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THE IMPACT OF SECURITY, SERVICE QUALITY, PERCEIVED USEFULNESS, PERCEIVED EASE OF USE, TRUST, AND PRICE VALUE ON USERS' SATISFACTION IN CLOUD-BASED PAYMENT SYSTEMS IN AUSTRALIA: A PLS-SEM ANALYSIS

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ABSTRACT

Over the past years, the ubiquity and versatility of cloud-based payment systems (CBPS) have become an evolutionary path in the payment process. However, despite is undeniable the various advantages of using the CPBS, compared to other countries the adoption rates are still very low in Australia. This suggests that people might not know the benefits of using them or they might not be satisfied with the current payment systems. In this context, the purpose of this research was to examine the impact of security and service quality on the factors (perceived usefulness, perceived ease of use, trust and price value) that have influence on users' satisfaction in cloud-based payment systems in Australia. Qualtrics was used to gather the data of 411 respondents to an online questionnaire survey. After that, the PLS-SEM (Partial Least Square Structural Equation Modeling) analysis took place. The findings suggest that security, service quality, trust, perceived usefulness, and price value have impact on user satisfaction and this, in turn, affects CBPS adoption. Perceived ease of use has no influence on user satisfaction, and therefore, it has no impact on CBPS adoption. Besides, it was found that, overall, demographics have no impact on user satisfaction in CBPS.

Keywords: Cloud-based payment systems, CBPS, user satisfaction, influence factors, demographics, TAM, PLS-SEM analysis

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INTRODUCTION

Over the past decades, pushed by the growth in e-commerce transactions, companies around the world have been developing new means of payment to adjust their systems to the current trend of cashless transactions among governments, organisations, and individuals (Kabir, Saidin & Ahmi 2015). Consequently, the growth of cashless payments has led to a boost in cloud-based payment systems (CBPS), or payments conducted over the Internet. Besides, the emergence of the cloud point of sale (POS) market (Wadhwani & Gankar 2019) has also contributed to the expansion of cashless transactions. In this sense, CBPS represents a natural evolution of the payment process as there was a need to diversify the payment methods with the intention of being used on different devices anywhere and at any time. Furthermore, CBPS can provide many advantages to SMEs (small and medium-sized enterprises) as they can avoid investing large amounts of capital to implement physical systems (Donoghue 2018). Moreover, CBPS users can make payments over the Internet from their mobile devices or desktop computers, which is a more flexible system than the traditional point of sales technology (Donoghue 2018). Thus, by offering CBPS to their users, organisations could enhance customer satisfaction with the whole payment process experience.

However, despite is undeniable the various advantages of using the CPBS, compared to other countries the adoption rates are still very low in Australia (Fisher 2020). This suggests that people do not know the benefits of using them or they are not satisfied with the current payment systems. In this context, the main aim of this research is to explore whether the security factors, service quality factors, trust factors, perceived usefulness factors, and price value factors affect user satisfaction in CBPS in Australia. Besides, this research will investigate whether personal aspects of users (age, gender, and income) have influence on those factors, and in turn, in CBPS adoption.

2.LITERATURE REVIEW

Satisfaction is related to “a phenomenon of particular importance in the evaluation process of a shopping, consumption, or product or service usage experience and is therefore vital in long-term consumer responses” (Grönroos, 1991, as cited in Liébana-Cabanillas, Munoz-Leiva & Rejon-Guardia, 2013, p. 750). Besides, after several interactions with their service provider (Zhou, 2015), user satisfaction is used to describe the individuals’ attitudes, feelings and expectations about what they perceive as an exceptional service (Sharma & Lijuan, 2015). Put it simply, user satisfaction refers to the levels of pleasure that an individual feels after receiving an outstanding customer service (Patel, 2016).

In this context, as user satisfaction has a great impact on the intention to use information technology (Albashrawi, 2017), financial institution providers and banks have been paying close attention to a wide variety of areas such as security, privacy, and service quality. This occurs because security and service quality have been pointed out as important factors to improve user satisfaction (Gossett, 2019; Prentice, Lopes & Wang, 2020). Besides, a myriad of authors has highlighted that trust factors (Zhou, 2013; Slade et al., 2015, Yan and Yang, 2015; Siau & Wang, 2018; Mondego & Gide, 2018) and price value (Jenkins & Ophoff 2016; Killian & Kabanda, 2017; Mbama, 2020)

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have also influence on the adoption of a payment system. Other academics stated that trust factors and security factors have a significant influence on cloud computing adoption (Priyadarshinee et al., 2017). Thus, these factors have influence on user satisfaction and this, in turn, affect the adoption of a new payment method.

2.1. Factors that affect user satisfaction

The previous section highlighted that user satisfaction has impact on individuals' intentions to adopt a new payment method. In this sense, this study took into consideration 6 different factors that were pointed out by several authors as crucial to enhancing user satisfaction: security, service quality, trust, perceived usefulness, perceived ease of use and price value. It is worth mentioning that these factors were based on previous studies (Mondego & Gide, 2021; Mondego & Gide, 2018; Mondego, Gide & Chaudhry, 2018), which pointed out the most relevant factors that have influence on the adoption of digital payment methods.

2.1.1. Security factors

Security refers to a set of techniques and methods to examine the data source and ensure that the privacy and integrity of the data are protected and safe (Teoh et al., 2013). In other terms, security refers to the guarantees that the systems provide in terms of integrity, authenticity, confidentiality, and non-replicability in order to ensure the transactions' security and trustworthiness (Zhang & Kang, 2019). In this context, "the perception of security is the extent to which a user trusts that the e-payment service providers would protect their sensitive data" (Yaokumah, Kumah & Okai, 2017, p. 45).

With the expansion of e-commerce, and, as a consequence, the growth of CBPS, banks and financial institutions have been using different strategies to detect and avoid fraud activities. "The lack of face-to-face or voice interaction on the Internet makes fraudsters more daring by providing them with anonymity, which makes the detection and prevention of online frauds more difficult" (Hossain & Udin 2018, p. 328).

In this regard, as fraudulent transactions have exponentially increased with the rise of global communication and modern technology (Chen et. al., 2018), financial institutions need to improve surveillance monitoring as well as it can offer better services to their clients (Government Accountability Office, 2018).

2.1.2. Service quality factors

Service quality refers to efficient and personalised services that provide a delightful experience to individuals, reducing the effort and the time spent on payment transactions (Gao & Waechter, 2015). In summary, service quality "represents the match between what users expect and what they receive" (Tam & Oliveira, 2016, as cited in Talwar et al. 2020, p. 5).

A study conducted by Alkhowaiter (2020) indicated that customer satisfaction in e-banking services is significantly impacted by the dimensions of service quality such as "tangibility, reliability, responsiveness, competence, access, communication, credibility and security" (p. 5). Also, Sharma & Lijuan (2015) suggested that user satisfaction and the sustainability of e-commerce technology are both influenced by information quality and online service quality. Finally, service quality, system quality and information quality have influence on user satisfaction, trust, perceived usefulness and flow (Zhou, 2013; Tam and Oliveira, 2017; Yuan et al., 2020).

2.1.3. Trust factors

Trust in the payment systems is related to the necessity that people have to rely on each other to validate any currency created (Yamaguti Mondego, 2019). In other words, "trust is a subjective belief that a party will fulfil their obligations and it plays an important role in uncertain financial transactions where users are vulnerable to financial loss" (Zhou, 2013, as cited in Slade et al., 2015, p. 213). A study conducted by Chandra, Srivastava & Theng (2010) pointed out the importance of consumer trust in mobile payment systems adoption. Similar research was conducted by Yan and Yang (2015), which suggested that trust has an impact on user behaviour in mobile payments. Moreover, Talwar et al. (2020) suggested that "information and service quality positively influence initial trust, which, in turn, has a positive association with confirmation and perceived usefulness" (p. 1).

2.1.4. Price value factors

Price value refers to the users' cognitive tradeoff between the monetary cost of the applications and the perceived benefits of using them (Venkatesh et al. 2012; Slade et al. 2015). Put it simply, price value is related to the contrast between the users' perceptions about the benefits of using an application and the value that they have to pay for using it. According to Kaasinen (2005, as cited in Jenkins & Ophoff 2016) "in an environment where values are not considered, each requirement is deemed as equally important and developed in this manner" (p.4). However, "this type of development could result in a product that is made up of a collection of useful features, but as a holistic unit, it might not offer considerable value to the consumer" (Kaasinen 2005, as cited in Jenkins & Ophoff 2016, p.4).

2.2. Moderating effect of personal factors

Personal factors refer to the users' characteristics such as age, gender, income etc. A study conducted by Liébana-Cabanillas, Sanchez- Fernandez & Muñoz-Leiva (2014) stated that the users' gender of a new payment system could affect the relationship between usefulness and ease of use, between users' trust and attitude, and among the attitude, usefulness, and intention to use. Arvidsson (2014) argued that the assessment of mobile payment services is directed influenced by the age of users, where the most senior users have a positive attitude toward the service. Mondego & Gide (2021) stated that personal factors of consumers such as age, gender and income have impact on user satisfaction in their bank providers.

On the flip side, Chong (2013) suggested that the users' gender of users has an irrelevant influence on the prediction of m-commerce adoption. Kristensen (2016) suggested that, at the point of sale, there are no relevant differences between older and younger consumers' perceptions. However, the social influence has more impact on older consumers' intentions to use the mobile payment at point-of-sale (Kristensen, 2016). Finally, Banu, Mohamed and Parayitam (2019) stated that in online banking customer satisfaction is not influenced by income.

Thus, as the studies using the demographics age, gender, and income in CBPS are limited (Liu et al., 2019) and present different points of view, this study included these moderating factors to test if personal factors can affect user satisfaction in CBPS.

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2.3. Theoretical framework: TAM

Over the past decades, many researchers have been investigating the impact of the new technologies on the new payment systems adoption from the perspective of merchants and consumers. These studies, which could be applied in several areas of business management and information systems, have been investigating the motives that lead people to adopt a new payment method. In this regard, various research models have been created to provide 'a visual representation of theoretical constructs (and variables) of interest' (Creswell 2009, as cited in Shuhaiber, 2016, p. 62).

Although many research models have been tested in different areas, this research project will adopt the Technology Acceptance Model (TAM), as it is a widely used research model according to various authors (Mondego & Gide, 2022, Mondego & Gide, 2018; Patil, Rana & Dwivedi, 2018; Boateng & Sarpong, 2019; Pal et al., 2019; Alkhowaiter, 2020). The main reason to use this research model is that it can predict the use of information technology and the determinants of acceptance (Kristensen, 2016).

Despite the behavioural intention to use a new technology is impacted by the external stimulus and the affective response to it, the 'TAM is based upon two central constructs: perceived usefulness and perceived ease of use [which] reside within the cognitive response area of human psychology' (Hampshire, 2016, p. 11). Perceived usefulness (PU) is defined as 'the degree to which a person believes that using a particular system would enhance his or her job performance' (Davis, 1989, p. 320). In contrast, perceived ease of use (PEOU) refers to 'the degree to which a person believes that using a particular system would be free of effort. This follows the definition of "ease": freedom from difficulty or great effort' (Davis, 1989, p. 320). It is noteworthy to point out that these external stimuli or external variables refer to the factors that could have an impact on users' behaviour. Factors such as the features of the system, the development of processes and training could have an indirect impact on the adoption of a new technology as they have a direct impact on users' perceived usefulness and perceived ease of use (Duan, 2012).

2.4. Proposed research model

This research utilised the two most studied TAM constructs (perceived usefulness and perceived ease of use) and introduced four new variables (security factors, service quality factors, trust factors, and price value factors) to explore their potential impact on user satisfaction and, consequently, CBPS adoption. Additionally, it investigated the moderating influence of demographics (age, gender, and income) on these factors and their effect on user satisfaction. Figure 1 illustrates the proposed conceptual research framework:

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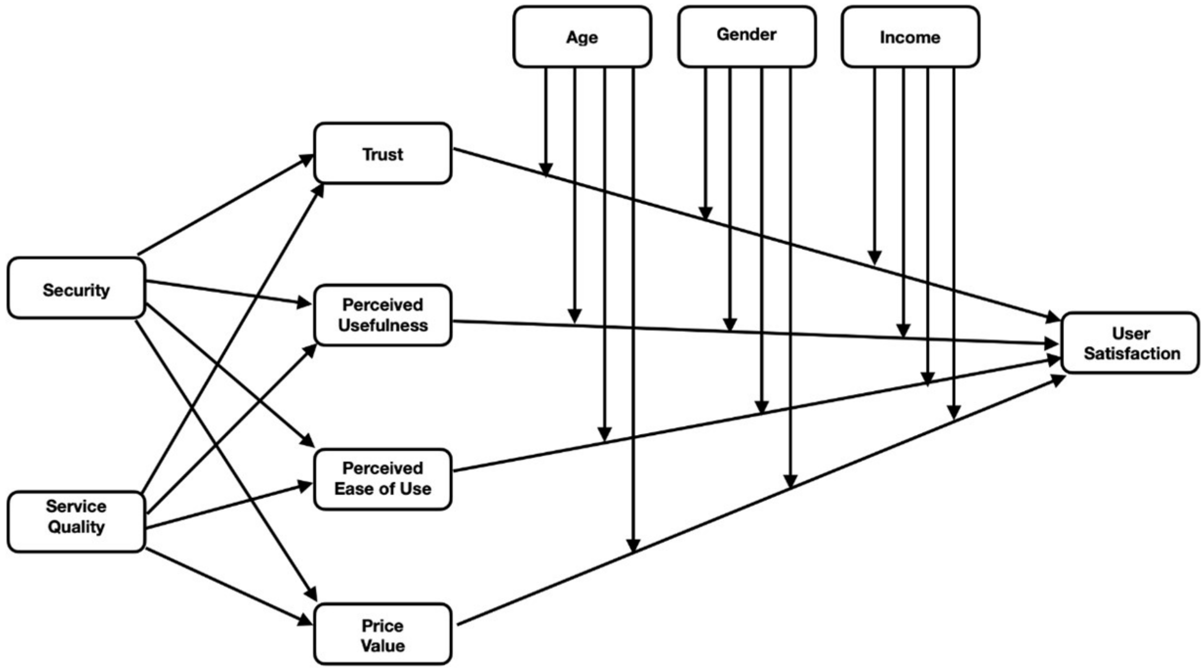

Figure 1 . Proposed research model
Source: Author

3. Research methodology

This study applied a quantitative approach to collect data. Qualtrics online survey platform was chosen to conduct the online questionnaire survey. It was set that the target population would be based on the different personal characteristics (age, gender, and income) of Australian citizens, and they should not be under 18 of age. In order to avoid bias regarding group identification, and to categorize the collected data, survey participants were encouraged to identify themselves in different groups and answer specific questions related to CBPS.

The answers of 424 survey respondents were gathered, however, only 411 answers were used in this study, as 13 answers were not complete. The data were stored in Excel spreadsheets and after transferred and organised in the Statistical Package for the Social Sciences (SPSS) system. After that, the data analysis took place using the PLS-SEM (Partial Least Square Structural Equation Modeling).

4.PLS-SEM analyses and research findings

As aforementioned, this study has chosen the PLS-SEM to test the relationships among variables as well as to point out key driver constructs. PLS-SEM is ideal for estimating the complex cause-effect relationships among variables (Kristensen, 2016), when the sample size of the analysed population is relatively low (Hair, Ringle & Sarstedt, 2011, as cited in Yamaguti Mondego, 2019). Hence, this research applied the rules of thumb for model evaluation proposed by Hair, Ringle and Sarstedt (2011) to examine the sample population. This model analyses data in two distinct stages: formative measurement models and structural models, which will be described in the next sections.

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4.1. Formative measurement models

Hair, Ringle and Sarstedt (2011) highlighted that the significance of formative measurement models is assessed by examining the relative importance of each indicator's weight and the absolute importance of the loadings. The main purpose of evaluating the indicators is to find out whether weights and loadings are significant as well as to verify whether they support keeping all the indicators (Hair, Ringle & Sarstedt 2011). However, 'when the indicators are not significant, there is no empirical support for the indicator's relevance in providing content to the formative index' (Hair, Ringle & Sarstedt, 2011, as cited in Yamaguti Mondego, 2019, p. 85). It is worth mentioning that there is a need to analyse the indicators. Indicators with outer loading greater than 0.70 should be maintained, while indicators with outer loading between 0.40 and 0.70 should be considered for elimination (Hair et al., 2013, as cited in Shuhaiber, 2016, p.149). Besides, the authors also suggested that outer loading below 0.40 from the scale should be eliminated.

In this sense, the findings suggested that there are some indicators' weights that need to be eliminated as they are not significant (negative values) or the outer loading is lower than 0.40 from the scale. Hence, the indicators security factors – trust (Q16), service quality factor – trust (Q25), and service quality factor – price (Q28) were eliminated from the scale.

After eliminating the indicators, this study examined the multicollinearity among latent variables, which is another important measure in the evaluation of formative models. The multicollinearity is applied to test the correlation between two indicators. Also, academics should investigate the degree of multicollinearity in the formative indicators to determine the redundancy of information (Cassel, Hackl & Westlund, 1999, as cited in Hair, Ringle & Sarstedt, 2011). Multicollinearity among constructs is measured through the Variance Inflated Factor (VIF), which assesses 'the potential for unstable indicator weights' (Cenfetelli & Bassellier, 2009, as cited in Hair et al., 2012, p.424). According to Hair et al. (2019, p.10), if values of VIF are 5 or above, it suggests that there are critical collinearity problems with the indicators of formatively measured constructs.

Hence, the ideal VIF values should be lower than 5 (Hair, Ringle & Sarstedt, 2011). In this context, after the indicators' weight and loading values were eliminated, this study identified that all values were under 5, which suggests that multicollinearity is not an issue concerning the formative indicators.

4.2. Structural model

Hair et al. (2019, p.11) pointed out that 'when the measurement model assessment is satisfactory, the next step in evaluating PLS-SEM results is assessing the structure model'. In this regard, the standard assessment criteria should include the coefficient of determination (R^2), the significance of path coefficients, and the blindfolding-based cross-validated redundancy measure Q^2, also described as the Stone-Geisser's Q^2 (Hair, Ringle & Sarstedt 2011; Hair et al. 2019).

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4.2.1. Coefficient of determination (R^2 value)

Before evaluating the structural relationships, there is a need to check the collinearity among the indicators, which must be assessed to ensure that it will not create bias in the regression outcomes (Hair et al. 2019, p. 11). According to Latan and Ramil (2013), issues regarding high collinearity in PLS-SEM could be detected through the high values of R-square (R^2). However, ‘If collinearity is not an issue, the next step is examining the R^2 value of the endogenous constructs’ (Hair et al., 2019, p. 11). In relation to structural models, R^2 values can be separated into three categories: substantial (0.75), moderate (0.50) and weak (0.25) (Yamaguti Mondego, 2019). It is noteworthy to mention that R^2 values can vary based on context and discipline. R^2 values of 0,75, for instance, are regarded as high in success driver studies, and R^2 values of 0.20 are perceived as high in consumer behaviour disciplines (Hair, Ringle & Sarstedt, 2011, as cited in Yamaguti Mondego, 2019). However, it could be satisfactory as 0.10, when predicting stock returns (Raithel et al., 2012, as cited in Hair et al., 2019, p. 11) or 0.90 in the physical process (Hair et al. 2019). Figures 2 and 3 show the R^2 values of the indicators’ weights and loadings before and after eliminating the negative values.

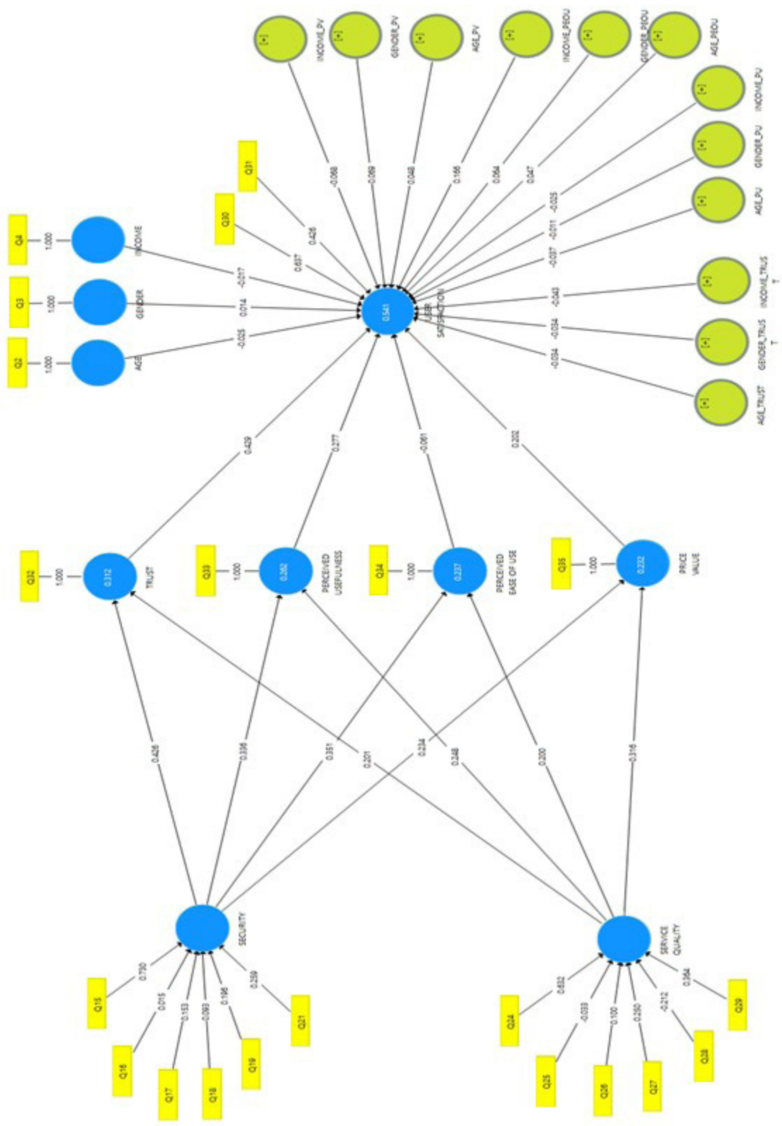

Figure 2: R^2 values before eliminating negative indicators

Source: Author

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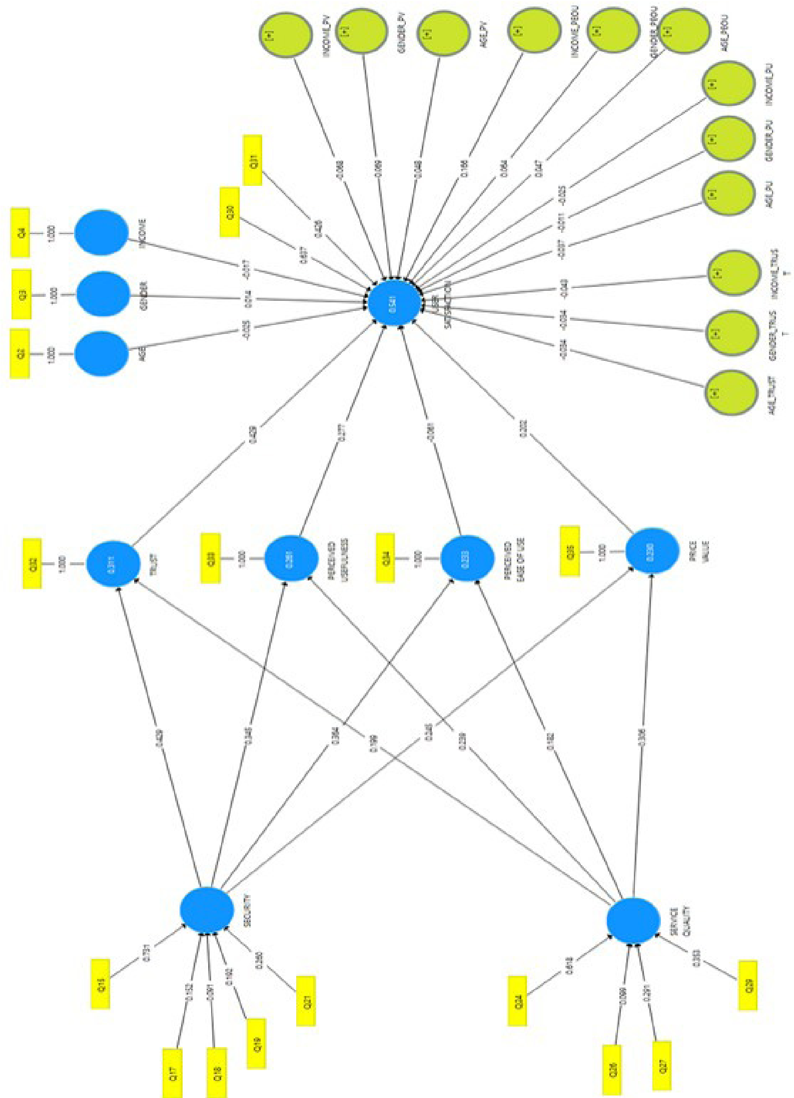

Figure 3: R² values after eliminating negative indicators
Source: Author

The findings presented R² values of 0.541, which is considered moderate in the structural model. This indicates that the 54.1 per cent variance of the endogenous variable (user satisfaction) for the proposed conceptual model, could be justified by the exogenous variables (security, service quality, trust, perceived usefulness, perceived ease of use and price value).

4.2.2. Path coefficients

The next stage of evaluating the structural model is to investigate the empirical t values and p values for all structural path coefficients. The purpose is to assess the robustness of the relationships among constructs (Yamaguti Mondego 2019) and 'assess the statistical significance and relevance of the formative indicator weighs' (Hair et al. 2019, p.13). In order to assess the significance of formative indicators' coefficients, the bootstrapping procedure was applied. The aim to apply the bootstrapping procedure is to verify whether a normal distribution of data will take place as PLS-SEM does not presume it (Hair, Ringle & Sarstedt, 2011, p. 148). Hence, following several studies,

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this study applied the bootstrapping procedure with a t value of 1.96 or a two-tails significant level at the 5 per cent (Latan & Ramil, 2013, as cited in Yamaguti Mondego, 2019, p. 88). Tables 1 and 2 indicate the outcome of the bootstrapping procedure:

Table 1: Path coefficient (Security and Service Quality)

	T Statistics	Critical value	Statistically significance (t > 1.96)	P Values	Critical value	Statistically significance (p < 0.05)
SECURITY -> PERCEIVED EASE OF USE	5.966	1.96	YES	0.000	0.05	YES
SECURITY -> PERCEIVED USEFULNESS	5.578	1.96	YES	0.000	0.05	YES
SECURITY -> PRICE VALUE	4.315	1.96	YES	0.000	0.05	YES
SECURITY -> TRUST	7.426	1.96	YES	0.001	0.05	YES
SERVICE_QUALITY -> PERCEIVED EASE OF USE	3.252	1.96	YES	0.000	0.05	YES
SERVICE_QUALITY -> PERCEIVED USEFULNESS	3.701	1.96	YES	0.000	0.05	YES
SERVICE QUALITY -> PRICE VALUE	4.433	1.96	YES	0.001	0.05	YES
SERVICE QUALITY -> TRUST	3.337	1.96	YES	0.001	0.05	YES

Table 2: Path coefficient (User satisfaction)

	T Statistics	Critical value	Statistically significance (t > 1.96)	P Values	Crit-ical value	Statistically significance (p < 0.05)
PERCEIVED EASE OF USE -> USER SATISFACTION	0.843	1.96	NO	0.399	0.05	NO
PERCEIVED USEFULNESS -> USER SATISFACTION	4.028	1.96	YES	0.000	0.05	YES
PRICE VALUE -> USER SATISFACTION	3.423	1.96	YES	0.001	0.05	YES
TRUST -> USER SATISFACTION	6.998	1.96	YES	0.000	0.05	YES

The results indicated that there are strong relationships between trust and user satisfaction (t=6.998, p=0.000), security and perceived ease of use (t=5.966, p=0.000), security and perceived usefulness (t=5.578, p=0.000), and security and trust (t=7.426, p=0.001). Significant relationships were also verified between perceived usefulness and user satisfaction (t=4.028, p=0.000), price value and user satisfaction (t=3.423, p=0.001), security and price value (t=4.315, p=0.000), service quality and perceived ease of use (t=3.252, p=0.000), service quality and perceived usefulness (t=3.701, p=0.000), and service quality and trust (t=3.337, p=0.000). However, the relationship between perceived ease of use and user satisfaction (t=0.843, p=0.399) is not significant as the t value is lower than the critical value (1.96) and the p value is greater than 0.05.

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4.2.3. Blindfolding and predictive relevance (Q^2)

Following the outcome of the path coefficient, another step to evaluate the predictive accuracy and relevance of the PLS path model is to apply the Stone-Geisser's Q^2 or the Q^2 value (Geisser, 1974; Stone, 1974, as cited in Hair et al. 2019). This 'metric is based on the blindfolding procedure that removes single points in the data matrix, imputes the remove points with the mean and estimates the model parameters' (Rigdon 2014; Sarstedt et al., 2014, as cited in Hair et al., 2019, p. 11). Hence, the predictive relevance of each endogenous latent construct's indicators was measured by using the blindfolding procedure (Yamaguti Mondego, 2019).

According to Hair et al. (2019, p. 11), 'Q^2 values should be larger than zero for a specific endogenous construct to indicate the predictive accuracy of the structural model for that construct'. Besides, Q^2 values greater than zero indicate that the exogenous constructs have predictive relevance for the endogenous construct under consideration' (Hair, Ringle & Sarstedt, 2011, p. 145). Furthermore, 'Q^2 values higher than 0, 0.25 and 0.50 depict small, medium and large predictive relevance of the PLS-path model' (Hair et al. 2019, p. 11). Table 3 illustrates the sum of the square observations (SSO), the sum of prediction errors (SSO) and the Q^2 values:

Table 3: Q^2 values

	Sum of the square observations (SSO)	Squared prediction errors (SSE)	$Q^2 = (1\text{-}SSE/SSO)$
PERCEIVED EASE OF USE	411.000	323.739	**0.212**
PERCEIVED USEFULNESS	411.000	313.217	**0.238**
PRICE VALUE	411.000	324.835	**0.210**
TRUST	411.000	290.075	**0.294**
USER SATISFACTION	822.000	464.724	**0.435**

The construct cross-validated redundancy analysis pointed out that Q^2 values vary from small to medium predictive relevance of the PLS-path model. The rule of thumb suggested by Hair et al. (2019, p. 12) considered only the Q^2 values greater than zero to indicate the predictive accuracy of the structural model. In this sense, all factors can be considered as Q^2 values are larger than zero. Price value, perceived ease of use, and perceived usefulness have the smallest Q^2 values (0.210, 0.212, 0.238 respectively), which suggests that the exogenous constructs have a small predictive relevance for the analysed endogenous constructs. Trust has a medium predictive relevance (Q^2= 0.294). Finally, the construct cross-validated redundancy analysis suggests that the Q^2 value for user satisfaction is 0.435, which indicates that exogenous constructs have a medium predictive relevance (0.25) for the analysed endogenous construct.

4.2.4. Moderating effects of demographics

The moderating effects of age, gender and income were measured by assessing the empirical t and p values for all structural path coefficients. Also, the bootstrapping procedure with a two-tails significant level of 5 per cent or t values of 1.96 was deployed to evaluate the significance of the coefficients of the formative indicators and test the relationships among variables (Latan & Ramil, 2013, as cited in Yamaguti Mondego, 2019. Table 4 indicates the outcome of the bootstrapping procedure:

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Table 4: Path coefficient

	T Statistics	Critical value	Statistically significance (t > 1.96)	P Values	Critical value	Statistically significance (p < 0.05)
AGE -> USER_SATISFACTION	0.671	1.96	NO	0.502	0.05	NO
AGE_PEOU -> USER_SATISFACTION	0.516	1.96	NO	0.606	0.05	NO
AGE_PU -> USER_SATISFACTION	0.470	1.96	NO	0.638	0.05	NO
AGE_PV_ -> USER_SATISFACTION	0.689	1.96	NO	0.491	0.05	NO
AGE_TRUST -> USER_SATISFACTION	0.590	1.96	NO	0.555	0.05	NO
GENDER -> USER_SATISFACTION	0.316	1.96	NO	0.752	0.05	NO
GENDER_PEOU -> USER_SATISFACTION	0.602	1.96	NO	0.547	0.05	NO
GENDER_PU -> USER_SATISFACTION	0.145	1.96	NO	0.885	0.05	NO
GENDER_PV -> USER_SATISFACTION	0.936	1.96	NO	0.350	0.05	NO
GENDER_TRUST -> USER_SATISFACTION	0.487	1.96	NO	0.626	0.05	NO
INCOME -> USER_SATISFACTION	0.406	1.96	NO	0.685	0.05	NO
INCOME_PEOU -> USER_SATISFACTION	**1.995**	**1.96**	**YES**	**0.046**	**0.05**	**YES**
INCOME_PU -> USER_SATISFACTION	0.314	1.96	NO	0.754	0.05	NO
INCOME_PV -> USER_SATISFACTION	0.953	1.96	NO	0.341	0.05	NO
INCOME_TRUST -> USER_SATISFACTION	0.656	1.96	NO	0.512	0.05	NO

Overall, the results indicated that there are no statistically significant relationships between the demographics (age, gender and income) and the constructs (TRUST, PEOU, PU and PV) as t values are lower and p values are higher than the critical values ($t > 1.96$ and $p < 0.05$). However, the only exception found was the relationship among income, perceived ease and user satisfaction, which presented t values slightly higher and p values slightly lower than the critical values ($t=1.995$, $p=0.046$).

5.CONCLUSION

This study has collected data from 411 online questionnaire survey participants. The data was collected and examined by using SmartPLS 3. This paper aimed to investigate the impact of security and service quality on the factors (perceived usefulness, perceived ease of use, trust and price value) that might have influence on users satisfaction in cloud-based payment systems in Australia. Besides, this research analysed the moderating effect of demographics (age, gender, and income) on the constructs, and their impact on user satisfaction.

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The findings of this study suggest that concerning formative measurement models suggests that multicollinearity is not an issue concerning the formative indicators as all values were under 5.

Regarding the structural model, this research analyses the coefficient of determination (R^2), the significance of path coefficients, and the blindfolding-based cross-validated redundancy measure Q^2. The results pointed out that, the coefficient of determination (R^2) is 0.541, which suggests that for the proposed conceptual model, 54.1 per cent variance of the endogenous variable (user satisfaction) could be determined by the exogenous variables (security, service quality, trust, perceived usefulness, and price value). In other words, these factors can have impact on user satisfaction. However, perceived ease of use, as aforementioned, has no impact on user satisfaction.

Concerning path coefficients (t values and p values), this study found out that price value, perceived ease of use, and perceived usefulness presented small Q^2 values (0.210, 0.212, 0.238 respectively), while trust has a medium predictive relevance (Q^2= 0.294). Put it simply, these factors are influenced by the exogenous constructs (security and service quality). User satisfaction Q^2 value is 0.435, which means that the exogenous constructs (perceived ease of use, perceived usefulness, trust, and price value) have a medium predictive relevance for the endogenous construct under consideration.

Finally, the findings suggested that there are no statistically significant relationships between demographics (age, gender and income) and the constructs (PEOU, PU, TRUST, and PV). Despite it was found a relationship among income, perceived ease and user satisfaction, overall, this research suggests that there are no statistically significant relationships among demographics and the analysed constructs, and this, in turn, has no impact on user satisfaction.

6. LIMITATIONS AND FURTHER RESEARCH

This study presented some limitations. First of all, it focused on Australian citizens 18 and over, who have at least a debit or a credit card. The main purpose was to gather information from people who have conducted any payment over the Internet (CBPS). Individuals under 18 were not included as they cannot be the primary cardholders in Australia (Bradney-George, 2021). Secondly, this research presented an overrepresentation of female participants (371 out of 411), which could create a bias in the analysis or affect the statistical significance of the analysis.

Further research should focus on the personal aspects of users as it found a gap in the literature related to this subject matter. Despite there are many studies that have explored the influence of demographics on payments conducted over the Internet, few of them investigated the impact of personal characteristics on user satisfaction in CBPS.

CONFLICT OF INTEREST

The author**s** declare that there is **no** conflict of interest in this research paper**.**

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