Role of Culture in Customer Acceptance of Neobanks

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Abstract. We examine customer acceptance of neobanks across national cultures using the technology acceptance model (TAM) extended with an additional construct, i.e. trust, accounting for scepticism surrouding digital innovations. We incorporate dimensions developed by Hofstede to evaluate national cultural effects on the modified TAM. For this, we collect primary quantitative data through questionnaires obtaining a sample including many nationalities. We assess our variant of the TAM using partial least squares structural equation modelling to quantify the complex relationships with reflective constructs.

We find that national cultural dimensions may not have a significant effect on the customer acceptance. Moreover, the original two independent constructs of the TAM, *perceived ease of use* and *perceived usefulness*, have a significant positive weak direct effect on acceptance. However, perceived ease of use has a significant positive strong effect on perceived usefulness and *trust*. Finally, the theorised trust dimension has a significant positive weak effect on both the perceived usefulness of, and the *behavioural intention to use* neobanks.

Keywords: Digital Banking · Neobanks · Culture · Digital Transformation

1 Introduction

Technological advancements pave the way for new industries, and change existing industries fundamentally. Indeed, the nature of the financial services industry is being changed by financial technologies, or FinTech, which refers to the use of technology to provide financial solutions [4]. According to KPMG [5], $60.2B were invested in FinTech companies across 2,914 deals in 2017, $150.4B across 3,639 deals in 2018, and $150.4B across 3,286 deals in 2019. Additionally, FinTech start-ups can test technologies and introduce new and innovative products faster than ever before [6]. This allows them to challenge well-established companies.

The concept of FinTech is not novel; it can be traced back to the first financial technology. The Trans-Atlantic transmission cable connecting North America and Europe has been operational since 1866, which provided the foundation for the first period of financial globalisation [4, 7]. This period is called FinTech 1.0, where the financial services industry was interconnected with technology, yet remaining mainly an analogue industry [4, 7].

J. van Hillegersberg et al. (Eds.): FinanceCom 2022, LNBIP 467, pp. 97–116, 2023.
https://doi.org/10.1007/978-3-031-31671-5_7

FinTech 2.0 started at least by 1987 and digitalised the financial services industry [8]. Yet, until 2008, the traditional regulated financial services industry largely controlled developments. Following the financial crisis of 2008 however, the regulatory, operating, and compliance environment changed, facilitating additional rapid advancements [8]. Start-ups and technology companies were beginning to disrupt the traditional industry by delivering their own products and services to business and consumers (e.g. Google Pay, PayPal, and Kickstarter) [6, 8]. This period is dubbed FinTech 3.0 [7].

In recent years a surge of neobanks—independent digital-only entities—in the banking sector occured [9]. They either have a banking licence or partner with traditional banks to deliver their products and services. Typically, neobanks focus on offering newer technologies at lower costs [10], and they can launch features and develop partnerships faster than traditional ones can [11]. To compete with neobanks, traditional banks are launching so called digital banks [9, 12].

By 2020, over 250 neobanks served over 350 million customers [10], inducing fierce competition in customer acquisition and retention in the banking sector [13], so knowledge about customer acceptance is essential to the entire industry. Between countries a remarkable difference in the proportion of consumers banking with neobanks exists, varying between 93 per cent in China for example, and around 4 per cent in the Netherlands and Germany [10]. This begs the question of whether customer acceptance is affected by national cultures.

1.1 Customer Acceptance and Culture

The TAM is predominantly used to measure the customer acceptance of a specific technology. The original model consists of the perceived ease of use of an application, positively impacting its perceived usefulness. Both the perceived ease of use and perceived usefulness constructs are theorized to directly positively affect behavioral intentions to use a technology having a positive impact on the actual system use.

A wide array of studies demonstrate the validity of the TAM, resulting in many revisions of the original version [14–16]. However, only a few have examined effects of national cultural differences on either the original or one of the revised TAMs. An often-used model for comparing national cultural differences is Hofstede's 6-D model. Hofstede [17] distinguished the following four dimensions: power distance, individualism, masculinity, and uncertainty avoidance. Two additional dimensions were added to the model later, namely long- versus short-term orientation, and indulgence [18].

So, two motivational factors for examining the cultural differences exist, namely: (1) the effect that national cultures have on the customer acceptance of neobanks, and (2) how to integrate them into a TAM.

2 Conceptual Model and Hypotheses

We note and address a lack of literature on the customer acceptance of neobanks, presumably since neobanks are a fairly new phenomenon. Also, few studies have incorporated the effects of national cultures in the TAM. Therefore, we examine the influence of national cultures on the TAM applied to neobanks, and insights obtained can be used by neobanks and other ones alike to make crucial strategic decisions. For instance, when expanding to new markets, they can determine where they have a strategic advantage.

Davis [31] devised the original TAM as an adaptation of the theory of reasoned action to tailor to the modelling of user acceptance of information technology. Many studies have shown the validity and reliability of this model [32]. Therefore, our conceptual framework is based on the TAM. On top of the TAM, we take trust into consideration as we found the lack of trust to be a disadvantage for neobanks in our systematic literature review. We add Hofstede's [2] national cultural dimensions to the TAM to measure for possible interaction effects. Our conceptual framework is visualised in Fig. 1.

Davis & Venkatesh [15] mention that research in TAM and psychology suggest that the users' intention to use, is the best predictor of actual system use. Therefore, the behavioural intention to use (BI), is the dependent variable in our study. BI is found to be determined by perceived usefulness (PU), and perceived ease of use (PEOU) [15]. More advanced models have been proposed, heavily catered to a work environment to remove potential biases [31]. We therefore, use the original three constructs.

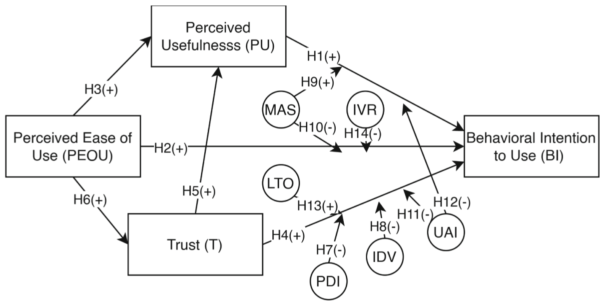

Fig. 1. Conceptual framework

PU is defined as: "the extent to which a person believes that using a particular system would enhance his or her job performance" [3, 15, 31, 33]. Whereas the definition is focussed on job performance, Pikkarainen *et al.* [19] have decided to omit the job aspect, so it can be used as user acceptance outside of the work environment. It is believed that PU is a major determining factor in the acceptance of information technology. Therefore, we formulate Hypothesis 1: *Hypothesis 1. PU has a positive effect on BI.* PEOU, is defined as "the user's perception of the extent to which using a particular system will be free of effort" [3, 15, 31, 33]. Davis [3] mentions that effort is a finite resource, and finds that PEOU has a positive effect on BI. Additionally, PEOU was found to have a positive effect on PU [3]. Therefore, the following two hypotheses are formulated in accordance with the original TAM: *Hypothesis 2. PEOU has a positive effect on BI; Hypothesis 3. PEOU has a positive effect on PU.*

In our systematic literature review, we found that trust is a disadvantage of neobanks compared to traditional banks. Therefore, we look to incorporate trust into the TAM to find potential correlations. Gefen *et al.* [20] modified the existing TAM to incorporate trust for measuring customer acceptance in online shopping. Gefen *et al.* [20] compile a list of previous conceptualisations in the following four options. (1) "a set of specific beliefs dealing primarily with the integrity, benevolence, and ability of another party", (2) a general belief that another party can be trusted, sometimes also called trusting intentions or the 'willingness' of a party to be vulnerable to the actions of another, (3) affect reflected in feelings of confidence and security in the caring response of the other party, or (4) a combination of these elements.

According to Gefen *et al.* [20], trust (T) helps a customer reduce social complexity, which in turn helps reduce subjective undesirable yet possible behaviours. Hence, we expect T to affect BI positively (cf., Hypothesis 4). Additionally, Gefen *et al.* [20] mention that using information technology that cannot be trusted will reduce usefulness (cf., Hypothesis 5). Finally, these authors mention that an unnecessarily hard-to-use website in the context of eCommerce does not show a consumer that the business cares or has the ability to care, or even raise suspicion that it is hiding something. Therefore, we expect PEOU to have a positive effect on T (cf., Hypothesis 6). *Hypothesis 4. T has a positive effect on BI; Hypothesis 5. T has a positive effect on PU; Hypothesis 6. PEOU has a positive effect on T.*

We employ Hofstede's [2] national cultural dimensions to measure the national cultural impact on customer acceptance. Yoon [21] tested the modification effects of five of the current six Hofstede dimensions on the acceptance of eCommerce. In our study we add the dimension of indulgence. Furthermore, Yoon [21] measured the dimensions at a personal level, while these are defined at societal levels by Hofstede [2]. So, we use the values determined by Hofstede [2] in our data analysis as opposed to measuring them at an individual level. A summary of each dimension can be seen in Table 1.

Table 1. Hofstede's [2] dimensions, abbreviations, and descriptions.

Hofstede's dimension	Abbreviation	Description
Power distance	PDI	"The extent to which the less powerful members of organizations and institutions accept and expect that power is distributed unequally" [2]
Individualism	IDV	"The degree to which people in a society are integrated into groups" [2]
Masculinity	MAS	"Refers to the distribution of values between the genders which is another fundamental issue for any society" [2]
Uncertainty avoidance	UAI	"The extent to which a culture programs its members to feel either uncomfortable or comfortable in unstructured situations" [2]
Long-term orientation	LTO	"Values found at this pole [long-term] were perseverance, thrift, ordering relationships by status, and having a sense of shame; values at the opposite, short term pole were reciprocating social obligations, respect for tradition, protecting one's 'face', and personal steadiness" [2]
Indulgence	IVR	"Indulgence stands for a society that allows relatively free gratification of basic and natural human desires related to enjoying life and having fun. Restraint stands for a society that controls gratification of needs and regulates it by means of strict social norms" [2]

According to Hofstede [2], most societies are unequal, however some are more unequal than others. Yoon [21] mentions that customers from high PDI countries believe that companies are more likely to take part in unethical behaviour compared to customers from low PDI countries. Thus, we expect customers from high PDI countries to have less trust in neobanks compared to those from low PDI ones. We propose the following hypothesis: *Hypothesis 7. A higher PDI has a negative effect on the relationship between T and BI.* Secondly, IDV measures the degree to which people within a society are integrated into groups [2]. On the one hand, in countries with a low IDV score, individuals are expected to care for themselves, and generally focus more on themselves [2]. According to Yoon [21], individualists identify themselves with a larger society, and they are good at meeting, relying on, and trusting strangers. On the other hand, individuals in a country with a high IDV score, are expected to care and focus on their families or coherent groups [2], and they are unlikely to trust someone outside of their group [21]. Thus, we expect that a higher level of IDV results in a lower effect of T on BI. *Hypothesis 8; A higher IDV has a negative effect on the relationship between T and BI.*

The MAS dimension touches on the distribution of values between the male and female gender [2]. Genders in feminine societies have minimal emotional and social role differentiation, and both genders are expected to be modest and caring [2]. Women in masculine countries are more assertive and competitive than women in feminine countries, but not as much as men [2]. This means that there is maximum emotional and social role differentiation between the genders [2]. Yoon [21] mentions that PU is closely related to achievements of goals and advancement, and therefore we expect the MAS dimension to have a positive effect on the relationship between PU and BI (cf., Hypothesis 9). Additionally, feminine values are also related to creating a comfortable and balanced (work) environment [2, 21]. Effort free use is also concerned with creating a pleasant experience, and for this reason, we argue that a lower degree of the MAS dimension results in a higher effect of PEOU on BI (cf., Hypothesis 10). *Hypothesis 9. A higher MAS has a positive effect on the relationship between PU and BI; Hypothesis 10. A higher MAS dimension has a negative effect on the relationship between PEOU and BI.*

The UAI measures societal discomfort (comfortability) in unstructured (structured) situations [2]. Hofstede [2] mentions that it is not the same as risk avoidance, and that uncertainty avoiding cultures try to reduce the likelihood of unstructured situations by behavioural codes, laws and rules; countries with weak uncertainty avoidance are more accepting of unstructured situations. According to Yoon [21] however, uncertainty avoidance and risk avoidance may have similar effects on trust. Therefore, we argue that the higher the value of the UAI dimension, the lower the effects of T on BI are (cf., Hypothesis 11). Additionally, Straub *et al.* [33] argue that the effect of PU in a higher UAI culture is weakened compared to one with a lower UAI. Therefore, we formulate Hypothesis 12. *Hypothesis 11. A higher UAI has a negative effect on the relationship between T and BI; Hypothesis 12. A higher UAI has a negative effect on the relationship between PU and BI.*

LTO relates to the degree that society focuses on the future. Countries with a higher score on this dimension tend to encourage saving money and efforts in modern education to prepare for the future [2]. Countries that score low on LTO, thus having a short-term orientation, gravitate towards maintaining traditions and norms while being suspicious of societal change [2]. Yoon [21] argues that long-term oriented societies encourage trust, as the future gains outweigh the short-term untrustworthy actions. Hence, we argue that a higher level of the LTO dimension results in a positive modification effect on the relationship between T and BI. *Hypothesis 13. A higher score on LTO has a positive effect on the relationship between T and BI.*

Finally, Hofstede [2] latest addition to the TAM is the indulgence versus restraint (IVR) dimension. A society with indulgence relates to a society that allows for relatively free gratification of basic and natural human desires linked with having fun and enjoying life [2]. Restraint relates to a society that controls this gratification through social norms [2]. As countries with a lower level on this dimension, thus indulgence, tend to remember positive emotions more likely, we argue that this positively affects the relationship between PEOU and BI. Therefore, we formulated the following hypothesis: *Hypothesis 14. A higher level of the IVR dimension has a negative modification effect on the relationship between PEOU and BI.*

3 Data Collection and Analysis

The theoretical constructs mentioned in the previous section – BI, PU, PEOU, and T – are all operationalized using validated items from prior research. We slightly alter the items to fit the topic, however the main concepts of the items remain. The constructs and the questions can be found in Table 2. All of the questions within all of the constructs, apart from trust, are based on validated items from the original creators of the technology acceptance model – namely Davis & Venkatesh [15], most TAM studies use these questions or slightly altered questions. Additionally, we add the relevant and validated items to the PU and PEOU constructs from the study from Gefen *et al.* [20] that incorporated trust for measuring customer acceptance in online shopping. Their validated items are taken into consideration for this study.

Table 2. Constructs and the relevant survey statements.

Construct	Statement
Behavioural intention to use (BI)	(Davis & Venkatesh [15])
BI1	Assuming I have access to a neobank, I intend to use it
BI2	Given that I have access to the system, I predict that I would use it
BI3	I will frequently use the services provided by a neobank
Perceived usefulness (PU)	(Davis & Venkatesh [15]; Gefen *et al.* [20])
PU1	Using a neobank enables me to utilise banking services more quickly

(*continued*)

Table 2. (*continued*)

Construct	Statement
PU2	Using a neobank improves my performance of utilizing banking services
PU3	Using a neobank for my banking services increases my productivity
PU4	Using a neobank makes it easier for me to utilise banking services
PU5	I find the neobank to be useful for me to utilise banking services
PU6	Using a neobank helps me to save money
Perceived ease of use (PEOU)	(Davis & Venkatesh [15]; Gefen *et al.* [20])
PEOU1	Learning to use the services by a neobank is easy for me
PEOU2	My interaction with the neobank is clear and understandable
PEOU3	I find a neobank to be flexible to interact with
PEOU4	It would be easy for me to become skilful at using the services of a neobank
PEOU5	I find the services of a neobank easy to use
Trust (T)	(Gefen *et al.* [20])
T1	Based on my experience with the neobank in the past, I know it is honest
T2	Based on my experience with the neobank in the past, I know it cares about customers
T3	Based on my experience with the neobank in the past, I know it is not opportunistic
T4	Based on my experience with the neobank in the past, I know it is predictable
T5	Based on my experience with the neobank in the past, I know it is trustworthy

Hinkin [34] finds that reverse scoring items reduce the validity of questionnaire response, and could lead to systematic errors to a scale. Additionally, reverse-scored items are typically employed by researchers to weaken pattern bias, however, item loadings for reverse-scored items were found to be lower than positively worded items that loaded on the same factor [34]. So, we designed our survey in a way that it does not reverse-score items. Furthermore, Hinkin [34] finds that the coefficient alpha reliability with Likert-type scales increase up to the use of five points, and then it levels off. Hence, we designed our survey with a 5-point Likert-type scale.

3.1 Sample Selection

We collected data in our study in two ways – namely by using an online service called Amazon Mechanical Turk, and by spreading the questionnaire on social media. The reason for using the crowdsourcing platform Amazon Mechanical Turk is to have a larger distribution of nationalities in our sample for the measurement of the cultural aspect. Additionally, the gathering of data on social media will be used to achieve data triangulation.

The Amazon Mechanical Turk "workers" have received a reimbursement of €0.5 for filling in the survey. Additionally, for every entry from social media €1,- has been donated to charity. The chosen charity is ShareTheMeal, from the United Nations' World Food Programme. This charity allows a child to be fed for a day for €0.8 and offers complete transparency as to where the meals are distributed. In total, €105,- were donated, equaling 150 meals for children.

The original dataset had a sample size of n = 273, two cases were dropped because of missing Hofstede dimension values. Out of the 271 respondents, 105 came through organic sources (e.g., LinkedIn, WhatsApp, Reddit) whereas the other 166 came through the Amazon Mechanical Turk paid source.

The distribution of the respondents' gender is not entirely balanced (see Table 3), with 200 male respondents, and 69 female respondents, two other cases identified as "other". The gender distribution should theoretically not impact the research, as we do not account for individualistic characteristics in our analysis.

The average age of the participants was 30.04 years old, with a median age of 29. Furthermore, the standard deviation of age is 8.173 years. The age within the sample ranges from 17 to 71, thus having a range of 54 years.

We removed two cases from the analysis due to missing Hofstede values, one from Costa Rica and the other from The Federated States of Micronesia. The major contributors are India with 94 respondents (34.7%), the United States of America with 63 respondents (23.2%), the United Kingdom with 62 respondents (22.9%), and the Netherlands with 17 respondents (6.3%). With the other nationalities having fewer than ten respondents.

Table 3. Descriptive statistics of respondents' characteristics.

Measure	Value	Frequency	Percent
Gender	Male	200	73.8
	Female	69	25.5
	Other	2	0.7
Age	25 or below	93	34.3
	Above 25	178	65.7
Previously used a neobank	Yes	240	88.6
	No	31	11.4

The distribution of the Hofstede dimensions is depicted in Table 4. Each of the Hofstede dimensions ranges on a 0–100 scale. We distribute the dimensions into three categories (low, medium, and high) for descriptive purposes. As can be seen, most of the dimensions tend to have the majority of cases in the medium category. Furthermore, the respondents' values of PDI, IDV, and UAI have more cases in the high category than the low category. For the LTO and IVR dimensions this is the opposite, as they have more cases in the low category compared to the high category. The MAS dimension leftover cases from the medium category are relatively evenly spread over the low and high categories.

Out of the 271 respondents, 240 indicated that they had previously used a neobank (cf., Table 1). The others were considered in our research, as these consumers' perceptions of neobanks still matter for their overall customer acceptance.

3.2 Data Analysis

We analyse the data using using partial least squares path modelling (PLS-SEM) in SmartPLS. This program has the ability to calculate interaction effects in various ways, namely the product-indicator, the two-stage, and the orthogonalisation approach. Henseler *et al.* [35] mention that a two-stage approach should be employed. According to Fassott *et al.* [36], in the first stage, the PLS path model is run to obtain the construct scores. These construct scores are then extracted. In the second stage, the interaction term is created by multiplying the construct scores. This interaction term is then inserted as an independent variable and used in a multiple regression on the construct scores of the dependent variable [36]. SmartPLS does all of this automatically.

Following the regression analysis, we analyse the goodness of model fit for both the measurement and structural model. Furthermore, the constructs are operationalised as reflective measurement models, as the reflective measurement model assumes that the covariance among the indicators can be explained by the reflective variable, as opposed to that the indicators build a construct together. We assess these reflective measurement models on construct reliability, convergent validity, discriminant validity, and indicator reliability. Lastly, we test the hypotheses by looking at the path coefficients, the indirect effects, the effect sizes, and the coefficients of determination.

Table 4. Distribution of Hofstede's [2] dimensions in three categories.

Dimension	Low ($0 \leq 30$)	Medium(>30–70<)	High ($\geq$70–100)
PDI	1	172	98
IDV	4	112	155
MAS	17	244	10
UAI	0	241	30
LTO	66	198	7
IVR	104	165	2

The first thing to assess before examining the measurement and structural model is the goodness of fit, which measures how well a statistical model fits a set of observations. Two types of models must be examined, namely the saturated model and the estimated model. According to Benitez *et al.* [38], the saturated model allows all of the constructs to be freely correlated, whereas the estimated model is the model specified by the researcher. Three discrepancy measures can be considered and analysed to promote transparency [35]. The three discrepancy measures are the following: the standardised root mean squared residual (SRMR), the unweighted least squares discrepancy (d_{uls}), and the geodesic discrepancy (d_g) [37].

The SRMR was introduced by Henseler *et al.* [39] as a measure for approximate model fit. A value of 0 would indicate a perfect model fit. According to Henseler [35] the SRMR value should be below the threshold of 0.08. This is based on the recommendations by Hu and Bentler [40]. They also mention a 0.10 threshold when being more conservative. The equation for SRMR as stated by Hu & Bentler [40] can be seen in Eq. 1, where; p = number of observed variables, s_{ij} = observed covariances, $\hat{o}_{ij}$ = the reproduced covariances, s_{ii} and s_{jj} are the observed standard deviations.

$$\mathrm{SRMR} = \sqrt{\left\{2\sum_{i=1}^{p}\sum_{j=1}^{i}\left[\left(s_{ij} - \hat{o}_{ij}\right)/\left(s_{ii}s_{jj}\right)\right]^2\right\} \div p(p+1)} \tag{1}$$

Limited information is available surrounding the usefulness, behaviour, relevance, and application of exact model fit criteria. We use bootstrap confidence interval results to estimate the exact model fits, and these are recommended to be below the 95% or 99% quantile [37]. This method can be applied to the bootstrap confidence interval of SRMR, however also of the d_{uls} and d_g [41]. d_{uls} and d_g are two approaches to quantify how much the empirical correlation matrix differs from the model-implied correlation matrix [35]. We interpret these values against the confidence intervals, as these values cannot be interpreted on their own [37]. Klesel *et al.* [42] mention the distance functions depicted in Eq. 2 and Eq. 3, where; K = number of rows from each correlation matrix, $\sigma_{ij,1}$ and $\sigma_{ij,2}$ are elements of the respective correlation matrices, and φ_i = the i-th eigenvalue of the correlation matrix.

$$\mathrm{d}_{uls} = \tfrac{1}{2}\sum_{i=1}^{K}\left(\sigma_{ij,1} - \sigma_{ij,2}\right)^2 \tag{2}$$

$$\mathrm{d}_{g} = \tfrac{1}{2}\sum_{i=1}^{K}\ln(\varphi_i)^2 \tag{3}$$

The saturated and estimated model fits prior to the removal of indicators are shown in Table 5. The model fit greatly improved after removing the indicators, which can be seen in Table 6. The SRMR was initially above the 0.08 threshold for both the models, but below the more lenient 0.10 threshold. After removing some indicators, the SRMR was 0.07 for the saturated model, well below the recommended threshold, and 0.082 for the estimated model, slightly above the 0.08 threshold but well below the 0.10 threshold. Thus, the SRMR indicates a relatively good model fit. When using bootstrapped confidence intervals to determine the exact model fit, all values are outside the 99% confidence interval, thus indicating a bad model fit. We also attempted to remove non-neobank users from the analysis, however this did not improve the approximate nor exact model fit. Sarstedt *et al.* [43] mention that researchers should be cautious when reporting and using model fit in PLS-SEM, as the criteria are in the early stages of research. For this reason, we decided to continue with our research despite not meeting the exact model fit criteria.

Table 5. Saturated and estimated model fit prior to the removal of indicators.

	Goodness of Model Fit (Saturated Model)			Goodness of Model Fit (Estimated Model)		
	Value	HI95	HI99	Value	HI95	HI99
SRMR	0.086	0.052	0.055	0.099	0.059	0.061
d_{uls}	2.390	0.082	0.970	3.173	1.123	1.216
d_g	0.579	0.351	0.375	0.647	0.386	0.423

Table 6. Saturated and estimated model fit after the removal of indicators.

	Goodness of Model Fit (Saturated Model)			Goodness of Model Fit (Estimated Model)		
	Value	HI95	HI99	Value	HI95	HI99
SRMR	0.070	0.048	0.050	0.082	0.056	0.060
d_{uls}	1.024	0.481	0.527	1.422	0.648	0.754
d_g	0.395	0.253	0.273	0.452	0.288	0.324

SmartPLS allows for the assessment of construct reliability, or composite reliability, through various measures—Cronbach's Alpha, Dijkstra-Henseler's rho (ρ_A), and composite reliability. These values range between 0 and 1, and a higher value indicates better reliability. According to Benitez *et al.* [38], Dijkstra-Henseler's ρ_A should be used. Dijkstra & Henseler [44] denote the equation for ρ_A as seen in Eq. 4, where; $\widehat{w}$ = the estimated weight vector of the latent variable, $\widehat{w}'$ = the number of indicators directly associated with the latent variable in $\widehat{w}$, and S = the empirical covariance matrix of the respective indicator.

$$\rho_A = \left(\widehat{w}'\widehat{w}\right)^2 * \frac{\widehat{w}'\,(S - diag(S))\widehat{w}'}{\widehat{w}'\left(\widehat{w}\widehat{w}' - diag\left(\widehat{\widehat{w}\widehat{w}'}\right)\right)\widehat{w}} \tag{4}$$

A value greater than 0.707 is desirable as this indicates that the latent variable can explain over 50% of the variance in the construct scores. The values for ρ_A can be found in Table 7 before the removal of the indicators. In both instances, all the values are above 0.707. The other two measures were also taken into consideration and show identical results. These values indicate reliable constructs.

Convergent validity measures the degree to which indicators that measure the same construct are related, and the average variance extracted (AVE) is typically used to

Table 7. Evaluation of the reflective measurement models.

Code	Construct/Indicator	ρ_A	AVE	Weight	Loading
	Behavioural intention to use (BI) (1: strongly disagree, 5: strongly agree) (Composite measurement model, mode B, dominant indicator: BI1)	0.765	0.671		
BI1	Assuming I have access to a neobank, I intend to use it			0.455***	0.863***
BI2	Given that I have access to the system, I predict that I would use it			0.402***	0.798***
BI3	I will frequently use the services provided by a neobank			0.361***	0.794***
	Perceived usefulness (PU) (1: strongly disagree, 5: strongly agree) (Composite measurement model, mode B, dominant indicator: PU1)	0.794	0.465		
PU1	Using a neobank enables me to utilise banking services more quickly			0.304***	0.761***
PU2	Using a neobank improves my performance of utilizing banking services			0.281***	0.755***
PU3	Using a neobank for my banking services increases my productivity			0.180***	0.633***
PU4	Using a neobank makes it easier for me to utilise banking services			0.241***	0.710***
PU5	I find the neobank to be useful for me to utilise banking services			0.281***	0.731***
PU6	Using a neobank helps me to save money			0.149***	0.451***
	Perceived ease of use (PEOU): (1: strongly disagree, 5: strongly agree) (Composite measurement model, mode B, dominant indicator: PEOU1)	0.803	0.558		
PEOU1	Learning to use the services by a neobank is easy for me			0.270***	0.750***
PEOU2	My interaction with the neobank is clear and understandable			0.276***	0.766***
PEOU3	I find a neobank to be flexible to interact with			0.254***	0.683***
PEOU4	It would be easy for me to become skilful at using the services of a neobank			0.265***	0.756***

(*continued*)

Table 7. (*continued*)

Code	Construct/Indicator	ρ_A	AVE	Weight	Loading
PEOU5	I find the services of a neobank easy to use			0.273***	0.778***
	Trust (T): (1: strongly disagree, 5: strongly agree) (Composite measurement model, mode B, dominant indicator: T1)	0.874	0.591		
T1	Based on my experience with the neobank in the past, I know it is honest			0.354***	0.824***
T2	Based on my experience with the neobank in the past, I know it cares about customers			0.292***	0.802***
T3	Based on my experience with the neobank in the past, I know it is not opportunistic			0.159***	0.708***
T4	Based on my experience with the neobank in the past, I know it is predictable			0.154***	0.662***
T5	Based on my experience with the neobank in the past, I know it is trustworthy			0.312***	0.832***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (lower p-values indicate greater confidence of the statistical test), one-tailed t-test (df = 239)

measure it [38]. The AVE shows how much of the variance in the indicators is explained by the latent variable [38]. A value of 0.5 is suggested by Benitez *et al.* [38] as this means that the latent variable can explain 50% of the variance in an indicator. Henseler *et al.* [45] state the formula seen in Eq. 5, where; ξ_j = the construct, λ_{jk} = the indicator loading, K_j = the number of indicators of the construct, and Θ_{jk} = the error variance of the k^{th} indicator. The values from BI, PEOU, and T are above the 0.5 mark, but PU is below it before removing several indicators. After the removal of several indicators, all values are above the 0.5 mark, indicating good convergent validity.

$$AVE\xi_j = \frac{\sum_{k=1}^{K_j} \lambda_{jk}^2}{\sum_{k=1}^{K_j} \lambda_{jk}^2 + \Theta_{jk}} \quad (5)$$

Discriminant validity measures whether or not reflective variables are different enough to represent two theoretical concepts [38]. Benitez *et al.* [38] and Henseler *et al.* [45] mention that the heterotrait-monotrait ratio (HTMT) should be used to assess discriminant validity. Henseler *et al.* [45] state Eq. 6, where; ξ_j and ξ_i are two different constructs, and K_j and K_i are their indicators.

$$\mathrm{HTMT}_{ij} = \frac{1}{K_i K_j} \sum_{g=1}^{K_i} \sum_{h=1}^{K_j} r_{ig,jh} \div \left(\frac{2}{K_i(K_i-1)} * \sum_{g=1}^{K_i} \sum_{h=1}^{K_j} r_{ig,ih} * \frac{2}{K_j(K_j-1)} * \sum_{g=1}^{K_i} \sum_{h=1}^{K_j} r_{jg,jh} \right) \quad (6)$$

The value should be below 0.85 or 0.90, where the 0.85 mark is the stricter one [39, 45]. The HTMT values before the removal of indicators can be found in Table 8. Note that only PEOU and BI exceed the 0.9 mark. PU and BI, and PU and PEOU have a value greater than 0.85. The three previous values are now above 0.9. Additionally, one can look at the bootstrapped values, these should be and are lower than 1 [37]. The values above 0.9 can be taken with a grain of salt because discriminant validity is only relevant to constructs that are similar, which is not the case for the constructs violating the HTMT criteria—BI and PU, BI and PEOU, PU and PEOU.

Table 8. Heterotrait-monotrait ratio prior to the removal of indicators.

	BI	PU	PEOU
BI	-	-	-
PU	0.855	-	-
PEOU	0.906	0.879	-
T	0.511	0.663	0.623

Finally, indicator reliability should be examined. According to Hair *et al.* [46] indicator reliability is the degree to which a set of indicators are internally consistent with their measurements. Benitez [38] mention that the unsquared factor loadings should be above 0.707, and the squared factor loadings above 0.499. The unsquared factor loadings can be seen in Table 7.

Initially, we found PU3, PU6, PEOU3, and T4 below the recommended threshold. Additionally, after removing T4, T3 had a value below 0.707, and was therefore removed. We removed the indicators following a stepwise approach by starting at the lowest loadings, as the loadings are recalculated after each removal. The removal of the indicators vastly improved the model fit, the AVE, and the construct reliability. However, it slightly worsened the discriminant validity as mentioned before. Furthermore, in both instances the factors were found to be significant at 0.001.

In Sect. 3, fourteen hypotheses were formulated, to be tested in accordance with the path coefficients and the confidence intervals. Path coefficients are standardised regression coefficients. The path coefficients indicate the change in standard deviations of the dependent variable when an independent variable increases by one standard deviation while keeping all other constructs unchanged [35, 38]. One can look at the t-values to determine the significance, however one can also look at the 95% confidence interval. When this does not cross the zero mark, there is at least a significant effect at a p-value of 0.05 [38] (Table 9).

Besides the path coefficients, the effect sizes are also shown in Table 6. Cohen's [47] f^2 equal or greater than 0.35 indicates a strong effect, equal or greater than 0.15 and less than 0.35 a moderate effect, equal or greater than 0.02 and less than 0.15 a weak effect, and less than 0.02 an unsubstantial effect [36].

As can be seen in Table 7, H1, H2, H3, H5, and H6 are significant at a p-value of 0.001, whereas H4 is significant at an alpha level of 0.01. The path coefficient for PU on BI is 0.321, meaning that BI moves 0.321 standard deviations when PU moves one standard deviation. Furthermore, it has a weak effect size ($f^2 = 0.103$). PEOU on BI has a path coefficient of 0.329 and has a weak effect size ($f^2 = 0.097$). PEOU on perceived

Table 9. Path coefficients and effect sizes.

Relationship	Path coefficients	Cohen's f^2
H1 | PU --> BI	0.321*** (4.505) [0.199, 0.435]	0.103
H2 | PEOU --> BI	0.329*** (4.194) [0.194, 0.451]	0.097
H3 | PEOU --> PU	0.613*** (12.043) [0.526, 0.693]	0.588
H4 | T --> BI	0.171** (2.632) [0.071, 0.288]	0.037
H5 | T --> PU	0.198*** (3.419) [0.104, 0.292]	0.061
H6 | PEOU --> T	0.537*** (11.992) [0.469, 0.612]	0.406
H7 | PDI * T --> BI	−0.157 (1.021) [−0.360, 0.131]	0.014
H8 | IDV * T --> BI	−0.240 (1.445) [−0.484, 0.042]	0.026
H9 | MAS * PU --> BI	−0.050 (0.588) [−0.146, 0.122]	0.005
H10 | MAS * PEOU --> BI	0.012 (0.132) [−0.152, 0.140]	0.000
H11 | UAI * T --> BI	−0.056 (0.989) [−0.139, 0.040]	0.005
H12 | UAI * PU --> BI	0.043 (0.771) [−0.040, 0.138]	0.004
H13 | LTO * T --> BI	−0.036 (0.595) [−0.128, 0.069]	0.003
H14 | IVR * PEOU --> BI	−0.055 (0.860) [−0.149, 0.064]	0.004

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (lower p-values indicate greater confidence of the statistical test), one tailed t-values in parentheses, 95% bootstrap percentile confidence intervals in brackets.

usefulness PU has a path coefficient of 0.613 and a strong effect size ($f^2 = 0.588$). The path coefficient of T on BI is 0.171 and has a weak effect size ($f^2 = 0.037$). Furthermore, T on PU also has a weak effect size ($f^2 = 0.061$). And a path coefficient of 0.198. Lastly, PEOU on T has a path coefficient of 0.537 and a strong effect size ($f^2 = 0.406$). We have enough statistical evidence to reject null hypotheses $H1_0$, $H2_0$, $H3_0$, $H4_0$, $H5_0$, and $H6_0$.

Additionally, all the interaction effects by the Hofstede dimensions are insignificant at a p-value of 0.05. Furthermore, the effect sizes across hypotheses H7 throughout H14 are all unsubstantial. This means that there is not enough statistical evidence to reject the null hypotheses and allows us to assume that the Hofstede dimensions do not have an interaction effect on either of the independent variables (PU, PEOU, and T) on behavioural intention to use (BI).

Finally, we inspect the unadjusted and adjusted coefficients of determination. The coefficients of determination indicate how much variance can be explained in a dependent variable by an independent variable [35]. Whereas the unadjusted R^2 does not take the sample size or the number of independent variables into consideration, the adjusted R^2 does [39]. The latter is most often used in more complex models and will always be lower. Both coefficients of determination will be denoted, however as this model is complex, the adjusted R^2 should be considered. The unadjusted R^2 of BI is 0.647, and the adjusted R^2 is 0.623. This means that either 64.7% or 62.3% of the variance in BI can be explained by PU, PEOU, and T. Furthermore, the unadjusted and adjusted R^2 of

PU is respectively 0.545 and 0.542, which means that 54.5% or 54.2% can be explained by the independent variables PEOU and T. Lastly, the coefficients of determination for T are 0.289 (unadjusted R^2), and 0.286 (adjusted R^2). Therefore, connoting that 28.9% or 28.6% of the variance can be explained by PEOU.

4 Conclusions

Neobanks are still in the early stages of development, and the majority of the customers are innovators or early adopters. The most frequently observed strategy by neobanks is cost leadership through offering competitive prices, lower loan rates, and higher interest rates [28]. Consumers favour these business models, however neobanks require a large customer base for them to be profitable, which is challenging because of the high competition in customer acquisition and retention [13, 23, 27].

We believe it is of utmost importance for neobanks to increase the customers' behavioural intention to use them. One way to improve their customer acceptance is by improving the perceived usefulness of their services and products. Neobanks are not bound to legacy systems, so we recommend them to **use their agility when it comes to operations and technology deployment**, allowing them to adapt quickly to changing customer needs [22, 29]. Finally, neobanks currently offer superior technology over traditional banks, and we suggest that the former **keep investing in technology** to stay ahead of the competition.

Our findings show that the most crucial factor in increasing customer acceptance is for neobanks to focus on improving customers' perceived ease of use, as this aspect showed the most substantial effects. In addition, we found in our literature review that customers—mainly the younger demographic—are frustrated with the outdated user experience offered by incumbents [22, 24, 25, 30]. Therefore, we suggest neobanks continue to **promote clear, understandable, and easy-to-use services** to maintain a competitive advantage and increase the consumers' intention to use them.

Additionally, we found that building trust is more cumbersome for neobanks, because trust is built on personal relationships over time, and digital platforms are perceived to be riskier [1, 25]. As previously mentioned, trust had a positive weak effect on the behavioural intention to use a neobank. To overcome this disadvantage, we advise neobanks to promote trust actively by **having transparent and straightforward user interfaces and interactions with their customers**. An example of how neobanks can promote transparency is by respecting consumers' control over privacy by being transparent in the collection and use of consumer data [25]. As neobanks are in the relatively early stages, we believe that time is needed for the majority of consumers to become acquainted and comfortable with them. After all, early adopters are dissimilar in the risk propensity compared to the majority formed by later adopters [48].

Finally, an important part of our investigations was to see whether national cultural differences impact the customer acceptance of neobanks. We found no significant interaction effects between the Hofstede dimensions and the modified TAM. Neobanks can use this information in several ways. Firstly, this indicates that neobanks do not need to change their business model across various countries to be accepted by customers, making expansions into other regions less complicated. Compared to traditional banks, neobanks can more rapidly expand due to their lean business models for which neither physical branches nor additional employees are needed. However, the regulatory framework should also be taken into consideration. Unlicenced neobanks are at an advantage over licensed neobanks, as they partner with incumbents to comply with regulations, which is faster than acquiring a banking licence [25, 26, 28]. However, a disadvantage is that these unlicenced neobanks can only offer a limited number of services and benefits compared to licenced ones, meaning that the services might not always live up to the customers' needs.

5 Limitations and Future Work

Our study has some limitations. First, in our literature review we did not employ a snowballing method, which could have resulted in a broader range of articles. The reason for not utilising this method is because the literature review was not our primary focus and it was performed to aid in the formulation of the method. Overall, the snowballing method would not have led to different results, however it could have resulted in additional insights. Secondly, we did not question the participants in a controlled environment. Additionally, the participants have experiences with different neobanks, which can mean that experiences vary. This means that the results are harder to generalize. An improvement would have been to have all the participants use a determined neobank or a set of neobanks, which would be followed by the designed questionnaire. This might change the perspectives of individuals who have not used neobanks before and might more accurately measure the TAM.

Furthermore, there may be a participation bias because most respondents used a neobank before. This indicates that they are less sceptical of neobanks than those that have not used a neobank before, which could have impacted the results. Finally, in the data analysis, we found that the model fit was suboptimal for the estimated model and the saturated model. Although the model fit criteria are in the early stages of research, and researchers are not certain whether it should be applied on PLS-SEM, this limitation should still be noted. Our study also did not tackle individual characteristics, such as age, which could influence the behavioural intention to use a neobank. We collected basic control variables, however these were not used in the data analysis as this was not the main focus of our study and would have complicated the conceptual model and the data analysis process significantly.

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