media. The survey questionnaire was in Finnish and was tested in a pilot study before the actual study. It contained multiple items related to the demographics of the respondents and their use of mobile payments. Of them, the 15 items reported in Table 1 (translated from Finnish to English) were used to measure the constructs of our research model. Each of the five constructs was measured reflectively by three items. The items measuring perceived usefulness and perceived ease of use were adapted from [24], whereas the items measuring social influence were adapted from [25] and [34]. In turn, the items measuring perceived security were adapted from [35] and [36], whereas the items measuring use intention were adapted from [25] and [37]. The standard five-point Likert scale (1 = strongly disagree … 5 = strongly agree) was used as the measurement scale. In order to avoid forced responses, the respondents also had the option not to respond to a particular item, which resulted in a missing value.

Table 1. Item wordings

Item	Wording
PU1	Using mobile payments would enable me to pay more quickly.
PU2	Using mobile payments would enable me to pay more efficiently.
PU3	Using mobile payments would enable me to pay more easily.
PEOU1	Learning to use mobile payments is easy.
PEOU2	Using mobile payments is clear and understandable.
PEOU3	I find using mobile payments easy.
SI1	People who are important to me think that I should use mobile payments.
SI2	People who are important to me expect that I use mobile payments.
SI3	People who are important to me have recommended that I use mobile payments.
PS1	I would feel secure sending sensitive information across mobile payment systems.
PS2	Mobile payment systems are a secure means through which to send sensitive information.
PS3	Mobile payment systems have sufficient technical capacity to protect my sensitive information.
UI1	I intend to use mobile payments in the near future.
UI2	I am likely to use mobile payments in the near future.
UI3	I am willing to use mobile payments in the near future.

The collected data was analysed with covariance-based structural equation modelling (CB-SEM), which was conducted by using the Mplus version 7.11 software [38] and by following the recommended guidelines for SEM in administrative and social science research [39]. As the model estimator, we used the MLR option of Mplus, which stands for maximum likelihood estimator robust to non-normal data. The potential missing values were handled by using the FIML option of Mplus, which stands for full information maximum likelihood and uses all the available data in model estimation.

The potential gender, age, and generational differences were examined by using multiple group analysis (MGA) and by following the procedure formalised in [40] for establishing measurement invariance. In it, increasingly strict constraints on parameter equality are added across the groups and the fit of the resulting constrained model is compared to the fit of the unconstrained model. In the first step, configural invariance is tested by estimating the model separately for each group while constraining only the simple structure of the model as equal across the groups. If the fit of this model remains approximately as good as the fit of the model without the group separation, then the hypothesis of configural invariance is supported. In the second and third steps, metric and scalar invariance are tested by additionally constraining the indicator loadings and intercepts as equal across the groups. If these additional constraints result in no statistically significant deterioration in model fit, then the hypotheses on metric and scalar invariance are supported. After this, the differences in the effects between the constructs can be tested by constraining the estimated effect sizes as equal across the groups one by one and examining whether this results in a statistically significant deterioration in model fit. If it does, then that particular effect can be considered to differ across the groups. In turn, the differences in the constructs themselves can be tested by examining their estimated mean scores in each group. In order to make the estimated model identifiable, one of the groups typically has to be specified as a reference group in which the construct mean scores are fixed to zero, meaning that the construct mean scores of the other groups indicate the size and statistical significance of the differences in comparison to that particular group. As a statistical test for examining the potential deteriorations in model fit, we used the χ^2 test of difference, in which the value of the test statistic was corrected with the Satorra-Bentler [41] scaling correction factor (SCF) due to the use of the MLR estimator. However, because the χ^2 test of difference is known to suffer from a similar sensitivity to sample size as the χ^2 test of model fit, we also considered the potential changes in the model fit indices as suggested in [40].

4 Results

We received a total of 323 responses to the online survey, of which 11 responses had to be dropped due to missing or invalid data. Thus, the sample size used in this study was 312 responses. The descriptive statistics of this sample in terms of gender, age, education, and prior experience in using mobile payments as well as the reference gender and age distributions of the Finnish adult population in 2020 [42] are reported in Table 2. As can be seen, the sample was quite well-balanced in terms of gender but tilted toward younger respondents aged under 45 years who had either a bachelor's or master's degree. Most of the respondents also already had some previous experience in using mobile payments and relatively many had used them for more than two years. In the following four subsections, we first estimate the model for all the respondents, evaluate it in terms of its reliability and validity at both indicator and construct levels, as well as report its estimates and goodness of fit with the data. Finally, we examine the potential gender, age, and generational differences.

Table 2. Sample statistics (N = 312)

	Sample (N)	Sample (%)	Finland (%)
Gender			
Man	172	55.1	49.0
Woman	140	44.9	51.0
Age			
18–24 years	46	14.7	9.5
25–34 years	130	41.7	15.8
35–44 years	94	30.1	15.9
45–54 years	25	8.0	14.8
55–64 years	14	4.5	16.1
65 years or over	3	1.0	28.0
Education			
Basic qualification	2	0.6	
Vocational qualification	30	9.6	
Matriculation examination	51	16.3	
Bachelor's degree	135	43.3	
Master's degree	85	27.2	
Doctoral degree	8	2.6	
No response	1	0.3	
Experience in using mobile payments			
Has never used	52	16.7	
Has used for less than one year	52	16.7	
Has used for one or two years	74	23.7	
Has used for more than two years	128	41.0	
No response	6	2.0	

4.1 Indicator Reliability and Validity

Indicator reliabilities and validities were evaluated by using the standardised loadings of the indicators, which are reported in Table 3 together with the mean and standard deviation (SD) of each indicator as well as the percentage of missing values. In the typical case where each indicator loads on only one construct, it is commonly expected that the standardised loading of each indicator is statistically significant and greater than or equal to 0.707 [43]. This is equivalent to the standardised residual of each indicator being less than or equal to 0.5, meaning that at least half of the variance in each indicator is explained by the construct on which it loads. The only indicator that did not meet this criterion was SI3, which is why we decided to drop it from the model. After dropping it, as shown in the final column of Table 3, all the indicators met the aforementioned criterion.

Table 3. Indicator statistics (*** = $p < 0.001$)

Item	Mean	SD	Missing	Loading before dropping SI3	Loading after dropping SI3
PU1	3.936	1.321	0.3%	0.927***	0.928***
PU2	3.888	1.277	0.0%	0.858***	0.858***
PU3	4.166	1.058	3.5%	0.836***	0.835***
PEOU1	3.939	1.288	0.0%	0.829***	0.829***
PEOU2	3.974	1.211	0.0%	0.888***	0.888***
PEOU3	4.147	1.244	0.0%	0.899***	0.899***
SI1	3.157	1.253	14.4%	0.917***	0.847***
SI2	3.084	1.348	8.3%	0.815***	0.880***
SI3	3.385	1.408	4.2%	0.582***	Dropped
PS1	3.240	1.287	0.0%	0.814***	0.813***
PS2	3.385	1.091	10.9%	0.834***	0.834***
PS3	3.324	1.313	0.0%	0.861***	0.861***
UI1	4.391	1.041	2.6%	0.869***	0.869***
UI2	4.416	0.955	2.9%	0.943***	0.944***
UI3	4.389	0.948	3.5%	0.949***	0.948***

4.2 Construct Reliability and Validity

Construct reliabilities were evaluated by using the composite reliabilities (CR) of the constructs [43], which are commonly expected to be greater than or equal to 0.7 [44]. The CR of each construct is reported in the first column of Table 4. As the reported values show, all the constructs met this criterion. In turn, construct validities were evaluated by examining the convergent and discriminant validities of the constructs by using the two criteria proposed in [43]. They both are based on the average variance extracted (AVE) of the constructs, which refers to the average proportion of variance that a construct explains in its indicators. In order to exhibit satisfactory convergent validity, the first criterion expects that each construct should have an AVE of at least 0.5. This means that, on average, each construct should explain at least half of the variance in its indicators. The AVE of each construct is reported in the second column of Table 4, showing that all the constructs met this criterion. In order to exhibit satisfactory discriminant validity, the second criterion expects that each construct should have a square root of AVE greater than or equal to its absolute correlation with the other constructs in the model. This means that, on average, each construct should share at least an equal proportion of variance with its indicators than it shares with these other constructs. The square root of AVE of each construct (on-diagonal cells) and the correlations between the constructs (off-diagonal cells) are reported in the remaining columns of Table 4, showing that this final criterion was also met by all the constructs.

Table 4. Construct statistics

	CR	AVE	PU	PEOU	SI	PS	UI
PU	0.907	0.765	0.875				
PEOU	0.905	0.761	0.819	0.873			
SI	0.854	0.746	0.563	0.475	0.864		
PS	0.875	0.699	0.551	0.510	0.384	0.836	
UI	0.944	0.848	0.783	0.682	0.560	0.584	0.921

4.3 Model Estimates and Model Fit

The results of model estimation for all the respondents in terms of the standardised effect sizes and their statistical significance, the proportion of explained variance (R^2) in use intention, as well as model fit are reported in the first column of Tables 5 and 6. Model fit was evaluated by using the χ^2 test of model fit and four alternative model fit indices recommended in recent methodological literature [45]: the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardised root mean square residual (SRMR). Of them, the χ^2 test of model fit rejected the null hypothesis of the model fitting the data ($\chi^2(67) = 152.147$, $p < 0.001$), which is common in the case of large samples [46]. In contrast, the values of the four model fit indices (CFI = 0.964, TLI = 0.952, RMSEA = 0.064, and SRMR = 0.036) all clearly met the cut-off criteria (CFI ≥ 0.95, TLI ≥ 0.95, RMSEA ≤ 0.06, and SRMR ≤ 0.08) recommended in [45]. Thus, we consider the overall fit of the model as satisfactory. Of the four antecedent factors, perceived usefulness, perceived security, and social influence were each found to have a positive and statistically significant effect on use intention, whereas the effect of perceived ease of use on use intention was found to be statistically not significant. Together, the antecedent factors were found to explain about 66.4% of the variance in use intention.

Table 5. Model estimates (* = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$)

	All	Men	Women	Younger / DN	Older / DI
Effects					
PU → UI	0.523***	0.503***	0.522**	0.330*	0.699***
PEOU → UI	0.083	0.030	0.152	0.177	-0.006
SI → UI	0.151*	0.111	0.202**	0.284**	0.014
PS → UI	0.195***	0.269**	0.130	0.163*	0.230*
R^2					
UI	0.664***	0.626***	0.728***	0.600***	0.767***

Table 6. Model fit

	All	Men	Women	Younger / DN	Older / DI
Fit test					
χ^2	152.147	112.086	141.445	122.344	126.982
df	67	67	67	67	67
p	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Fit indices					
CFI	0.964	0.966	0.934	0.958	0.948
TLI	0.952	0.954	0.910	0.943	0.929
RMSEA	0.064	0.063	0.089	0.069	0.081
SRMR	0.036	0.042	0.040	0.044	0.041

4.4 Gender, Age, and Generational Differences

For examining the potential gender, age, and generational differences, the sample was split into two mutually exclusive and collectively exhaustive groups that were compared against each other: men (N = 172) vs. women (N = 140) and younger users aged under 35 years (N = 176) vs. older users aged 35 years or over (N = 136). Of them, when taking into account that the data was collected in mid-2020, the younger and older users can also be alternatively labelled as DN and DI because they represent users who were born after and before 1985 (1985 has been used as the cut-off year for separating DN from DI in several prior studies (e.g., [47–49]), although some prior studies have also used 1980 (e.g., [18, 22]) or 1983 (e.g., [23]) as the cut-off year). The results of model estimation for these four groups in terms of the standardised effect sizes and their statistical significance, the proportion of explained variance (R^2) in use intention, as well as model fit are reported in the remaining columns of Tables 5 and 6.

The results of the measurement invariance tests for the gender, age, and generational differences are reported in the first three rows of Tables 7 and 8. As can be seen, in the case of the gender as well as age and generational differences, the fit of the configural invariance model deteriorated slightly in comparison to the model without the group separation (cf. Table 6) but still remained satisfactory in terms of three of the four model fit indices (i.e., CFI, RMSEA, and SRMR). Thus, the hypothesis on configural invariance was supported. Similarly, the results of the subsequent model comparisons supported the hypotheses on metric and scalar invariance, as the χ^2 tests of difference suggested no statistically significant deterioration in model fit ($p \geq 0.05$), and most of the model fit indices suggested improvement rather than deterioration in model fit.

Table 7. Invariance tests for the gender differences

Invariance	χ^2	df	SCF	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$	Δdf	p
Configural	253.446	134	1.0771	0.952	0.934	0.076	0.041			
Metric	250.787	143	1.0974	0.956	0.944	0.070	0.043	1.591	9	0.996
Scalar	257.951	152	1.0905	0.957	0.949	0.067	0.044	6.201	9	0.720
PU → UI	256.868	153	1.0952	0.958	0.950	0.066	0.044	0.015	1	0.903
PEOU → UI	256.759	153	1.0969	0.958	0.950	0.066	0.044	0.166	1	0.684
SI → UI	258.220	153	1.0920	0.957	0.949	0.066	0.044	0.516	1	0.473
PS → UI	258.945	153	1.0940	0.957	0.949	0.067	0.045	1.224	1	0.269

Table 8. Invariance tests for the age and generational differences

Invariance	χ^2	df	SCF	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$	Δdf	p
Configural	249.177	134	1.0599	0.953	0.937	0.074	0.043			
Metric	252.627	143	1.0793	0.956	0.944	0.070	0.051	6.255	9	0.714
Scalar	260.258	152	1.0726	0.956	0.948	0.068	0.052	6.720	9	0.666
PU → UI	261.872	153	1.0754	0.956	0.948	0.068	0.052	1.642	1	0.200
PEOU → UI	259.886	153	1.0789	0.957	0.949	0.067	0.052	0.608	1	0.436
SI → UI	266.242	153	1.0712	0.954	0.945	0.069	0.054	7.043	1	0.008
PS → UI	260.675	153	1.0740	0.956	0.948	0.067	0.053	0.631	1	0.427

The results of the remaining model comparisons, which were used to examine the gender, age, and generational differences in the effects of the antecedent factors on use intention, are reported in the last four rows of Tables 7 and 8. As can be seen, a statistically significant ($\Delta\chi^2(1) = 7.043$, $p = 0.008$) difference was found only in the effect of social influence on use intention in the case of the age and generational differences, which was found to be stronger for younger users (i.e., DN) than older users (i.e., DI). In turn, the standardised construct mean scores, which were used to examine the gender, age, and generational differences in the antecedent factors and use intention themselves, are reported in Table 9. Here, men and younger users (i.e., DN) act as reference groups in which the construct mean scores are fixed to zero and against which the construct mean scores of women and older users (i.e., DI) are compared. As can be seen, statistically significant gender differences were found in the construct mean scores of perceived ease of use and perceived security, which were found to be lower for women than men. In contrast, statistically significant age and generational differences were found only in the construct mean score of perceived ease of use, which was found to be lower for older users (i.e., DI) than younger users (i.e., DN).

Table 9. Differences in construct mean scores ([a] = fixed to 0, * = $p < 0.05$, *** = $p < 0.001$)

Construct	Men	Women	Younger / DN	Older / DI
PU	0.000[a]	-0.134	0.000[a]	-0.179
PEOU	0.000[a]	-0.211*	0.000[a]	-0.349***
SI	0.000[a]	-0.182	0.000[a]	-0.231
PS	0.000[a]	-0.272*	0.000[a]	0.073
UI	0.000[a]	-0.081	0.000[a]	-0.152

5 Discussion and Conclusions

In this study, we examined the potential gender and age differences in the use intention of mobile payments and its antecedents in terms of the effects of the antecedent factors on use intention as well as the antecedent factors and use intention themselves while also considering the critical prerequisite of measurement invariance. Moreover, through a careful selection of the compared age groups, we extended the examination to cover also the potential generational differences between DN and DI. The examination was based on a research model in which the use intention of mobile payments was hypothesised to be explained by perceived usefulness, perceived ease of use, social influence, and perceived security. Overall, we found this model to perform very well in explaining the intention to use mobile payments and to have a good fit with the data as well as satisfactory reliability and validity at both indicator and construct levels.

In terms of the gender differences in the effects of the antecedent factors on use intention, we found no differences. When reflecting this finding against prior research, it supports the findings by Jaradat and Faqih [11], Lwoga and Lwoga [12], as well as Lee et al. [13], who also found no differences in the effects of perceived usefulness or performance expectancy, perceived ease of use or effort expectancy, and social influence or subjective norm on use intention. The only exception to this was the finding by Lwoga and Lwoga [12] that the effect of perceived ease of use on use intention is stronger for men than women, which is not supported by our findings. In addition, our findings also do not support the findings by Liébana-Cabanillas et al. [8, 10] that the effect of perceived usefulness on use intention is stronger for men than women.

In terms of the gender differences in the antecedent factors and use intention themselves, we found women to have lower scores of perceived ease of use and perceived security than men, meaning that they perceived the use of mobile payments as less easy and less secure. One likely explanation for this is that women have typically been found to have lower technology readiness (e.g., [50]), lower self-efficacy toward technology use (e.g., [51]), as well as lower trust perceptions (e.g., [52]) and higher risk perceptions (e.g., [53]) toward online shopping, which may influence also their perceptions concerning the use of mobile payments. When reflecting this finding against prior research, it supports the findings by Hamza and Shah [14] as well as Acheampong et al. [15] that men have higher scores of perceived ease of use or effort expectancy than women. In contrast, our findings do not support the prior findings by Hamza and Shah [14] as well as Acheampong et al. [15] that women have higher scores of subjective norm or social influence than men. In addition, while our findings also support the findings by Hamza and Shah [14] that there are no differences in the scores of perceived usefulness and use intention between men and women, they do not support the finding by Acheampong et al. [15] that men have higher scores of performance expectancy than women.

In terms of the age and generational differences in the effects of the antecedent factors on use intention, we found the effect of social influence on use intention to be stronger for younger than older users, meaning that their motivation to use or not to use mobile payments is more strongly influenced by the perceived opinions of other people. This finding is not surprising when considering that the younger and older users in our study were equivalent to DN and DI of whom the daily lives of DN are typically assumed to be more intertwined with the use of digital technologies in comparison to DI, also in terms of social aspects [21]. Thus, they are likely to be more susceptible to social influences when it comes to the use of these technologies. When reflecting this finding against prior research on age differences, it does not support the finding by Liébana-Cabanillas [10] that there is no difference in the effect of external influences on use intention. However, our findings support the findings by Liébana-Cabanillas [9–10] that there is no difference in the effect of perceived usefulness on use intention.

Finally, in terms of the age and generational differences in the antecedent factors and use intention themselves, we found older users to have lower scores of perceived ease of use than younger users, meaning that they perceived the use of mobile payments as less easy. Like the previous finding, this finding is scarcely surprising when once again considering that the younger and older users in our study were equivalent to DN and DI of whom DN are typically assumed to be more technologically savvy in comparison to DI [19–22], thus likely influencing also their perceptions concerning the use of mobile payments. When reflecting the finding against prior research on age differences, it supports the finding by Acheampong et al. [15] that younger users have higher scores of effort expectancy than older users. However, the findings by Acheampong et al. [15] also suggest that younger users have higher scores of performance expectancy but lower scores of social influence, which is not supported by our findings.

From a theoretical perspective, the findings of the study promote the understanding of the potential gender, age, and generational differences in the antecedents of the acceptance and use of mobile payments by addressing some of the methodological issues of the prior studies on gender and age differences as well as by being the first study to examine generational differences in the effects of the antecedent factors on use intention as well as in the antecedent factors and use intention themselves. For example, the prior study by Fischer et al. [18] examined the generational differences only in the effects of the antecedent factors on the attitude towards use, not on use intention itself. In turn, from a practical perspective, the providers of mobile payment systems can potentially use the findings to further promote the adoption of their systems via more positive user perceptions. For example, as women and older users representing DI were found to perceive the use of mobile payments as less easy and less secure, the providers should highlight mobile payments as an easy and secure payment option in the case of these user segments. In addition, as social influence was found to have stronger effects on use intention among younger users representing DN, this user segment may be particularly susceptible to more socially oriented marketing campaigns.

6 Limitations and Future Research

We consider this study to have three main limitations. First, the study focused only on Finnish consumers, which is why the generalisability of its findings to other countries calls for confirmation. Second, in terms of the antecedents of the intention to use mobile payments, the study focused only on perceived security instead of perceived trust and perceived risk, which have also commonly been hypothesised to act as antecedents of use intention in prior studies. Third, the study did not focus on the potential interactions between gender and age, such as whether there are differences in the effects of the antecedent factors on use intention or in the antecedent factors and use intention themselves between younger men, older men, younger women, and older women. Future studies should address these limitations by replicating the study in other countries, testing alternative research models, and focusing on the aforementioned interactions. In addition, future studies should examine more thoroughly the explanations for the gender, age, and generational differences that we found in this study. Instead of the positivist paradigm and statistical generalisations that were used in this study, these studies may benefit from the use of also other types of research paradigms and generalisations, such as the interpretive paradigm and analytical generalisations (cf. [54–56]).

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