UNIVERSITY PERCEPTION OF LEARNING IN THE USE OF DIGITAL PAYMENTS – TAM3

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Abstract
The article analyzes the perception of postgraduate university students on learning related to digital payment systems. The technology acceptance model (TAM3) was used to evaluate the ease of use and usefulness of these systems. An instrument was applied to university professionals with questions posed by constructed identities [that is, gender (male, female) by socioeconomic stratum (one, two, three, four and five). Where 370 university students participated. Which completed an online survey. The results showed that there is a low degree of development in the use of digital payment systems. A descriptive and variance analysis was performed to examine differences in perception according to gender and socioeconomic stratum. The findings provide information on the perception of university students about learning and using digital payment systems.

***Keywords**: TAM3, University perception, digital payments, Learning.*

INTRODUCTION

Digital technology has fundamentally transformed the way we interact with the world around us. In the field of education, this technological revolution manifests itself in a growing dependence on digital tools for learning and the management of academic resources. The Technology Acceptance Model - TAM, is a theoretical framework widely used to understand and analyze the acceptance of technology by users. The TAM has been widely used in evaluating users' acceptance and explaining users' behavior through assessing the impact of information on users in terms of trust, attitudes and intentions. (Le & Cao, 2020). One of the key areas of this transformation is the use of digital payments, which have gained prominence as an efficient and secure way to conduct financial transactions in the university environment. The original version of the TAM placed much of the weight of the explanatory model on two types of beliefs: the perception of the usefulness of the technology and the perceived ease of use of the technology. (Albero et al., 2017). The TAM explores why potential users of technology are inclined (or not) to adopt said technology. (Do et al., 2022)
Technology Acceptance Model (TAM) or what is known to as the technology acceptance model of the theories of the use of IT systems which are already believed to be highly influential and are primarily used to predict consumer acceptance of the use of information systems. (Amiruddin et al., 2021). The TAM is a theoretical model that focuses on the perception of the usefulness and ease of use of technology as key factors in its adoption. It helps researchers and practitioners understand why

people adopt or reject technology and design strategies to encourage its adoption. TAM models are used to understand how external variables affect the perceived usefulness and ease of use of a technological product, which in turn influences people's attitude and intention to use said product. These models are valuable for understanding technology adoption and human behavior related to it. The TAM models consist of factors known as external variables, which can affect Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) to determine the Attitude (ATT) of human behavior intention (BI) to the use of technology products. (Lin et al., 2022). PU and PEOU are often regarded as the two most important constructs in TAM. (Chen et al, 2022)

Individual skills related to the use of Information and Communication Technologies (ICT) have become a necessary condition for professional success, as well as a crucial factor in private life. (Urquidi et al., 2019). Therefore, the importance of ICT skills in today's society is essential for both professional success and personal life. This idea can serve as a basis for deeper research and analysis on how ICT competencies impact various areas of society and how they can be promoted and evaluated effectively. TAM shows that the perceived usefulness of information technology and the perceived ease of use are the two main determinants of the behavioral intention to use. (Tsai et al., 2022). In the age of technology and digitalization, technology acceptance plays a crucial role in people's lives and the success of organizations. The Technology Acceptance Model (TAM) has been a widely recognized and used theory to understand how individuals adopt and use technology. Initially developed by Davis (1989). In this sense, the Technology Acceptance Model 3 (TAM3) emerges as a valuable theoretical tool to understand students' perceptions regarding learning through digital payments. The TAM3, an evolution of Davis's (1989) original model, focuses on perceived usefulness (PU) and perceived ease of use (PFE) of technology as key determinants of usage intention and adoption. the same.

The exponential growth of digital payments in the educational context raises crucial questions related to the perception, acceptance and adoption of this technology by university students. The rapid evolution of technology is highlighted, especially in the field of education, where affordable open-source applications and services designed to improve teaching and learning are being developed and offered. This can have a significant impact on how people actually access and use technology. TAM advocates actual usage of technology is being determined by their behavioral intentions. (Chahal y Rani, 2022). Innovation in technology is happening at a dizzying rate. Hassle-free, open-source applications and services established on the Internet and designed to boost teaching and learning have now been made available to the general public at limited or no cost. (Chancusig Chisag et. al., 2020)

The technology acceptance model (TAM) identifies why individuals adopt new technologies in various domains and is a popular topic of research in the information systems field. (Ho et al., 2020). But it is not only in information systems, the TAM has served as a conceptual framework for a wide range of research in various fields, in many areas such as computing, because the relevance of this model lies in its ability to explain and predict the adoption of technology, which in turn has significant implications for innovation, competitiveness and strategic decision making. As TAM has matured over the decades, there has been steady growth in the scientific literature related to this theory. Various researchers have applied and adapted the model to a wide variety of contexts and have contributed to its theoretical evolution. Over the last three decades, many scholars have modified TAM (e.g., TAM 2, TAM 3, and extensions of TAM) because perceived usefulness and perceived ease of use are influenced by many external variables; they may affect the intention to use technology together. (Huang et al., 2021). This boom in research has led to a substantial body of literature on TAM, raising the need for comprehensive bibliometric analysis to better understand its evolution, identify trends, and highlight areas of continued interest.

Up to TAM 3, self-efficacy is only used to measure its effect on perceived ease of use. Even though there have been many studies in the field of acceptance of online information technology that use self-efficacy to test not only its effect on perceived ease of use, but also perceived usefulness, trust, perceived risk, attitude, and usage intention. (Sidanti et al., 2021)

The Technology Acceptance Model (TAM) is a theoretical model that allows some flexibility in its application, especially with regard to external variables, which does not impose rigid restrictions on the consideration of external variables, which allows it to be used flexibly and adapted to the needs and circumstances of researchers in different contexts of technology adoption. This makes it a versatile tool in research on technology acceptance and adoption. However, the explanation of external variables is not always required in the TAM model, thus signifying that the TAM is an open model and may be flexibly used by researchers based on the given circumstances. (Zhang et al., 2021) This bibliometric analysis will not only contribute to the current understanding of the state of knowledge in the field of TAM, but will also serve as a valuable tool for researchers, academics and practitioners seeking guidance in their future research and in making strategic decisions related to technology adoption. All studies on the TAM include several indicators of each construct in order to achieve a more precise answer. Furthermore, in the case of using several items, their levels of reliability and validity would have to be checked for the study in question. (López-Bonilla y López-Bonilla, 2012). This model identified the antecedents of the actual system use that takes place in a newer technology. (Alsaffar et al., 2022). Among various theories and approaches, the TAM model has been extensively used in information technology and internet-based services to understand the adaptation decision-making process. (Ishfaq & Mengxing, 2022). The relevant position of the Technology Acceptance Model (TAM) is highlighted in the field of information technology and online services, where it is used to analyze people's adaptation decision making towards technology. This suggests that the TAM model is an effective and widely accepted tool for understanding how users adopt and use technologies in a digital environment. The TAM assumes that the actual use of a technology originates from the individuals' behavioral intentions to use that technology. (Taheri et al., 2022). The technology acceptance model (TAM) is a commonly adopted theoretical framework that is used to analyze and understand users' behaviors toward a certain technology type. (Moon et al., 2022).

While originally for use in understanding the adoption of technology in the workplace, the TAM3 instrument saw the perspective change to that of the individual. Importantly, these models and their respective instruments were designed to be flexible. (Saravanos et al., 2022).

The objective of this study is to explore and analyze the university perception of learning in the use of digital payments, using the TAM3 as a conceptual framework. The main objective of this study is to shed light on how university students perceive the usefulness and ease of use of digital payments in their academic experience and how these perceptions influence their intention to adopt this technology in their daily lives within the educational field. These findings may be useful to professors, researchers, academics, and practitioners interested in understanding and promoting technology adoption and improving competitiveness in their organizations.

METHODOLOGY

To address this study, a mixed methodology was used, this allowed us to obtain a more complete and enriching vision of the university perception of learning in the use of digital payments. Initially, a quantitative analysis was carried out using the technology acceptance model (TAM) as a conceptual framework, collecting data through structured questionnaires that assessed university students' perceptions of the usefulness and ease of use of digital payments in their academic experience. The population consisted of 370 college students who completed an online survey. The questionnaire was sent to the students in the online discussion forum hosted in the class group of the Moodle platform. The data were analyzed using descriptive statistics and analysis of variance (ANOVA) to examine differences in perception between different groups of students, such as, for example, according to their socioeconomic stratum and gender. During the interviews, various aspects were addressed, including the underlying causes of perceptions about the usefulness and comfort of use, the obstacles perceived in the incorporation of digital payments, and recommendations to enhance their application in the environment. educational.

RESULTS

The entire sample made up of "Postgraduate university students", according to their socioeconomic stratum, they consider that learning about the different digital payment systems facilitates their use. The data is grouped according to their perception of learning in relation to the use of payment systems:

Totally disagree, disagree, agree, totally agree.

The variables were used:

P4 - Socioeconomic stratum - (stratum 1, stratum 2, stratum 3, stratum 4, stratum 5) of university students.

P3 - Gender of University Students (female, male).

P23 - Learning - facilitates use - Do you consider that learning in relation to the different digital payment systems facilitates their use? Whose responses were totally disagree, disagree, agree, totally agree, with the JASP statistical software the use of ANOVA was applied between subjects.

Specifically, we test that university students have a different socioeconomic stratum than their gender and whether learning is related to the stratum. The “Descriptives” menu allows us to obtain a first overview of the data. The Descriptive Statistics table shows the means, standard deviations, variances, minimums of the question: Do you consider that learning about the different digital payment systems makes their use easier? Whose responses were totally disagree, disagree, agree, totally agree.

Table 1 shows the measures of central tendency and dispersion of the responses to the question "Do you consider that learning about the different digital payment systems makes their use easier?" for different categories. In the "Agree" column, it is observed that the mean is 2.588, with a standard deviation of 0.875. This indicates that, on average, participants slightly agree that learning facilitates the use of digital payment systems. While in the "Disagree" column, the mean is 2.600, with a standard deviation of 0.699. This suggests that participants have a similar opinion regarding disagreeing with the statement. In the "Totally Agree" column, the mean is 2.647, with a standard deviation of 0.900. This indicates that participants are more inclined to totally agree with the statement, and in the “Totally Disagree” column, the mean is 2.481, with a standard deviation of 0.849. This suggests that some participants have strong opposition to the claim.

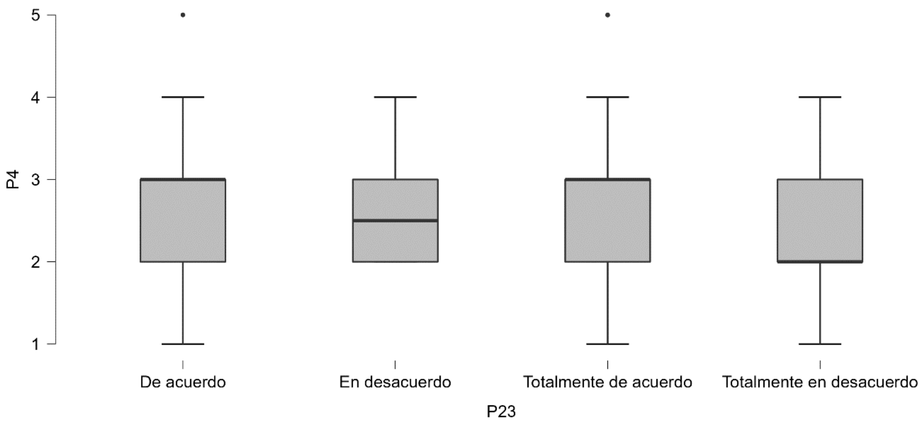
Table 1.
Descriptive statistics of university perception of learning in digital payment systems

	P4			
	Agree	Disagree	Totally Agree	Totally Disagree
Valid	177	10	156	27
Missing	0	0	0	0
Mean	2.588	2.600	2.647	2.481
Std. Deviation	0.875	0.699	0.900	0.849
Variance	0.766	0.489	0.810	0.721
Minimum	1.000	2.000	1.000	1.000
Maximum	5.000	4.000	5.000	4.000

Figure 1 shows a box and whisker plot or boxplot, visualizing the distribution of the data and providing information about the median, quartiles, and outliers of a data set. In this case, the boxplot represents the perception of users about the learning and ease of use of different digital payment systems, according to their socioeconomic stratum. The vertical axis of the graph represents the user response scale, ranging from "Totally Disagree" to "Totally Agree”. Likewise, it shows the distribution of responses in each socioeconomic stratum. Each box represents the interquartile range, that is, the range that covers the middle 50% of the responses.

The line in the middle of the box represents the median, which indicates the most common response in that stratum. The whiskers in the graph represent the full range of responses, excluding outliers. By observing the boxplot, you can analyze the variability of the responses in each socioeconomic stratum and compare the medians between the strata. This provides information on how the perception of learning and ease of use of digital payment systems differs between different socioeconomic levels.

Figure 1.
Boxplots of university perception of learning in digital payment systems according to socioeconomic stratum



Note. P4 - Socioeconomic stratum - (stratum 1, stratum 2, stratum 3, stratum 4, stratum 5); P23 - Learning - facilitates use - Do you consider that learning in relation to the different digital payment systems facilitates their use? JASP Team (2022). JASP (Version 0.16.3) [Computer software].

Table 2 shows the results of the one-way ANOVA, providing information on the means and standard deviations of the participants' responses in relation to the variable P4 and P23. Where the variable P4 is analyzed, observing that women have a mean of 2.484 and a standard deviation of 0.879, while men have a mean of 2.830 and a standard deviation of 0.826. Regarding the variable P23, women have a mean of 2.556 and a standard deviation of 0.860, while men have a mean of 2.807 and a standard deviation of 0.953.
These results indicate that, on average, men tend to agree more with the relationship to different digital payment systems than women. However, it is important to note that the differences between the groups are not very large, since the standard deviations are relatively similar.

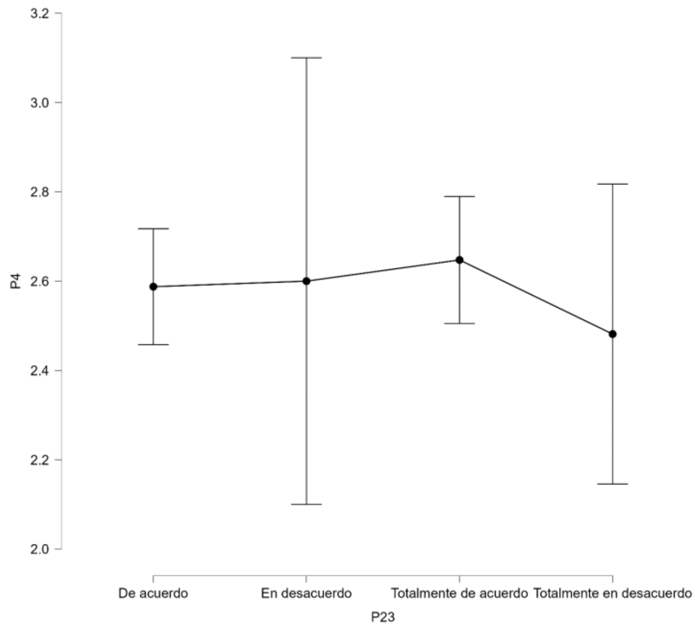
Table 2.
One-way ANOVA results for variable P4

Descriptives - P4

P23	P3	Mean	SD	N
Agree	Female	2.484	0.879	124
	Male	2.830	0.826	53
Disagree	Female	2.857	0.690	7
	Male	2.000	0.000	3
Totally Agree	Female	2.556	0.860	99
	Male	2.807	0.953	57
Totally Disagree	Female	2.438	0.814	16
	Male	2.545	0.934	11

Figure 2 shows the relationship of the responses of the participants in the study, representing the responses of different groups, such as gender and level of agreement. This visualization of the distributions of the responses in each group helps to understand the trends and differences in the responses of the participants.

Figure 2.
Descriptive graphs of university perception of learning in digital payments



JASP Team (2022). JASP (Version 0.16.3) [Computer software].

Table 3 shows the results of the "Polynomial Contrast" for the variable P23, linear, quadratic and cubic comparisons were made. Regarding the linear comparison, it was found that there was no significant difference between the groups, since the t value was -0.384 and the p value was 0.701. In the quadratic comparison, a significant difference was also not found, with a t value of 0.107 and a p value of 0.915, and in the cubic comparison, again no significant difference was found, with a t value of -0.976 and a p value of 0.330.

Table 3.
Polynomial Contrasts - P23

Polynomial Contrast - P23					
Comparison	Estimate	SE	df	t	p
linear	-0.055	0.142	362	-0.384	0.701
quadratic	0.019	0.180	362	0.107	0.915
cubic	-0.207	0.212	362	-0.976	0.330

JASP Team (2022). JASP (Version 0.16.3) [Computer software].

Table 4 shows the results of the Bayesian Binomial Test. This test was used to compare the proportions of two groups and determine if there is a significant difference between them, the gender proportions were compared in variable P3. For the Female group, it is observed that there are 246 cases out of a total of 370, which represents a proportion of 0.665, while for the Male group, there are 124 cases out of a total of 370, which represents a proportion of 0.335.
The test is performed by comparing these proportions with a reference value of 0.5. The Bayes factor (BF_{10}) was used to evaluate the evidence in favor of the alternative hypothesis that the proportions are different. In this case, the value of the Bayes factor is 4.886e+7, indicating strong evidence in

favor of the alternative hypothesis. This suggests that there is a significant difference in the gender proportions in variable P3.

Table 4.
Bayesian Binomial Test Results

	Level	Counts	Total	Proportion	BF_{10}
P3	Female	246	370	0.665	4.886e+7
	Male	124	370	0.335	4.886e+7
P7	Rural zone	25	370	0.068	1.437e+70
	Urban zone	345	370	0.932	1.437e+70

Note. Proportions tested against value: 0.5. The shape of the prior distribution under the alternative hypothesis is specified by Beta(1, 1).

Figure 3 shows the results of an inferential analysis carried out in relation to the variable P3 and the female gender. The "Prior and Posterior" plot represents the probability distribution before and after the analysis. In the graph "P3 - Female Prior", the probability distribution before the analysis is shown, where it can be seen that the probability is uniformly distributed, indicating that there is no clear preference towards any particular category.
In the graph "P3 - Posterior Female", the probability distribution after the analysis is shown, here, it can be seen that the probability has been concentrated in a narrower range, indicating that the analysis has provided additional information and reduced uncertainty.

Figure 3.
Inferential graphs of the variable P3 - Female
Prior and Posterior

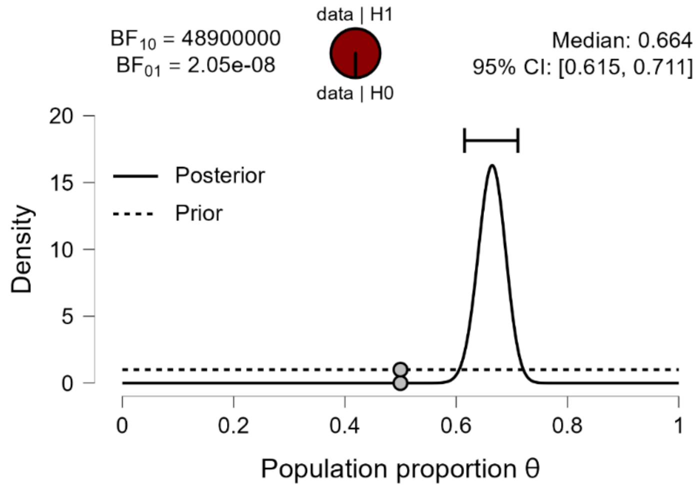


Figure 4 presents an analysis of the relationship between density and population proportion in the context of the study. The X-axis represents density, while the Y-axis represents the proportion of the population.
In the graph of the female group, a density distribution that resembles a normal curve is observed. The population proportion distribution also shows a shape similar to a normal curve, with a peak around 0.665, suggesting that most women are found in areas with a population proportion close to that value. In the male group graph, the density distribution also resembles a normal curve. However, the distribution of the population proportion shows a more dispersed shape, with a peak around 0.335, indicating that the male population proportion is more distributed in different values compared to the female group.

Figure 4.
Comparison of population density and proportion based on male gender (Prior and Posterior)

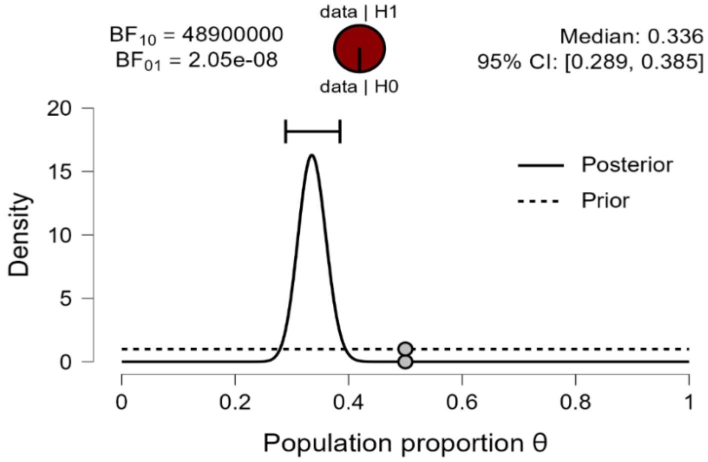


Figure 5 shows the analysis of variable P7 in relation to the rural area, both in terms of the prior and posterior distributions. In the prior distribution, a symmetrical bell shape can be observed, indicating a uniform distribution of probabilities before the analysis is performed. This means that there was no specific prior information on variable P7 in the rural area. In the posterior distribution, after performing the analysis, a change in the shape of the distribution can be observed. A skewed distribution is now shown, with a concentration of probabilities at the upper end. This indicates that after the analysis, more precise information has been obtained about the variable P7 in the rural area. In summary, the analysis in Figure 5 shows how the prior and posterior distributions can change after performing a specific analysis of the variable P7 in the rural area. The posterior distribution provides a more accurate and up-to-date estimate of the variable in question.

Figure 5.
Pre and post distributions of P7 in rural areas

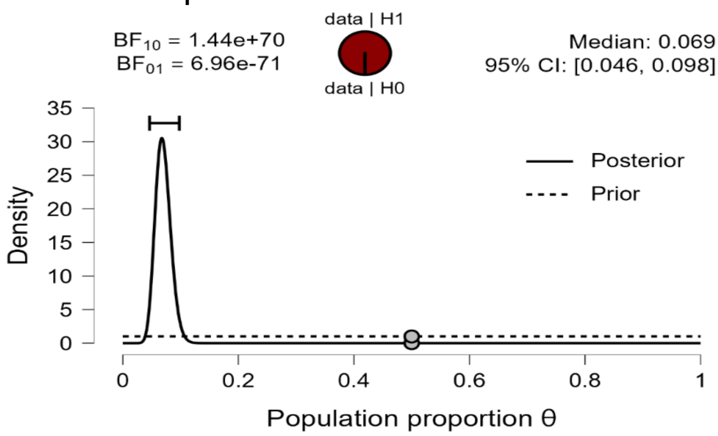


Figure 6 shows the analysis of P7 in relation to the urban area, both in terms of the prior and posterior distributions. The prior distribution represents the initial belief about the proportion of the population in the urban area. It shows a uniform distribution, which means there is no strong belief about the proportion. The posterior distribution, on the other hand, is based on the observed data and updates the initial belief. In this case, the posterior distribution shows a greater concentration of probability around a higher proportion in the urban area. This indicates that the observed data supports the idea that the proportion of the population in the urban area is higher.

Figure 6.
P7 - Urban Area - Prior and Posterior

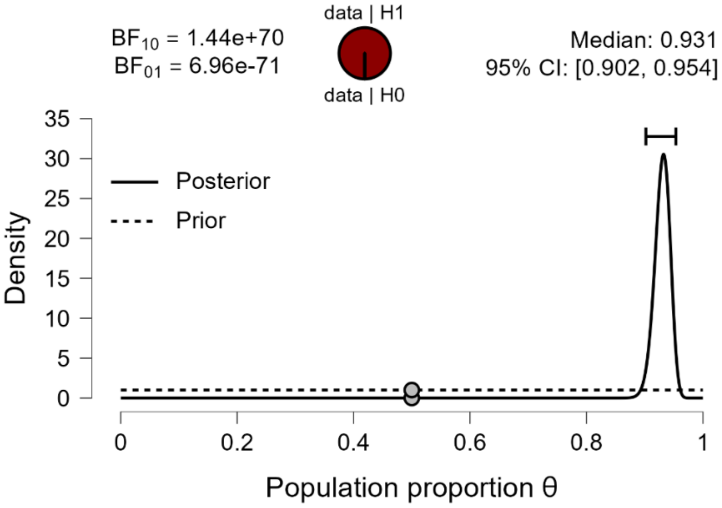


Table 5 presents an analysis of Bayesian contingency tables, showing the distribution of the data according to the two variables: P8 y P3. Variable P8 represents the educational level of the participants, with two categories: "Postgraduate in progress" and "Undergraduate in progress".
The variable P3 represents the gender of the participants, with two categories: "Female" and "Male." The table shows the counts and percentages of each category of P8 and P3, both within each row and within each column. For example, in the "Female" row, it is observed that there are 48 participants who are studying a postgraduate degree and 198 participants who are studying an undergraduate degree, which represents 19,512% and 80,488% respectively of the participating women.
In the "Postgraduate course in progress" column, it is observed that 64% of the participating women are pursuing a postgraduate degree, while 36% of the participating men are pursuing a postgraduate degree. Additionally, the total percentage of each category is shown in relation to the total number of participants. For example, 12.973% of the participants are women who are pursuing a postgraduate degree, while 7.297% of the participants are men who are pursuing a postgraduate degree.

Table 5.
Bayesian Contingency of Graduate and Undergraduate Courses by Gender

Contingency Tables

		P8		
P3		**Postgraduate in progress**	**Undergraduate in progress**	**Total**
Female	Count	48.000	198.000	246.000
	% within row	19.512 %	80.488 %	100.000 %
	% within column	64.000 %	67.119 %	66.486 %
	% of total	12.973 %	53.514 %	66.486 %
Male	Count	27.000	97.000	124.000
	% within row	21.774 %	78.226 %	100.000 %
	% within column	36.000 %	32.881 %	33.514 %
	% of total	7.297 %	26.216 %	33.514 %
Total	Count	75.000	295.000	370.000
	% within row	20.270 %	79.730 %	100.000 %
	% within column	100.000 %	100.000 %	100.000 %
	% of total	20.270 %	79.730 %	100.000 %

Table 6 presents the results of the Bayesian contingency table tests. The value of BF_{10} (Bayes Factor in favor of the null hypothesis) is 0.127, indicating that the evidence in favor of the null hypothesis that the “Female” group is equal to the “Male” group is weak. This suggests that there are significant differences between the study groups. The total number of cases analyzed is 370.

Table 6.
Bayesian Multinomial Independence Test Results Table

	Value
BF_{10} Independent multinomial	0.127
N	370

***Note*. For all tests, the alternative hypothesis specifies that group *Female* is not equal to *Male*.**

Table 7 presents the Log Odds Ratio (Logarithmic Odds Ratio) along with a 95% credibility interval. The Log Odds Ratio is a measure used in statistical analyzes to evaluate the association between two categorical variables. In this case, the Log Odds Ratio is used to analyze the association between the variables P3 (educational level) and P8 (gender). The Log Odds Ratio value in Table 7 is -0.143. This value indicates the magnitude and direction of the association between the variables. A negative value indicates an inverse association, meaning that there is a relationship between the variables, but in the opposite direction. In this case, the negative value suggests that there is an inverse association between educational level (P3) and gender (P8). The 95% credibility interval provides an estimate of the uncertainty associated with the Log Odds Ratio. In this case, the interval goes from -0.676 to 0.390. This means that with a 95% confidence level, the true value of the Log Odds Ratio is likely to be within this range. In summary, Table 7 shows the Log Odds Ratio and the 95% credibility interval to analyze the association between educational level and gender. The negative value of the Log Odds Ratio suggests an inverse association between these variables, but further analysis is required to fully understand the nature of this association.

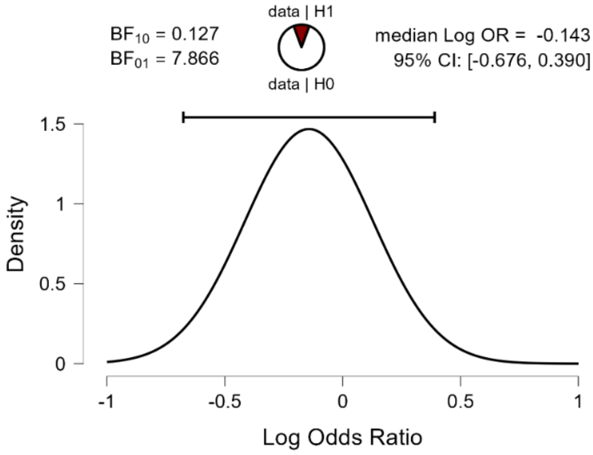
Table 7.
Bayesian Log Odds Ratio

	95% Credible Interval	
Log Odds Ratio	**Lower**	**Upper**
-0.143	-0.676	0.390

Figure 7 shows the Log Odds Ratio (Logarithmic Odds Ratio) graphs for variables P3 and P8. These graphs represent the relationship between variables and the probability of belonging to a specific category. On the x-axis of the graphs is the variable P3, which can be Female or Male. The Log Odds Ratio is shown on the y-axis, which is a measure of the association between the variables. The Log Odds Ratio represents the logarithmic difference between the odds of belonging to one category compared to another. A positive value indicates a higher probability of belonging to the category on the x-axis, while a negative value indicates a higher probability of belonging to the category on the y-axis.

Graph of P3-P8 shows the differences in the probabilities of belonging to the Female and Male categories in relation to the variable P8. The 95% credibility intervals are shown as error bars around the estimated Log Odds Ratio points. These graphs provide visual information about the association between variables and help to better understand the relationship between them.

Figure 7.
Log Odds Ratio Plots - P3 - P8



CONCLUSIONS

As universities and financial services providers continue to expand digital payment options, understanding student perception becomes essential to guide the effective implementation of these technologies and ensure a more efficient and satisfying academic experience. Ultimately, this study seeks to provide meaningful recommendations and insights that contribute to the development of educational and financial strategies more aligned with the needs and perceptions of college students in the digital age.

It is important to understand university student's perceptions of digital payment systems to guide their effective implementation and improve the academic experience because it is proven that the use of digital payment systems in the educational field is increasingly important and is considered essential to improve the efficiency and satisfaction of the academic experience of university students. Finally, there is a need to understand and adapt educational and financial strategies to the needs and perceptions of students in the digital age, that is why the use of the technology acceptance model (TAM) becomes a valuable tool to explain and predict the adoption of technology in various fields, including digital payment systems. The socioeconomic status and gender of students can have an impact on their perception and adoption of digital payment systems.

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