MGI

Master's degree Program in
Information Management

UNDERSTANDING HOW M-PAYMENT INFLUENCES INDIVIDUAL PERFORMANCE:

Task-technology fit and Culture-technology fit perspective

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Dissertation

presented as partial requirement for obtaining the master's degree Program in Information Management

NOVA Information Management School
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TASK-TECHNOLOGY FIT AND CULTURE-TECHNOLOGY FIT PERSPECTIVE

By

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Master Thesis presented as partial requirement for obtaining the master's degree in Information Management, with a specialization in Knowledge Management and Business Intelligence

Supervisor: Carlos Tam

January, 2023

STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading
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Lisbon, 2023

Abstract

M-payments are rapidly spreading around the globe with the growing use of digital payment methods such as Apple Pay or money transfer platforms (e.g., MB Way). Many studies address m-payment but most focus on the user adoption phase. We seek to understand individual performance with the combination of the task-technology fit model and the culture-technology fit. This will enable us to determine how culture impacts performance. The research methodology is based on an online survey questionnaire with 199 participants. The results show that technology characteristics play a role in TTF, and TTF influences the use and individual performance. Furthermore, the moderators' time perception and context have a significant effect in individual performance over use.

Keywords

M-payments; task-technology fit (TTF); culture-technology fit (CTF); individual performance; context; time perception

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1. Introduction

Mobile commerce (m-commerce) has become a mainstream activity among the online population (L. Wang, 2019). The number of m-payments globally will increase by almost 1.1 trillion dollars in 2023 from 708 billion recorded in 2019 (*Global Market Size of Digital Payments Industry Soares*, 2020). One example of this growth is mobile payment (m-payment), a recent payment method used for many financial transactions, including mobile banking (m-banking). Its most important benefit is enabling users to execute payments anytime and anywhere (Mouakket, 2020). Benefits such as this were especially important during the Covid-19 outbreak, which triggered the migration of consumers away from cash and toward digital payments, according to the World Payments Report 2020 (Capgemini, 2021). Today it is possible to rely on more than cash/debit cards, since the options for making payments have increased (Yan, 2021). These and other facts demonstrate a growing shift of commerce to digital platforms. This research studies the importance and drivers of m-payment in individual performance.

Even though many studies have been conducted regarding m-payment, not many are related to individual performance. De Luna (2019) investigated the main factors that influence the adoption of three different mobile payment systems from a customer behavioural standpoint. Jocevski (2020) focused on understanding how m-payment platform providers can achieve platform growth to retain a volume of users. Through extensive research the author defined three main activities that address the growing challenge of m-payment platforms: (a) rethinking retailer relationships, (b) developing partnerships to complement each other, and (c) Integrating and using front-end mobile technology to deliver the proposed value. (Zhao and Bacao, 2021) investigated users' mental determinants of m-banking adoption during the Covid-19 outbreak, finding that mental and technological perception affect their adoption intentions. Also, recently Al-Qudah (2022) developed a study to analyse the intention to use a particular mobile payment system (apple wallet app) in the United Arab Emirates (UAE). As can be seen, to the best of our knowledge, most of the studies concerning m-payment focus on users in the adoption phase. We wish to investigate if users evaluate the benefits of using m-payment methods before adopting them. Knowing this can be valuable in defining its adoption and retention. Our approach is to study the relationship between m-payment and individual performance and undertake the following research question (RQ):

RQ: What are the drivers of m-payment individual performance?

We seek to understand the determinants that influence m-payment usage when correlated with cultural context and time perception, and how they positively influence and help to increase individual performance. To answer our research question, we developed a joint model from the task-technology fit (TTF) model (Goodhue and Thompson, 1995) and the culture-technology fit (CTF) model (Lee, 2007) by associating individual performance and usage dimensions with the cultural moderators of context and time perception. Based on this, the study contributes to the literature by being the first research in which the TTF and CTF models are combined to comprehend individual performance and m-payments. The result of the combination between two established theories results in a single model that will contribute to the information system (IS) area of study. Instead of relying solely on TTF's direct influence, we also study the moderating effects of culture and time perception on individual performance. Findings will help m-payments business managers to understand the right strategies to attract m-payments users and retain those already acquired.

2. Literature Review

2.1 M-Payment

In previous literature m-payment has been defined as a business or personal activity involving the use of a mobile electronic device to facilitate economic transactions (De Luna, 2019). It consists of three leading contactless technologies, including Near Field Communication (NFC), Quick Response (QR) codes, and Short Message Service (SMS). The first and second (NFC and QR) are proximity technologies. They allow for in-store payments by approaching the terminal with a mobile device. The third method (SMS) is remote and relies on mobile devices exchanging text messages (De Luna, 2019).

Among many benefits, m-payment systems have allowed financial transactions to be executed anywhere and anytime, increased the security of transactions, diminished transaction fees, and made it possible for organizations to gather helpful information about their customers' purchasing behaviours (Bezhovski, 2016). With these convenient and secure features, the business landscape has changed dramatically through the broad adoption of m-payment, which has revealed that there is vast business potential in several contexts, especially under pandemic situations (Zhao and Bacao, 2021).

Many studies have been conducted to examine the factors involved in adopting m-payments. (De Luna, 2019), using the technology acceptance model (TAM), investigated the main factors that influence the adoption of NFC, QR, and SMS from a behavioural standpoint – i.e., perceived usefulness (technology's potential to improve consumers' lives) and subjective norms (the extent to which individuals' perceptions are influenced by those they consider to be important when adopting a new system and performing a particular action). On a similar note, Zhao and Bacao (2021) investigated the influence of technological and cognitive factors on Chinese users' adoption intentions under an emergency situation (the Covid-19 pandemic) by integrating literature theories such as the unified theory of acceptance and use of technology (UTAUT) and the mental accounting theory (MAT). Their research explains that mental and technological perception significantly affects the adoption intention of m-payment during the pandemic and that users' perceived benefits are primarily affected by social influence and trust.

Also, Bezhovski (2016) developed work that evaluated the current state and expected growth of m-payment and examined the factors that affect consumer adoption. The aim of Jocevski (2020) was to understand how mobile payment providers address the challenges of platform growth from a business model perspective. The author's investigation identified three possible approaches that might ultimately redesign the BM and attract retailers to join the platform offered by m-payment providers.

Following our literature review we conclude that there is a knowledge gap in the study of the post-adoption phase of information systems, particularly m-payments. Most studies we found focused on the adoption phase. However, in our perspective it is essential to understand how m-payment affects the overall performance of individuals.

2.2 Task-technology fit (TTF), culture-technology fit (CTF), and hypothesis

As demonstrated above, there have been many models adopted. Many researchers have studied factors that might affect m-payment adoption, such as behavioural intentions, mental factors, technology perception, subjective norms, and perceived usefulness. This study proposes an individual performance focus by applying the TTF (Goodhue and Thompson, 1995) and the CTF (Lee, 2007) models.

The TTF model can work with other models, such as the unified theory of acceptance (UTAUT), to study the factors influencing university students' intentions of using massive open online courses (Wan, 2020); the technology acceptance model (TAM) to understand the continuance intentions of using gamification for university training (Vanduhe, 2020); and even the theory of planned behaviour (TPB) to explore students' adoption behaviour regarding learning management systems during Covid-19 (Khoa, 2021). In our case, combining the TTF with the CTF models seems to be the most appropriate to develop the suggested conceptual model of the study, which aims to appreciate the importance of context, time perception, and use as a potential cause of impact on individual performance.

Figure 1 illustrates the proposed model that focuses on examining how performance as a source of efficiency can ultimately impact the ease and speed with which a person can perform m-payment tasks (Tam and Oliveira, 2019). Improved efficiency, improved effectiveness, and higher quality are suggested benefits that indicate better individual performance (Goodhue and Thompson, 1995). To comprehend the impacts of the m-payment concept on individuals, we apply the TTF model and test the effect of technology, tasks, and use on individual performance as well as time perception and context from the CTF model. We explain below all the dimensions of the TTF model and the impact of the context and time perception dimensions from the CTF model.

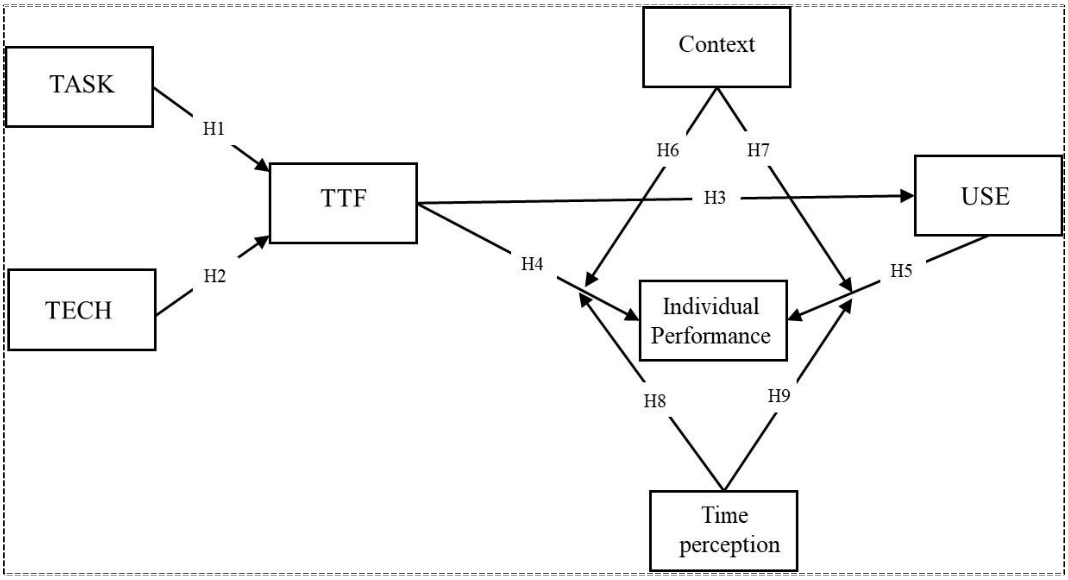

Figure 1 - Research model

Turning inputs into outputs ultimately influences the individual's dependence on information technologies and has been used to describe task characteristics (Goodhue and Thompson, 1995). It is fair to assume that technology will be used more if m-payment and individual tasks match. Technology characteristics are the tools used by individuals to perform their tasks; As a whole, these include computer systems (e.g., hardware, software, and data), along with user support services (e.g., training, helplines). The model focuses on the impacts of a particular system or the more general impact of the entire system. Characteristics make M-payment attractive to users and allow them to perform tasks such as making payments, transferring money, and using mobile wallets. Task and technology characteristics are the dimensions that precede task technology fit. The model argues that if the task depends on a technology's capabilities, but the technology is inadequately designed and has insufficient utilities to complete the task, the TTF will deteriorate (Wang, 2020). In this sense, TTF is defined as the degree to which a specific technology assists an individual to perform tasks (Goodhue and Thompson, 1995). Therefore, TTF is the relationship between task requirements, individual abilities, and the functionality of the technology.

The use dimension defines the employment of a technology used to complete a task (Goodhue & Thompson, 1995); frequency of use and diversity of applications employed are measures that are commonly used. Also, benefits like availability, safety, speed, convenience, and low cost make m-payments attractive for users. The dependent variable of the model is individual performance. This dimension relates to accomplishing a portfolio of tasks for which improved efficiency, effectiveness, and higher quality are all features that affect performance. This dimension suggests that if individuals can appropriately use information technologies at work and in their day-to-day lives, individual performance can be positively influenced. In short, it is believed that individuals could manage their dependence on information technologies and rely on their task characteristics to increase job productivity at their workplace (Cheng, 2020). Considering this background, the hypotheses we propose are the following:

H1: Task characteristics influence task-technology fit.

H2: Technology characteristics influence task-technology fit.

H3: TTF positively affects the use of m-payments.

H4: TTF positively affects individual performance.

H5: Use of m-payments affects individual performance.

Culture-technology fit has previously been used as a measure that determines the resemblance between the characteristics of an IT (in our case, m-payments) and someone with individual cultural features (Lee, 2007). We propose studying culture's moderating effects on individual performance. However, we look specifically at how context and time perception may influence our models' dependent variable.

When we think about language, we must consider that it does not exist in isolation. When humans learn a new language, we do so inside a cultural context. Thus, language has been over many centuries influenced by social context as an emotion carrier, an artistic expression, and, most importantly, as a communication tool (Hillier, 2003). Originally, the context was studied as a human-to-human communication influencer; however, it should also be studied in the interaction between people and technology. Several investigations have divided context into explicit written and implicit symbolic expressions (Lee, 2007). For instance, Calhoun (2002) concluded that cultures with high contexts such as Korea, tend to feel overloaded with explicit information when dealing with IT. In contrast, cultures with less cultural context, like the United States of America, tend to process the same information more easily (Leidner and Kayworth, 2006). This leads us to conclude that context might influence how persons use m-payments, ultimately affecting individual performance. Considering that m-payment systems have a propensity for an explicit communication approach, we conclude that people who exhibit high cultural context and are more prone to symbolic communication are also more likely to not use m-payments, whereas people with low cultural contexts are more likely to use m-payments.

Hall also asserted that time perception should be separated into monochronic (M-time) culture and polychronic (P-time) culture (Hall and Reed Hall, 1987). An M-time-influenced person tends to focus and perform one action at a time or in a sequential way; thus, time for this type of culture is more prone to affect individuals' tasks. On the other hand, P-time cultures perform tasks simultaneously; people of this particular culture tend to do many things at once. Previous literature reports that people with P-time culture are more likely to stop a task to search for new information. If we keep in mind that m-payment tasks are performed on mobile devices with generally small screens, we might be able to infer that people with P-time tendencies could find it difficult to complete m-payment tasks compared to M-time culture users (Lee, 2007). All this has led us to conclude that time perception and context significantly influence users' reactions to m-payment systems. Hence, we formulate the following hypotheses:

H6: Context moderates the effects of TTF on individual performance.

H7: Context moderates the effects of use on individual performance.

H8: Time perception moderates the effects of TTF on individual performance.

H9: Time perception moderates the effects of use on individual performance.

3. Methodology

3.1 Measurement

We target our research on the users of m-payment. The study was mostly carried out in Portugal, but we also gathered information from other parts of the world. M-payment services can be used by anyone with a mobile device anytime and anywhere. All measurement items are included in *Appendix* and are adapted from Goodhue and Thompson (1995); Lee (2007); Lin and Huang (2008); Zhou (2010). Task characteristics (TASK), technology characteristics (TECH), and use (USE) are adapted from (Zhou, 2010); task technology fit (TTF) is adapted from Lin and Huang (2008); individual performance (IP) is adapted from Goodhue Thompson (1995), and context (CT) and Time perception (TO) are adapted from Lee (2007).

3.2 Data

An English language questionnaire was distributed to m-payment users in order to collect data. Content validity was reviewed for the questionnaire. In order to ensure consistency, we translated the English questionnaire into Portuguese and back into English (Brislin, 1970). Most items have a scale of 7 points ranging from strongly disagree (1) to strongly agree (7). We performed a pilot test of the survey on 30 people who were not included in the final sample. All measurement items are an adaptation of previous literature. The data were collected using an online survey platform from a well-known website, conducted between May and July 2022. After collecting 199 valid responses we started developing a demographic analysis from which we found that 57% of the respondents are women; 67 (34%) of respondents are younger than 25 years old; and 78 (39%) of the respondents are between 25 and 34 years. Concerning education levels, 94% of the respondents have a bachelor's degree, a master's degree, or higher. The detailed descriptive statistics developed from the data are in Table 1.

To investigate the common method bias, we resorted to Kock (2015). According to the author, if the variance inflation factor (VIF) is greater than 3.3, there is an indication of pathological collinearity, which may also mean that the model has a common method bias. After running a full collinearity test using SmartPLS, we determine that our model is free of common method bias.

Table 1 - Sample characteristics

Distribution (n=199)					
Gender			Education		
Male	86	43%	High School or below	12	6%
Female	113	57%	Bachelor	99	50%
			Master's degree or higher	88	44%
Age					
<25	67	34%	Occupation		
25-34	78	39%	Employee	124	62%
35-44	21	11%	Self-employed	12	6%
>44	33	17%	Student	46	23%
			Other	14	7%
			Unemployed	3	2%

4. Results

Partial least squares structural equation modelling was used to analyse the data (PLS-SEM) (Hair Jr, 2021), supported by the Smart PLS v3.0 software. PLS-SEM can be used to estimate path models with latent variables and their relationships. The high statistical power of PLS-SEM makes it a useful method for exploratory research for which theory is less developed. The main objective, however, is to find substantial effects. Using a two-step validation process, we began by testing the reliability and validity of the instrument and ended with a structural model (Anderson and Gerbing, 1988). Based on Kolmogorov-Smirnov's test, not all items in our data are normally distributed ($p < 0.01$), and the model we propose has not yet been tested in the literature. We therefore conclude that PLS is the proper method for this research (Hair, 2012). It is also important to mention that our sample meets the PLS requirement of having ten times the largest number of structural paths directed at a particular construct in the model (Chin, 2014).

The empirical content of the model is extracted from the data, and interactions improve the model through estimations between the model and the data (Sarstedt, 2017).

4.1. Measurement model

The quality of the model depends on the verification of reliability and validity. Many researchers rely on rules of thumb (used in the next paragraph) for evaluating measurement models. These rules of thumb concern four different crucial values inside a measurement model: composite reliability (CR) is used to assess internal reliability, loadings are used to evaluate individual indicator reliability, the average variance extracted (AVE) is used to verify convergent validity, and lastly, to determine discriminant validity we must take into account two factors: cross-loadings and the square root of AVE (Hair, 2014). It is customary to assess construct reliability using Cronbach's alpha (CA), but for assessing construct reliability, CR is used instead of CA, since the former considers indicators with different loadings, while CA assumes that all indicators are equal in reliability (Tam and Oliveira, 2016).

As seen in Table 2, the cross-loading criteria were met by removing TECH4 from our model estimation, which resulted in no indicator having loadings below their cross-loadings, thus meeting the two-step discriminant validity criteria. As seen in Table 3, the values concerning CR and CA are greater than 0.7, which means the model has adequate results for both internal consistency and indicator reliability. Also as seen in Table 3, the AVE for each construct is above the 0.5 threshold assuring convergent validity. As a result, all the measures of the measurement model are correct, meaning that we can assess the conceptual model and hypotheses based on the constructs of our model (Hair, 2014; Tam and Oliveira, 2017).

Table 2 - PLS loadings and cross-loading

Constructs		Task	Tech	TTF	Use	IPerf	Context	TimeP
Task characteristics	TASK1	**.916**	.384	.374	.429	.367	.144	.153
	TASK2	**.939**	.450	.392	.556	.504	.242	.198
	TASK3	**.851**	.379	.310	.446	.352	.254	.174
Technology characteristics	TECH1	.444	**.918**	.592	.451	.439	.154	.287
	TECH2	.422	**.939**	.679	.527	.506	.210	.356
	TECH3	.376	**.905**	.649	.465	.494	.197	.325
Task technology fit	TTF1	.367	.643	**.900**	.518	.558	.341	.249
	TTF2	.361	.616	**.910**	.547	.575	.258	.234
	TTF3	.410	.670	**.934**	.528	.598	.302	.294
	TTF4	.285	.563	**.837**	.456	.447	.235	.183
Use	USE1	.526	.533	.533	**.907**	.684	.275	.339
	USE2	.469	.498	.530	**.917**	.752	.288	.264
	USE3	.432	.373	.478	**.869**	.660	.270	.288
Individual performance	IP1	.419	.508	.565	.753	**.949**	.309	.401
	IP2	.419	.504	.564	.717	**.943**	.301	.377
	IP3	.430	.437	.570	.694	**.884**	.265	.291
Context	CT1	.197	.248	.367	.309	.331	**.866**	.169
	CT2	.228	.110	.196	.227	.211	**.732**	.188
	CT3	.088	.022	.041	.113	.108	**.778**	.100
Time perception	TP1	.088	.209	.115	.184	.210	.197	**.776**
	TP2	.167	.351	.263	.298	.380	.161	**.901**
	TP3	.209	.297	.264	.320	.343	.170	**.838**

Table 3 - Means, standard deviations, correlations, and reliability and validity measures (CR, CA, and AVE) of latent variables

Constructs	Mean	SD	CA	CR	Task	Tech	TTF	Use	IPerf	Context	TimeP
Task	5.639	1.449	.886	.930	**.903**						
Tech	5.936	1.152	.910	.944	.449	**.921**					
TTF	5.628	1.119	.918	.942	.400	.697	**.896**				
Use	5.839	1.334	.880	.926	.530	.524	.573	**.898**			
IPerf	6.091	1.152	.916	.947	.456	.522	.611	.780	**.926**		
Context	4.518	1.318	.739	.836	.234	.205	.318	.309	.316	**.794**	
TimeP	5.368	1.133	.796	.877	.194	.352	.271	.330	.386	.203	**.840**

4.2. Structural model

After analysing the measurement model and concluding that all requirements were satisfied, we followed the second step of validating the research model, the structural model. This model is crucial when trying to predict and explain target constructs. The structural theory focuses on showing the constructs' paths by examining their significance level within the model. We also resorted to bootstrapping, a technique to resample many samples from the original data and calculate a model for each subsample. The bootstrapping value can be used to verify the standard error and determine the significance of the paths using t-values (Hair, 2014).

Figure 2 shows the path coefficients and t-statistics derived from bootstrapping 5000 resamples, and their values. TTF explains 49.5% of the model's variation, and the task characteristics are not statistically significant in explaining TTF. Therefore, H1 is not confirmed. Tech characteristics ($\hat{\beta}$ = 0.648, $p < 0.001$) are statistically significant in explaining TTF, thus confirming hypothesis H2. Additionally, the use of m-payments justifies 32.9% of the variation, which is explained by TTF ($\hat{\beta}$ = 0.573, $p < 0.001$), supporting H3. Finally, both H4 and H5 are statistically supported since 72.7% of the variation in individual performance is justified by TTF ($\hat{\beta}$ = 0.230, $p < 0.001$) and m-payments use ($\hat{\beta}$ = 0.480, $p < 0.001$). Four different hypotheses represented the moderating variables, but only two are statistically significant and consequently confirmed, H7 and H9. Due to their negative values (H7 $\hat{\beta}$ = - 0.262, $p < 0.001$ and H9 $\hat{\beta}$ = - 0.133, $p < 0.05$), the high values of context and time perception will both be weaker in the relationship between the use of individual performance and the individual performance itself.

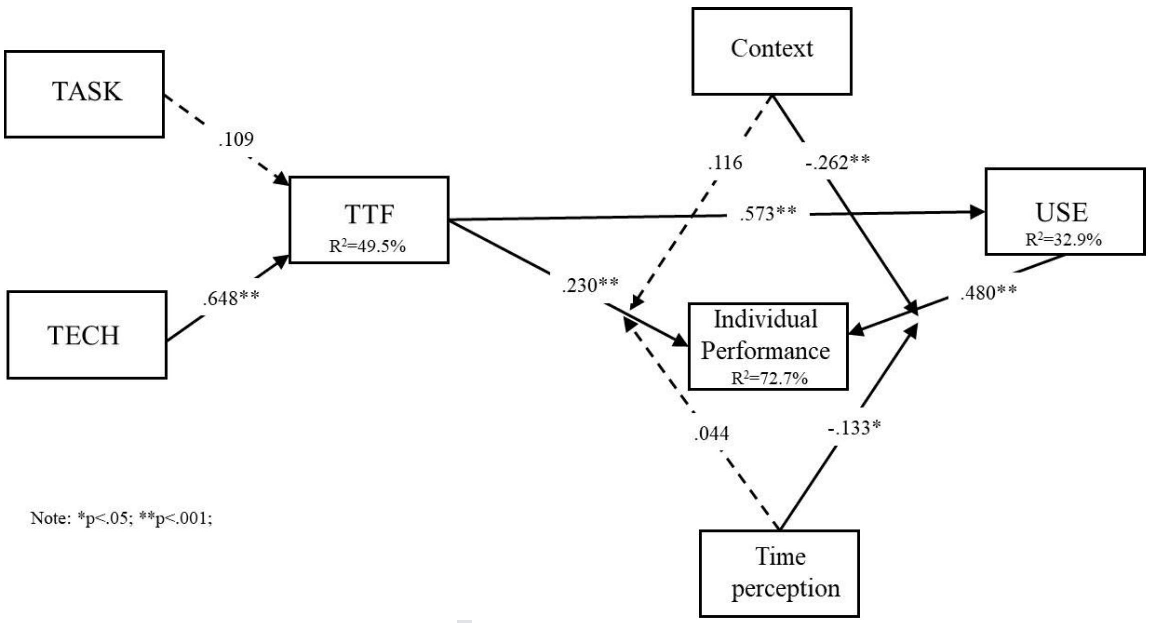

Figure 2 - Structural model results

5. Discussion

Among previous literature it is possible to acknowledge the fair number of studies conducted using the TFF model to explain individual performance. However, there has not yet been an empirical investigation explaining culture's influence on m-payments use and individual performance. As shown in Figure 2, the research model accounts for 49.5% of the variation in TTF, thus confirming H2. This result means that there is a significant impact of the technology characteristics on TTF. Similar results are reported in previous literature (Kang, 2022). Also, the research model accounts for 32.9% of the variation in use, thus confirming H3. This percentage indicates a strong influence of TTF in the use of m-payments. These results are also backed by previous literature (Tam and Oliveira, 2019). Additionally, the research model accounts for 72.7% of the variation in individual performance, thus confirming H4 and H5. This result means that there is a significant impact of the technology characteristics on individual performance. This is too research-based (McGill and Klobas, 2009). The model also shows which of the hypotheses are not confirmed. Amongst them is H1, which represents the relationship between task characteristics and TTF. Because there is no confirmation of H1, we can acknowledge that task characteristics are not important to users since they can obtain the same tasks in other and already existing technologies such as mobile banking. We conclude that because users are not as interested in the tasks, technology is what is most valued by them. Kang (2022) also found that task characteristics are less important and have a much smaller influence compared to technology characteristics.

Regarding the moderating dimensions, the model shows that time perception significantly affects the path that connects the use to individual performance. Thus, we can confirm H9. This information indicates that the moderating effect of time perception, according to the negative value, suggests the major influence of use over individual performance amongst users with low time perception. For people with high time perception, the use is not important in explaining individual performance. Finally, context significantly affects the path that connects the use to individual performance, and hence H7 is confirmed. The moderating effect of context suggests a greater impact of high use on individual performance when people tend to have low context. Thus, our results reveal that high context levels mean that the effect of the use on individual performance is not an important aspect. This information is in Figures 2 and 3.

Figure 3 shows the effects of the moderating dimensions on individual performance. The results demonstrate the same logic for both moderators. People with a low context or a low time perception have a greater influence on individual performance. We can then acknowledge that with low context, individual performance is greater – the same applies to time perception.

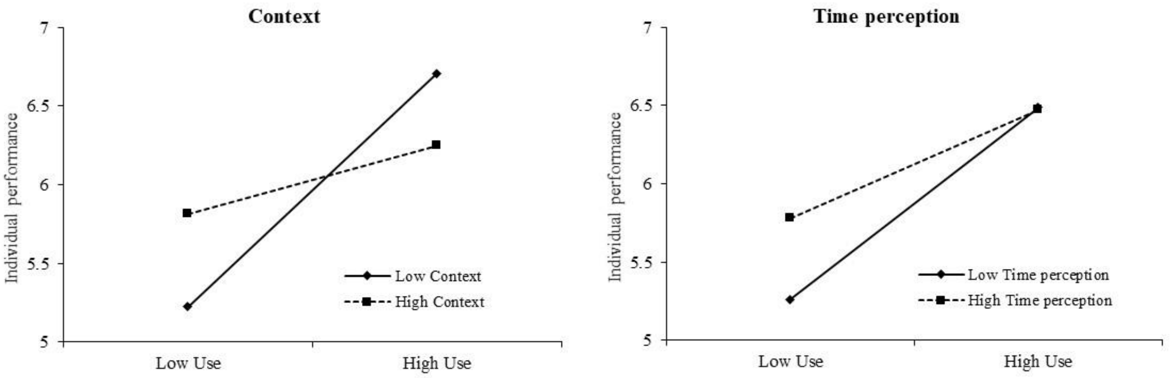

Figure 3 - Moderator effects

5.2 Theoretical Implications

Our literature review reveals a substantial number of studies regarding m-payments, but most of them are focused on determining the reasons that encourage users to adopt this technology (Alkhowaiter, 2020). From this body of work, we assessed that investigating a post-adoption phase would better contribute to the literature. In an article by Larsen (2003), the taxonomy of information systems success antecedent (ISSA) theory determines three main phases to study an independent variable. The first phase is the adoption phase, which may be described as the process leading up to the application of a system (in this case, an m-payment system). The second phase consolidates the ideas and comportment of the implemented system (intentions to use, user satisfaction, and acceptance are some of the variables surrounding this stage). The third phase focuses on individual and organizational impact related to technology performance. This last is the phase we investigated in our study, in which we sought to understand the drivers of individual performance from an m-payment perspective. This is a new perspective to add to the m-payment literature.

From a theoretical point of view, this thesis uses the TTF and CTF models to explain individual performance and how cultural dimensions may affect it. Regarding TTF, we were able to determine that people in an m-payment context tend to value technology characteristics over task characteristics, which might signify that similar tasks are already being fulfilled by different technologies or that the technologies might not be sufficient to meet users expected performance levels (Kang, 2022), making the technology the attractive focal point for individuals. By combining moderating cultural dimensions with the TTF model, we create a new notion of the TTF (Tam and Oliveira, 2019). From this new cultural approach, rather than just evaluating usability and individual impacts, we can now understand how context and time perception influence individual performance when using m-payments. Cultural differences exist in every region, and time perception varies from person to person. Our model shows that the effect of TTF and use on individual performance is positive. However, the model also shows that people with high time perception tendencies reduce the positive impact of the use on m-payments. Meanwhile, people with high cultural contexts decrease the effect of the use on individual performance. We believe that future investigators will find this study helpful, especially in technology and individual performance areas. The model combination we present herein can be used to evaluate determinant factors in technology performance and cultural impacts. Therefore, we believe this paper to be of great value for future research.

5.3 Practical implications

The research carried out in this paper provides insights to decision-makers regarding information systems characteristics that managers can use to upgrade the performance of those who use m-payment services. The paper also brings a new perspective to the literature since most of the studies regarding m-payments are focused on the adoption phase. On the contrary, we investigate a post-adoption phase which helps us understand user performance and retention. Additionally, we found that TTF and use significantly affect individual performance. By understanding task characteristics in the Portuguese context, we are also able to conclude that the characteristics of an m-payment technology are of great value to individuals, while task characteristics are no longer a significant concern. An adequate and advantageous service might determine whether a person uses m-payments instead of other traditional methods such as the service advantages including time savings and reduced difficulty in performing m-payment tasks, and whether these affect performance.

We have also included cultural dimensions in the investigations to create new insights that improve individual performance. For instance, we can affirm that people with higher cultural contexts tend to find m-payments more complex and challenging to use, which negatively impacts performance. Regarding time perception, we can infer that people with high time perception will also harm performance. With this in consideration, businesses should provide a service with more symbolic information in cultures with more elevated cultural contexts. For time perception we can infer that polychronic cultures like Portugal find it hard to use m-payment technologies. The model's results on time perception make particular sense since Portugal has a polychronic culture (Pina e Cunha, 2005). Only low time perception will positively affect individual performance when using an m-payment technology in a Portuguese context.

Service developers and business managers could define different strategies for culturally specific targets based on the information reported in this paper.

6. Conclusion

It is vital for service providers to maintain users and improve the performance of m-payments. With the combination of the TTF and CTF models and two cultural dimensions, this study examined the factors influencing m-payment usage in relation to specific cultural contexts and perceptions of time, and how they positively influence and increase individual performance. The relationship between use and individual performance was also found to be significantly influenced by both time perception and context. This means there is an influence on user behaviours from the cultural relationship between use and individual performance. This might represent a challenge for anyone investigating cultural impacts and individual performance. Our results show that TTF explains the use and that TTF, together with use, explains 72.7% of the variation in individual performance. A cultural dimension may assist service providers in segmenting m-payment users and developing a variety of strategies as well, as this study empirically demonstrates.

We must acknowledge the several limitations of this paper's investigation. First, the study centres around the m-payments context, but different technologies may produce different results. Secondly, we used only two of the many cultural dimensions. In future research other cultural dimensions can be applied to provide other insights about m-payment users. Finally, even though we use TTF and CTF to explain individual performance in m-payments, other researchers might find it interesting to use other theories such as MAT or UTAUT to explore the effects of other factors.

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Appendix

Appendix - Items

Construct		Item	Adapted from
Task characteristics	TASK1	“I need to manage my accounts anytime anywhere”	(Zhou, 2010)
	TASK2	“I need to do transfer anytime anywhere”	
	TASK3	“I need to have a real-time control in my accounts”	
Technology characteristics	TECH1	“M-payment provides ubiquitous services”	(Zhou, 2010)
	TECH2	“M-payment provides real-time services”	
	TECH3	“M-payment provides a quick service”	
	TECH4	“M-payment provides secure services”	
Task technology fit	TTF1	“M-payment services are appropriate”	Lin and Huang (2008)
	TTF2	“M-payment account management services are appropriate”	
	TTF3	“Real-time M-payment services are appropriate”	
	TTF4	“In general, M-payment services are enough”	
Use	USE1	“I often use M-payment”	(Zhou, 2010)
	USE2	“I use M-payments to make transfers”	
	USE3	“I use M-payment services as an alternative to money”	
Individual performance	IP1	“M-payment enables me to accomplish tasks more quickly.”	(Goodhue and Thompson, 1995)
	IP2	“M-payment makes it easier to accomplish tasks”	
	IP3	“M-payment is useful to perform the financial tasks I usually do”	
Context	CT1	“When using an Internet service, I prefer to see symbolic information in the form of pictures or drawings, instead of detailed information in text form”	(Lee, 2007)
	CT2	“When I use e-mail or a chat room, I prefer indirect expressions (e.g., emoticons) to direct expressions (e.g., text)”	
	CT3	“When I am searching for information, symbolic iconic representation is more convenient than detailed textual information”	
Time perception	TP1	“When I use the M-payments, I only use the services I planned to use beforehand”	(Lee, 2007)
	TP2	“Before connecting to an M-payments system, I usually decide which service I am going to use”	
	TP3	“When I search for information on M-payments, I search for one piece at a time”	