Unlocking Pathways to Mobile Payment Satisfaction and Commitment

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Abstract:
Although mobile payment services are unlikely to become obsolete, their market dominance has been challenged following the intensified market competition. A research model is developed to uncover the drivers of users' hedonic and utilitarian motivations (i.e., application, marketing, and internal stimuli) as the key to fostering satisfaction and commitment toward mobile payment services. Data were gathered from a survey and analyzed via the dual-stage Structural Equation Modelling-Artificial Neural Network (SEM-ANN) technique to capture both linear and non-linear relationships. The findings suggested that information value, monetary value, self-congruence, and reward and recognition drive hedonic and/or utilitarian motivations, which in turn promote users' satisfaction and commitment toward mobile payment services. The ANN analysis reveals the existence of a non-linear hidden attribute. The research provides theoretical insights and practical implications for the field of mobile payment services.

Keyword:
mobile payment, user experience, mobile commerce, user satisfaction, user commitment

Introduction

The payment industry is undergoing a radical shift, with consumers increasingly preferring mobile payment (m-payment) over traditional payment methods (e.g., cash) due to the advancement in smart mobile devices and the proliferation of mobile commerce. Bhala1 defines m-payment as the authorization and transfer of payment via Internet-connected mobile devices. M-payment is generally considered the next frontier of the electronic payment systems. The global number of m-payment users is expected to rise from 950 million in 2019 to 1.31 billion in 2023,2 with the global market size of m-payment expected to hit 3 trillion USD by 2024.3 The Asia-Pacific market is expected to lead in terms of the global m-payment market revenue due to the large population and on-going digital transformation.4 The m-payment market is growing competitive given that more players are entering the fray, including banks, internet-based start-ups, and technology giants such as Facebook, Google, Apple, and PayPal. The dominance of a single company is expected to be chipped away in the dynamic environment of m-payment.

The phenomenon is particularly relevant to certain regions such as Southeast Asia, including countries such as Malaysia and Vietnam, where the digital payment adoption rate is increasing tremendously and deemed the upcoming megamarket for digital consumer finance,5 driven by tailwinds from e-commerce. A recent report has shown that e-commerce spending in the region is forecasted to hike by 162% to hit 179.8 USD billion by 2025, and 91% of transactions will involve digital payment.6 As indicated by Kaur,6 m-payment emerges as the preferred payment option for Southeast Asia consumers and the number of users is predicted to increase by 58% from 2020 to 2025. Despite the upbeat growth prospect of the m-payment industry, the pace of future growth and sustained competitiveness of m-payment service providers is largely hinged on the ability of m-payment service providers in addressing the concerns of consumers. To explain, due to the similarities of the primary functions of the m-payment platforms, the switching rate is high, implying that consumers can easily move away from the existing platform if they are not satisfied with the service.7 However, it remains to be seen how and whether the industry can overcome the challenges of fostering usage satisfaction and commitment in the m-payment service encounters. The study is guided by the main research question: What are the antecedents of m-payment users' satisfaction and commitment?

Although there has been a burgeoning body of research into the m-payment phenomenon, the current literature focuses primarily on the drivers and inhibitors of m-payment adoption and usage.[8-11] Furthermore, little attention has been paid to comprehending the specific characteristics of m-payment applications that influence users' satisfaction and commitment. Prior m-payment studies have largely relied on the Technology Acceptance Model (TAM) and its extensions to elucidate the antecedents of users' perceptual and behavioral outcomes in m-payment platforms.[12-15] Only a scant number of studies have approached the issue using a more comprehensive lens to explore the potential role of marketing environmental factors, application features, and system designs in advancing the current understanding of user satisfaction and commitment.

Besides, value has been deemed an indispensable mechanism to explain post-adoption behavior in the mobile technology context, thus is expected to exert a significant impact on consumers' behavioral responses to mobile payment.[16] The unidimensional approach taken by the authors of existing studies in conceptualizing perceived value (PV) has been deemed suboptimal.[17] This shortcoming has prompted the present study to validate the applicability of a multidimensional PV in the mobile payment context. Further, past research has failed to consider the joint impact of hedonic and utilitarian motivational factors as a mechanism in users' m-payment evaluation processes. According to Tamilmani et al.,[18] the current view overemphasizes functional aspects of m-payment because financial transactions are generally seen as obligatory tasks in a transactional process; however, circumstances have changed due to the increasingly competitive market environment, in which hedonic attributes have emerged as a factor of differentiation to promote users' satisfaction and commitment.

Based on the research gaps, there is a dire need to investigate the roles of internal and external stimuli in the formation of users' hedonic and utilitarian motivations, which affect users' satisfaction and commitment to m-payment services. The study adds to the literature on m-payment in two ways. First, the study develops and validates a research model that articulates the effects of various antecedents (e.g., application, marketing, and internal stimuli) on users' utilitarian and hedonic motivations toward m-payment services, as well as the subsequent outcomes, namely satisfaction and commitment, that are highly relevant to the industry. Second, a dual-stage Structural Equation Modelling-Artificial Neural Networks (SEM-ANN) analysis was used to capture the non-compensatory and non-linear relationships between the exogenous and endogenous variables. The technique helps elucidate the complex nature of the conceptual model, as SEM is first used for hypothesis testing, complemented by the identification of salient determinants through ANN.

Literature Review

Stimuli-Organism-Response Theory

The stimulus-organism-response (SOR) paradigm was used as a theoretical foundation to support the proposed ideas. Tolman[19] devised the S-O-R model to explain an organism's decision-making process in various scenarios. More precisely, the organism selects, observes, and processes inputs from the external environment to create a mental map that incorporates both external and internal components, ultimately resulting in behavioral response. In the S-O-R paradigm, "S" represents the external stimulus that prompts consumers to react; "O" represents the internal process in the organism that is guided by psychological aspects of consumers (i.e., perception and motive), and dictates the subsequent actions to take; and "R" represents the behavior chosen by consumers in response to the external stimulus.

The S-O-R paradigm has been widely used in the literature to explain the effects of retail shopping environments on consumer behavior, including satisfaction and commitment.[20,21] Recent research into mobile payment and other mobile application-based services has embraced the central tenets of the S-O-R theory in explaining consumers' responses.[11,22,23] For instance, grounded in the S-O-R theory, Wu and Tang[24] validated the trust mechanism that fosters loyalty toward mobile payment. Likewise, Yuan et al.7 explicated the role of the overall quality of mobile payment (stimulus) on trust (organism) and loyalty (response). In the present study, the proposed stimuli include application stimuli (i.e., convenience value and reflection opportunity), marketing stimuli (i.e., information value and rewards and recognitions), and internal stimuli (i.e., monetary value and self-congruence). The organism includes both cognitive and emotional reactions, which are investigated in a parallel and non-exclusive manner. The cognitive state and emotional state are concerned with users' information processing and affective conditions (i.e., emotions and sentiments), respectively. Chopdar and Balakrishnan[25] suggested using hedonic and utilitarian motivations to represent the cognitive and affective processes, respectively. Finally, user satisfaction and user commitment are manifestations of the responses studied in this research. To clarify, user satisfaction reflects users' positive assessment of the entire m-payment service experience, whereas user commitment describes users' "persistent desire to maintain a valued connection".[26(p70-87)]

Hypotheses Development

Convenience Value (CV)

The utility of convenience referred to as convenience value (CV), is derived from the use of m-payment services, in which payment can be made anywhere and at any time, at a lower perceived cost than traditional electronic payment services.[27] In the physical sense, m-payment services eliminate the need for consumers to carry bulky purses or wallets containing numerous "plastic cards," as they can now link their bank accounts directly to their m-payment accounts. The ease of use of m-payment has been established as the primary motivator that drives the use of mobile applications in the first place.[28,29] Numerous studies posited that CV supplements utilitarian motivation to m-payment adoption by fulfilling consumer demands for a hassle-free transaction process.[30,31,32] For instance, Yan et al.[32] have found that perceived transactional convenience plays a big part in determining the perceived usefulness of QR code m-payment, which in turn influences their motivation to embrace the technology. Furthermore, the convenience of m-payment, which relates to the portability, simultaneity, and speed of m-payment services, has been established contributing to the pleasure of m-payment usage.[33] In sum, the present study hypothesizes that:

H1(a): Convenience value positively relates to hedonic motivation
H1(b): Convenience value positively relates to utilitarian motivation.

Reflection Opportunity (RO)

Given that m-payment systems allow users to immediately inspect past transaction records, which cannot be done in cash, debit cards, and credit cards, reflection opportunity (RO) has been incorporated into the research model as a driver of hedonic and utilitarian motivations. RO refers to the capability of information and communication technology to enable users to examine prior transactions.[34] The ability of m-payment applications to enable transaction trace-back fulfils consumers' functional requirements to record spending and compare bills for financial planning and record-keeping; on the other hand, the autogenerated spending report, summarized by time, place, and category may create a sense of novelty that contributes to hedonic motivation, particularly during the early phase of m-payment development, which in turn drives users to adopt m-payment services. Moreover, RO is an underappreciated but highly relevant construct in the m-payment literature,[35] thus integrating it into the proposed research model is likely to yield novel findings that benefit both theoretical and practical realms of m-payment. In short, the present study stipulates that:

H2(a): Reflection opportunity positively relates to hedonic motivation.
H2(b): Reflection opportunity positively relates to utilitarian motivation.

Rewards and Recognitions (RR)

Rewards and recognition (RR) are mobile promotional tools that marketers use to engage with users. Users can earn reward points by participating in various marketing activities in exchange for incentives (such as rebates and gifts) and receive recognition for reaching certain milestones.[36] The RR system has been regarded as a successful method of motivating consumers to use m-payment systems. Concerning utilitarian motivation, users may adopt or continue to use an m-payment platform for reward point collection, thereby achieving their utilitarian goals of saving money and gaining some material gains. Moreover, users may consider RR as a component of the gamification incorporated in m-payment platforms, where earning loyalty points and taking advantage of special offers can translate into hedonic motivation.[37] To note, previous research (e.g., Yi and Jeon[38]) has established that RR affects users' perceptual and behavioral outcomes in m-payment applications. In sum, the present study hypothesizes that:

H3(a): Rewards and recognitions positively relate to hedonic motivation.
H3(b): Rewards and recognitions positively relate to utilitarian motivation.

Information Value (IV)
Information value (IV) refers to the assessment of the perceived advantages of merchant-provided information in comparison to the perceived costs of information search by users.[27] IV is assessed based on two criteria: (1) information content, which refers to the comprehension, distinctiveness, and flexibility of the information offered; and (2) information quality, which examines the relevance, adequacy, accuracy, and timeliness of the information presented.[39] Previous research has established that m-payment provides consumers with utilitarian benefits via relevant and timely payment-making information.[31] Moreover, it has been shown that certain information – for instance, promotional information – can evoke pleasure.[40] In short, IV entices users to employ m-payment systems through both extrinsic and intrinsic incentives. In sum, the present study stipulates that:

H4(a): Information value positively relates to hedonic motivation.
H4(b): Information value positively relates to utilitarian motivation.

Self-Congruence (SC)
Self-congruence (SC) has been used interchangeably with other terms such as "self-image congruence," "self-congruity," and "image congruence".[41] SC serves as a salient predictor of consumers' brand evaluation and related perceptual and behavioral outcomes such as consumer satisfaction, perceived enjoyment, perceived value, and brand commitment.[42,43] Here, SC is defined as the match between the brand's image and the user's self-image.[44] Past research has evidenced the biasing influence of SC in fostering favorable judgment of utilitarian benefits; hence, users may be more inclined to buy or use a brand, product, or service due to the utilitarian derived from the sense of SC.[45,46] Additionally, utilitarian motivation can be manifested in user behaviors, such as intentionally choosing a brand, product, or service due to the purpose of reflecting an ideal social image in order to facilitate the conveyance of intended messages to social others, implying a hidden functional benefit of SC.[45] Besides, SC can elicit customers' intrinsic hedonic motivation, in which consumers may feel more pleasure in the usage of innovation that is congruent with their self-expression, alleviating the stress of self-discrepancy.[47] In sum, the present study stipulates that:

H5(a): Self-congruence positively relates to hedonic motivation.
H5(b): Self-congruence positively relates to utilitarian motivation.

Monetary Value (MV)
Monetary value (MV) refers to the financial advantages associated with m-payment, which includes enhanced perceived monetary benefits and/or non-monetary benefits, which offset the perceived monetary costs or perceived monetary risks, that may inhibit the use of innovation.[27,48] According to Xu et al.,[49] consumers can be driven extrinsically and intrinsically to continuously adopt innovation by positive MV. The m-payment services provide consumers with numerous opportunities to retrieve monetary benefits from the marketing programs (i.e., promotions, vouchers, cash back, and gifts); and non-monetary advantages (i.e., information access and automated bookkeeping) from normal application use, hence outweigh the perceived monetary cost and/or perceived monetary risk of m-payment.[40,50] From the viewpoint

of utilitarianism, consumers may be motivated to stick with m-payment applications due to the satisfaction of the monetary and/or non-monetary returns expected from the costs invested to acquire m-payment in the first place.[50] Besides, MV can increase consumers’ hedonic motivation, through monetary rewards obtained from the usage of m-payment as the monetary rewards can indeed evoke a sense of pleasure and joyous rush.[51] Hence, the following hypotheses are formulated:

H6(a): Monetary value is positively related to hedonic motivations.
H6(b): Monetary value is positively related to utilitarian motivations.

Hedonic Motivation (HM) and Utilitarian Motivation (UM)
Based on the Theory of Motivation, users' behaviors are guided by hedonic motivation (HM) and utilitarian motivation (UM).[52] Several works of literature embrace the theory to better explain the antecedents of m-payment usage, emphasizing the importance of HM and UM.[53] According to Oliveira et al.,[54] there is a significant association between users’ hedonic and utilitarian motivations and overall satisfaction with m-payment services. To elaborate, when users expect a specific action to garner a positive outcome, they are more prone to act,[55] and if the outcome matches the expectation, users will be prompted to repeat the behaviors, resulting in habit development. For instance, Barnes[56] found that users who are motivated to use an alternate reality website due to utilitarian or hedonic incentives are likely to foster a habit of using the website in the long run. Similarly, Hsiao et al.[57] discovered that utilitarian and hedonic incentives can lead to the habit of social media usage. Furthermore, various marketing literatures have proven that consumer PV can result in favorable brand evaluation.[58] Based on an in-depth review of current m-payment literature, no study to date has probed the effects of UM and HM on users’ satisfaction (SA) and commitment (CM) toward m-payment services. To fill the research gap, the present study hypothesizes that:

H7(a): Utilitarian motivation positively relates to user satisfaction.
H7(b): Utilitarian motivation positively relates to user commitment.
H8(a): Hedonic motivation positively relates to user satisfaction.
H8(b): Hedonic motivation positively relates to user commitment.

Conceptual Model
An S-O-R paradigm is used to investigate how perceived value affects consumer satisfaction and commitment to m-payment services. Figure 1 depicts the conceptual model.

<Figure 1 about here>

Research Methodology
The targeted sample comprised Vietnamese m-payment users who have used m-payment at least once in the past year. Ho Chi Minh was chosen as the area for data collection because the city was ranked first in Vietnam for the number of m-payment users.[59] Purposive sampling was employed by presenting a qualifying question to filter out non-m-payment users. Purposive sampling is appropriate to be taken in the present study because (i) the sampling frame of the mobile payment users is not available, and (ii) the study requires specific information that can be obtained only from a certain group of people (i.e., m-payment users).[60] Vietnam was selected as the focal study context because Vietnam has been reported as one of the countries with substantial growth in mobile payment. As indicated by the PayNXT360 report, the value of mobile payment industry in Vietnam is expected to note a compound annual growth rate of 22.8% to reach US$ 27,693.5 million by 2025.[61] An online questionnaire-based survey was

conducted by distributing the Google Form link through various social media sites. The questionnaire items were adapted from previous literature with minor modifications to suit the context of m-payment. The measurement items for DC and RO are adopted from Pal et al.[31]; RR and AS from Jones et al.[62] and Kim et al.[63];IV from Okazaki and Mendez[64]; SC from Sirgy[44]; MV from Venkatesh et al.[40]; HM and UM from Im et al.[65]; and SA and CM from Karjaluoto et al.[35] and Kleijnen et al.[66]. All measurement items were anchored on a 7-point Likert Scale, ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). Using G*Power software (version 3.1.9.2), with parameters set at 0.08 power level, 0.05 alpha value, 0.15 impact size and 10 predictors used, the minimum sample size of 118 has been identified. The total eligible responses of 303 collected exceeded the minimum sample size.

Data Analysis

Demographic Profiles

Table 1 shows that male respondents made up 45.20% of the sample, while female respondents accounted for 54.80%. The sample comprises mostly adults aged 21 to 35 (65.36%). The majority of the respondents have a bachelor's degree (84.16%). In terms of income, 59.74% earned less than or equal to 420USD per month, followed by those who earned between 421 USD to 840 USD. Next, 35.97% of respondents reported using m-payment services about 11-20 times in the last 12 months.

<Table 1 about here>

Common Method Bias

Given that both independent and dependent variables were collected at a single point of time and from a single source, common method bias (CMB) may be an issue in the research. The issue is addressed with a two-pronged approach that combines procedural and statistical approaches. First, the respondents were notified that there will be no correct or incorrect responses prior to the survey. In addition, the respondents were informed that full anonymity will be granted, and their privacy will be safeguarded.[67] In reference to Ooi et al.[68], Harman's Single Factor test was executed to identify the potential threat of CMB. The results showed that a single component accounted for just 47.3% of the overall variation. Given that the result is below 50%, there is unlikely a CMB issue in the dataset.

Assessing the Outer Measurement Model

According to Hair et al.[69], the reliability and validity of the variables must be determined and validated during the measurement model assessment stage. To begin, construct reliability was evaluated using composite reliability (CR) and Dijkstra-rho Henseler's (rho A). A prior study indicated that CR and rho A values of 0.7 and above indicated a high degree of reliability.[70] As shown in Table 2, the CR value exceeded the minimum criterion of 0.7. The study examined convergent validity using the average variance extracted (AVE) and item factor loading (FL). The basic rule of thumb is that factor loadings should be greater than 0.7, whereas AVE should be greater than 0.5. As shown in Table 2, all factor loadings were larger than 0.7 and AVE values exceeded the 0.5 thresholds.[69] Therefore, the convergent validity of the variables was satisfactory. Discriminant validity was evaluated using a non-parametric bootstrap approach and Heterotrait-Monotrait (HTMT) scores (HTMT<0.90) and HTMT inference ratios of correlations. [68] The lower and upper bounds of the 95 percent confidence interval for all values in Table 3 were less than 1, demonstrating adequate discriminant validity of which the proposed variables are statistically distinct from each other.[70]

<Table 2 about here>

<Table 3 about here>

Inspecting the Inner Structural Model

Following the validation of the construct measurements' validity and reliability, the Standardized Root Mean Square Residual (SRMR) was used to determine the model fitness of both the estimated and saturated models. The SRMR values were reported to be 0.056 and 0.073, respectively, which were both less than 0.08, indicating an acceptable model fit.[71] Prior to analyzing the inner structural model, the collinearity test was used to determine the presence of components that were closely coupled. All constructs had variance inflation factors (VIF) between 1.000 and 4.410, which was less than the cut-off value of 5.0,[72] indicating less concern for the threat of multicollinearity. Table 4 and Figure 2 demonstrated that 8 out of the 16 hypotheses were validated. Contrary to the earlier expectations, CV and RO had an insignificant effect on HM and UM; as such, H1a-b and H2a-b were mostly unsupported. Furthermore, H4a and H5a were eliminated given the relationships between IV, SC, and HM was insignificant. The results suggested that RR and MV have considerable influences on HM and UM; hence, supporting H3a-b and H6a-b. Finally, results reveal that HM and UM have positive influences on CM and SA; thus, H7a-b and H8a-b are supported. Additionally, Table 4 revealed that the research model accounts for 65.7% and 64.3% of the variance in HM and UM, respectively, and 62.7% and 63.6% of the variance in CM and SA, respectively, suggesting a high degree of in-sample prediction.[72] All the Q2 values observed in Table 5 for CM and SA to m-payment were greater than 0, suggesting that the model was sufficiently predictive. Given that none of the roots mean squared error (RMSE) indices in the PLS-SEM model exceeded those in the linear model benchmark, the model had a high predictive capability.[73]

<Table 4 about here>

<Table 5 about here>

<Figure 2 about here>

Predictive Relevance and Effect Size

The study probed the structural model's prediction ability by calculating Stone-Q Geisser's value. If the values are greater than zero, the model is deemed to have predictive relevance and vice versa.[69] The ultimate value of Q2 for cross-validated redundancy is greater than zero, as indicated in Column Q2 (1-SSE/SSO) in Table 6; therefore, the model's predictive relevance was established. Additionally, Table 7 calculates the effect size (f2) for each of the exogenous constructs. The effect size quantifies the contribution of an external latent construct to the R2 value of an endogenous construct.[74] According to Gefen et al.[75] a small, medium, and large effect size is represented by the threshold values of 0.02, 0.15, and 0.35, respectively. If the value is less than 0.02, the exogenous construct has no impact. HM and UM, as shown in Table VII, had a medium impact on CM, with values of 0.233 and 0.169, respectively. UM, on the other hand, had a high impact on SA (0.312) in comparison with HM which had a weak effect on SA (0.122).

<Table 6 about here>

<Table 7 about here>

Importance-Performance Map Analysis

By evaluating the importance-performance maps, the research expanded the PLS-SEM findings (IMPA). IMPA enables the identification of essential target constructs with a large aggregate impact but low performance, which enables better strategic planning. According to Table VIII, the most important precursors of CM towards m-payment are HM (0.482), UM (0.445), MV (0.283), RR (0.214), IV (0.163), SC (0.145), RO (0.027) and CV (0.022). Additionally, the most important precursors of SA towards m-payment are UM (0.492), UM (0.284), MV (0.213), RR (0.171), IV (0.141), SC (0.134), CV (0.027) and RO (0.026). On a performance level, CV (86.85) and RO (84.12) was the most predictive factors of CM and SA towards m-payment, followed by IV (79.18), SC (79.10), UM (77.90), HM (77.17), MV (77.06), and RR (76.11). The emphasis should be on HM for CM and UM for SA since the construct exhibited high importance (0.482; 0.492) but poor performance (77.17; 77.90).

<Table 8 about here>

Artificial Neutral Network (ANN) Analysis

While PLS-SEM can be applied to assess linear relationships between constructs, Tan et al.[76] argued that the simplicity of linear assumption might not be adequate to capture the complexities of real-world decision-making. Therefore, to overcome this problem, the study adopted the Artificial Neural Network (ANN) analysis to identify both linear and non-linear relationships as it can perform better predictions than traditional regression methods.[76,77] The conceptual model for this study was further decomposed into 4 ANN models as shown in Figures 3, 4, 5 and 6. In ANN Model A, the number of generated hidden neurons was 2, while 3 hidden neurons were generated for ANN Model B, and 2 hidden neurons for ANN Model C and D respectively. To avoid model overfitting, the study adopted a ten-fold cross-validation approach with 10 ANN networks in which the data was partitioned into a 90:10 ratio for training and testing purposes.[78,79,80] The Root Mean Squared Error (RMSE) values for training (learning) and testing (predicting) stages in Table 9 show that all values for ANN Model A, B, C and D are small and thus can be regarded as having excellent goodness-of-fit.[17] The R2 was calculated from the RMSE values in which ANN Model A, B, C and D can predict HM, UM, SA, and UM with an accuracy of 64.97%, 68.16%, 52.82% and 62.65%, respectively. The normalized importance (%) was calculated using a sensitivity analysis. Table 10 showed that MV (100%) is the most significant predictor, followed by RR (79.051%) for ANN Model A. For ANN Model B, RR (100%) is the most important predictor, followed by MV (79.455%), SC (78.963%) and IV (69.741%). UM (100%) is the most important predictor, followed by HM (65.893%) for ANN Model C. HM (100%) is most important in ANN Model C, followed by UM (68.663%). In comparing the differences in ranking between PLS-SEM and ANN, the results in Table 11 showed that all models are consistent except Model B.

<Figure 3 about here>

<Figure 4 about here>

<Figure 5 about here>

<Figure 6 about here>

<Table 9 about here>

<Table 10 about here>

<Table 11 about here>

Discussion

The present study revealed several interesting findings pertaining to the formation of satisfaction and commitment to m-payments services. In short, the results indicate that the application, marketing, and internal stimuli are associated with hedonic and utilitarian motivations, which in turn determine m-payment satisfaction and commitment.

CV, for example, was found to have a negligible effect on HM and UM. Although the results were compatible with previous research by Pal et al.[31], H1(a) and H1(b) remain unsubstantiated. The difference in the contextual background may explain why Vietnamese consumers do not view the usage of cash and card to be inconvenient – as cash and card remain the main means of payment in Vietnam – and thus, the CV of m-payment is not as prominent to Vietnamese users. Likewise, RO has shown an insignificant influence on users' motivations to use m-payment. The findings contradict the research by Leinonen et al.[81] and Pal et al.[31], the incongruency may be attributed to the m-payment spending behaviours of Vietnamese consumers, whereby the transactional amount in m-payment is generally small with no evident need for regular tracking. Additionally, the low usage rate of m-payment can be the cause of insignificant impacts on RO as tracking of transactions is trivial given the m-payment is only used occasionally. In sum, H2(a) and H2(b) are unsupported.

As previously stated, RR has a considerable favourable impact on both HM and UM, supporting H3a and H3b. Indeed, in the early stages of adoption, it has become a usual practice for m-payment service providers to invest in a variety of promotional initiatives to encourage users' adoption. The monetary incentives satisfy consumers' utilitarian motive to save money, while exposure to various marketing appeals that carry emotional implications, such as a collection of reward/loyalty points and lucky drawings, provides a sense of accomplishment and pleasure. IV is found to have a beneficial influence on UM but not on HM; hence, H4a is not supported but H4b is. The probable explanation for the insignificant finding may be that the information presented on the m-payment services in Vietnam is generally functional in nature without adequate hedonic elements, such as gamification, thereby rendering the sense of pleasure or enjoyment unperceived.

Next, SC has a significant effect on UM but not on HM. Hence, H5b is supported but H5a is not. The findings are not in line with prior research that found a positive effect of SC on HM.[45,82] Taken together, the findings seem to indicate that SC loses its relevance in stimulating HM in the context of functional product usage such as m-payment. Miranda[83] supported this view in which the author posits that the need for congruence between consumers' self-concept and brand image differs across product categories. Particularly, unlike luxury products, convenience products and alike are limited in terms of their symbolic meanings, thereby constraining the power of self-congruence especially in evoking HM. On the contrary, MV demonstrates significant positive effects on both HM and UM, whereby H6a and H6b are both supported. Although the MV and UM link is hindsight intuitive, the effect of MV on HM is a rather novel finding, particularly in the m-payment context. Rewards, discounts, and rebates given in m-payment services offer beyond utilitarian benefits, but they might as well elevate the shopping/spending enjoyment by undermining the immediate pain associated with paying during consumption, known as the concept of "coupling".[84] Also, the monetary value derived from m-payment services facilitates the justification of guilt-mitigating associated with spending and even makes spending an act of prudent saving – through discount and cash back.[85]

Finally, the results show that UM yields a substantial effect on SA, whereas HM is a stronger predictor for CM. The findings are in line with the research by Karjaluoto et al.[35] Consumers mainly adopt m-payment services for functionality; thus, it is expected that the evaluation of the m-payment applications will be based primarily, on utilitarian aspects, though HM has a significant positive relationship with SA. In sum, H7(a) and H7(b) are accepted. The hedonic aspect of the m-payment applications augments consumer commitment to m-payment services, as the joyous experiences help to build a stronger brand relationship, which leads to stronger loyalty, thus H8(a) is supported. H8(b) is also substantiated as consumers are more likely to stick around with a technology that evokes their affection and level of excitement. In short, it is validated that HM and UM work in a parallel manner in the evaluation process, by which both constructs are considered conjunctively.

Implications

Theoretical Implications

The intense competition amongst m-payment services has made the understanding of stimuli-motivation-behavioural outcome sequence ever important in ensuring sustainable business performance, particularly the external and internal stimuli of application features and value perception. The present study considered a multidisciplinary perspective by integrating concepts from information systems and marketing to setting up the applicability of the S-O-R model in the mobile payment context. The study contributed to the S-O-R model by revealing the structures for achieving consumers' m-payment satisfaction and commitment. More specifically, the study validated the utility of the S-O-R model with the inclusion of market, application, and internal factors as stimuli, and hedonic and utilitarian motivation as organisms, which sequentially develop satisfaction and commitment toward m-payment services. The findings provide theoretical inferences on the ways consumer motivations are shaped jointly by different perceptions towards m-payment applications and internal psychology (i.e., self-congruence), The research contributed to the current m-payment literature by identifying the salient internal and external factors (i.e., RR, SC, and RO) that affect consumer satisfaction and commitment towards m-payment services, thereby complementing past research that largely emphasized on the TAM perspective. More specifically, the research extends the self-congruence concept which has its ground in the branded/symbolic products to the m-payment context, suggesting a new uncharted consumer psychology area relates to m-payment that is worth further pursuit. Moreover, some novel findings uncovered in this research may shed some light on how cultural background may change the way consumers evaluate the functionality of m-payment applications. For instance, CV though may serve as a significant contributor to SA and CM in other cultural settings that find physical cash and cards to be a troublesome payment method but not in Vietnam where this research was undertaken Next, the findings shed light on the importance of hedonic aspects of m-payment services, which have been under-represented in prior literature, whereby HM has been established to significantly impact satisfaction, and serve a predictor of commitment towards m-payment services.[18]

Managerial Implications

The findings offer several key takeaways for managers. First, given that IV serves as a salient antecedent of UM, managers are encouraged to examine the value of the information at a more detailed level, whereby the content should serve a purpose (i.e., add knowledge) for the readers. In addition, the quality of the content should communicate information in an accurate, timely, and understandable manner to make the transactional process (the fulfilment of UM) more efficient for consumers. Moreover, the interesting findings on the relationship between SC and UM have also provided useful insights for managers, particularly the differentiation between m-payment service providers in terms of brand image deserves more attention. Managers can develop ad campaigns that reflect the ideal personality, which consumers may want to convey to their peers (i.e., tech-savvy, and modern) to drive usage under the premise that an advertisement that matches the self-concept of a person is more effective than one that conflicts. Furthermore, managers should enhance the monetary incentives by providing better rewards and recognition, as well as greater deals that reduce the costs of product acquisition via m-payment applications for them to stand out from the competition. For instance, the managers can refer to Momo, an m-payment service provider in Vietnam, which provides consumers with the option to share information related to the rewards and recognition they received in the application on social media. The strategy not only spreads awareness of the m-payment applications to encourage new adoptions but also strengthens the self-brand connection as past research have suggested that consumers are more likely to stick with their recommendations for the sake of consistency in behaviours.[86] In a similar vein, the managers should enhance the loyalty programs by establishing a novel reward system for the referrals to encourage new adoptions as well as ensure consumer retainment, as RR has been found to have salient effects on UM and HM, which in turn leads to SA and CM. Finally, the research has uncovered that UM plays a more crucial role in driving satisfaction than HM, whereas HM has a more prominent effect in encouraging commitment, thus managers should prioritize and ensure that the primary function of the m-payment applications is satisfactory to ensure the usage experience of m-payment services.

Limitation and Future Research Directions

The current study has several limitations. To begin with, the cross-sectional design of the study has limited the identification of changes in behavior over a period. For example, perceived convenience value may change over time as technology innovation spreads. It is important to examine consumer behavior toward m-payment at a later stage of the diffusion process when the use of rewards and other monetary promotions are reduced; as such, future works are suggested to conduct a longitudinal study to validate the findings. Second, the study is bounded by the geographical factor where the data were sourced from a single country, thus cross-cultural research should be conducted in the future to compare the findings with other cultural settings, given that this line of research in the technology domain remains understudied. Third, although the present research validates the role of the external environment and internal conditions, in relation to SA and CM, future researchers could discover other possible variables and theoretical frameworks that can extend the current findings. For example, it would be fruitful to understand the role of data privacy and service failure in relation to SA and CM towards m-payment, to yield more in-depth insights into the m-payment literature and practice. Finally, the rapid advancement and extended application of artificial intelligence could bring enormous changes to the mobile payment ecosystem and thus deserve more attention.

Conclusion

The payment landscape is witnessing significant transformation, building on the accelerating growth in m-payment services, and emerging markets, including Vietnam, is spearheading this change. Over time, the m-payment marketplace has attracted the entrances of different players, rendering the market competition increasingly intense. The study provides insights on the mechanism affecting satisfaction and commitment toward m-payment service providers, from the perspectives of the market, application, and internal stimuli. Based on the findings, it has been shown that both hedonic and utilitarian aspects of m-payment need to be taken care of to promote satisfaction and commitment. The findings obtained are of value to m-payment service providers to strategize their marketing plans, particularly for customer retention purposes.

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Figure 1: Research Model

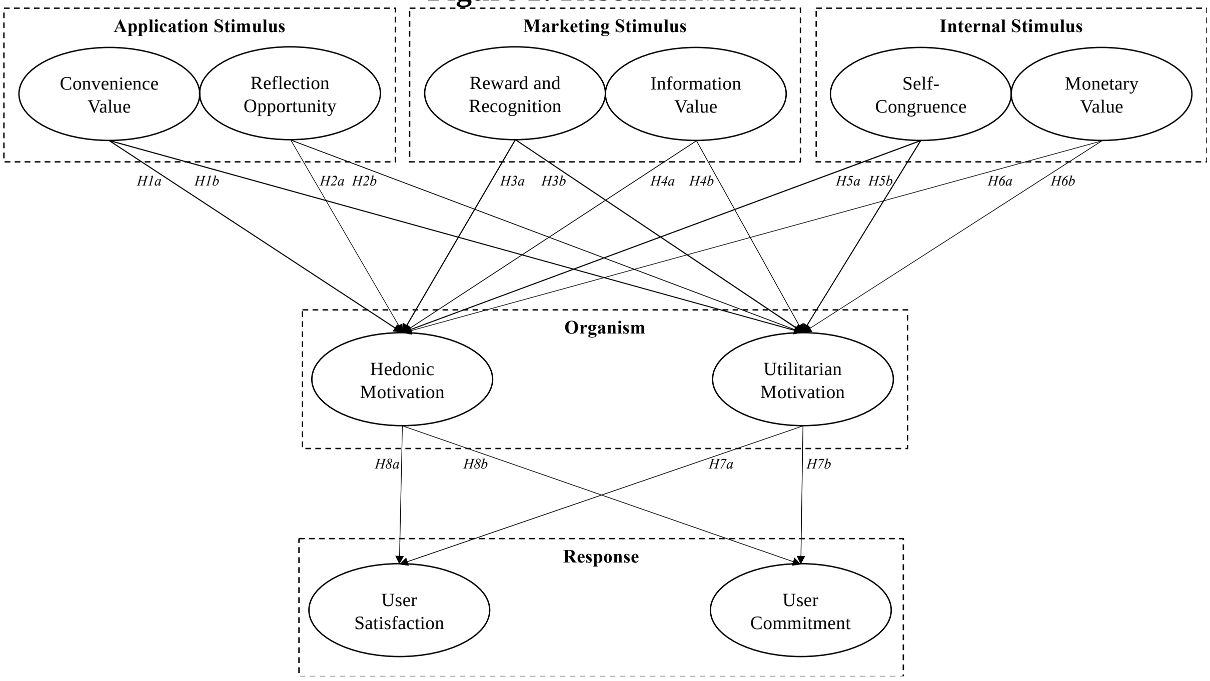


Figure 2: Structural Model Testing

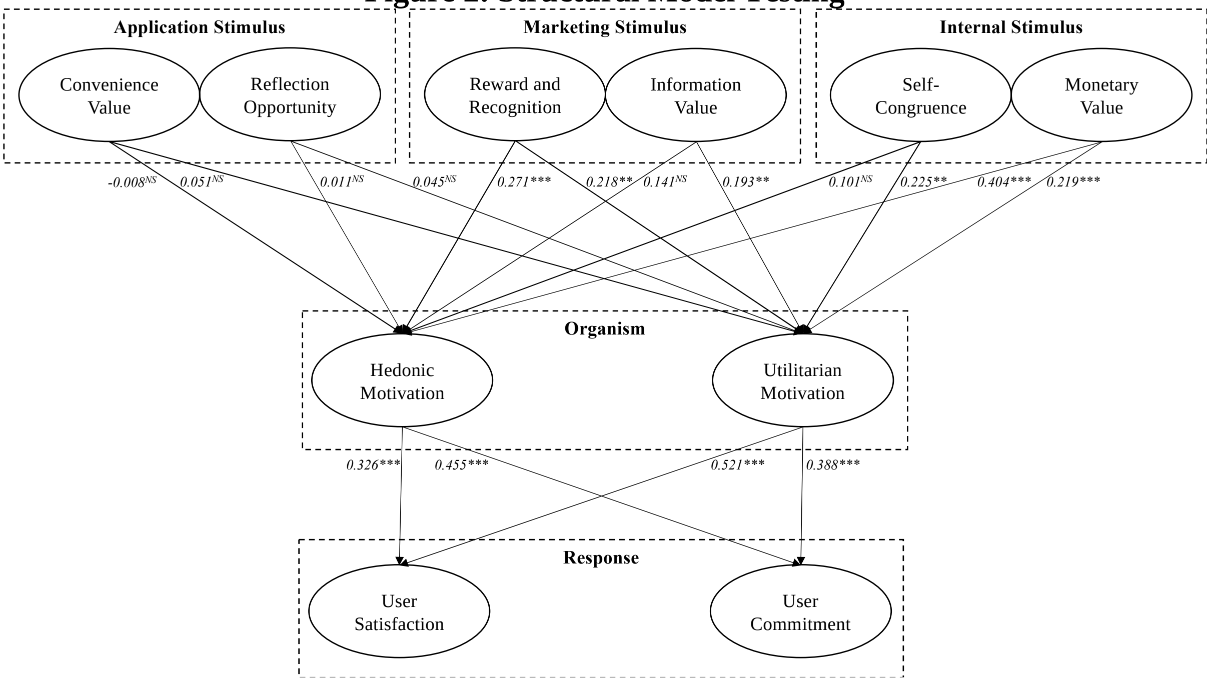
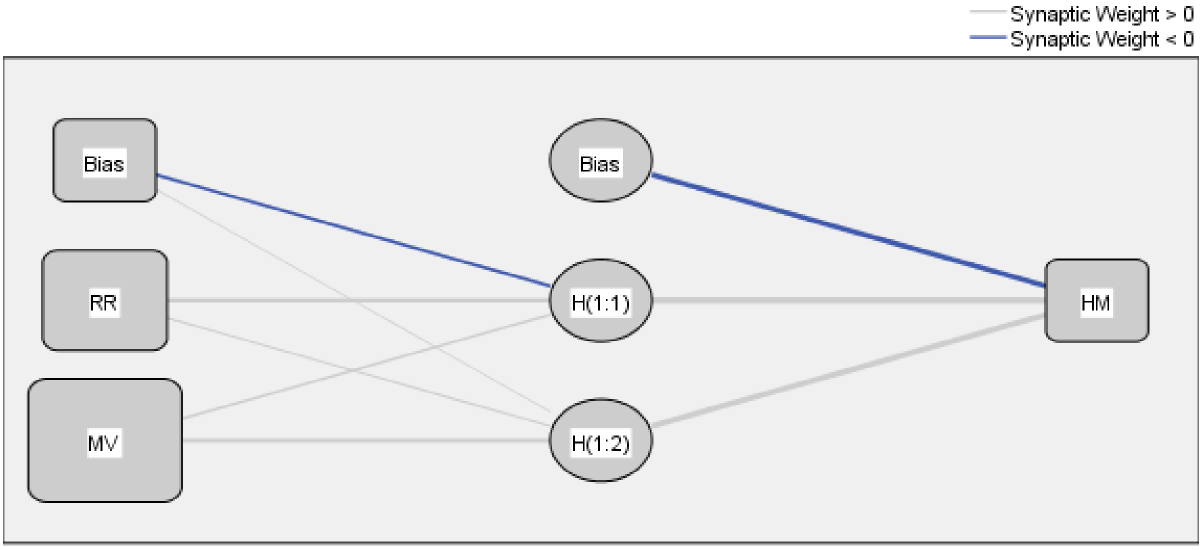


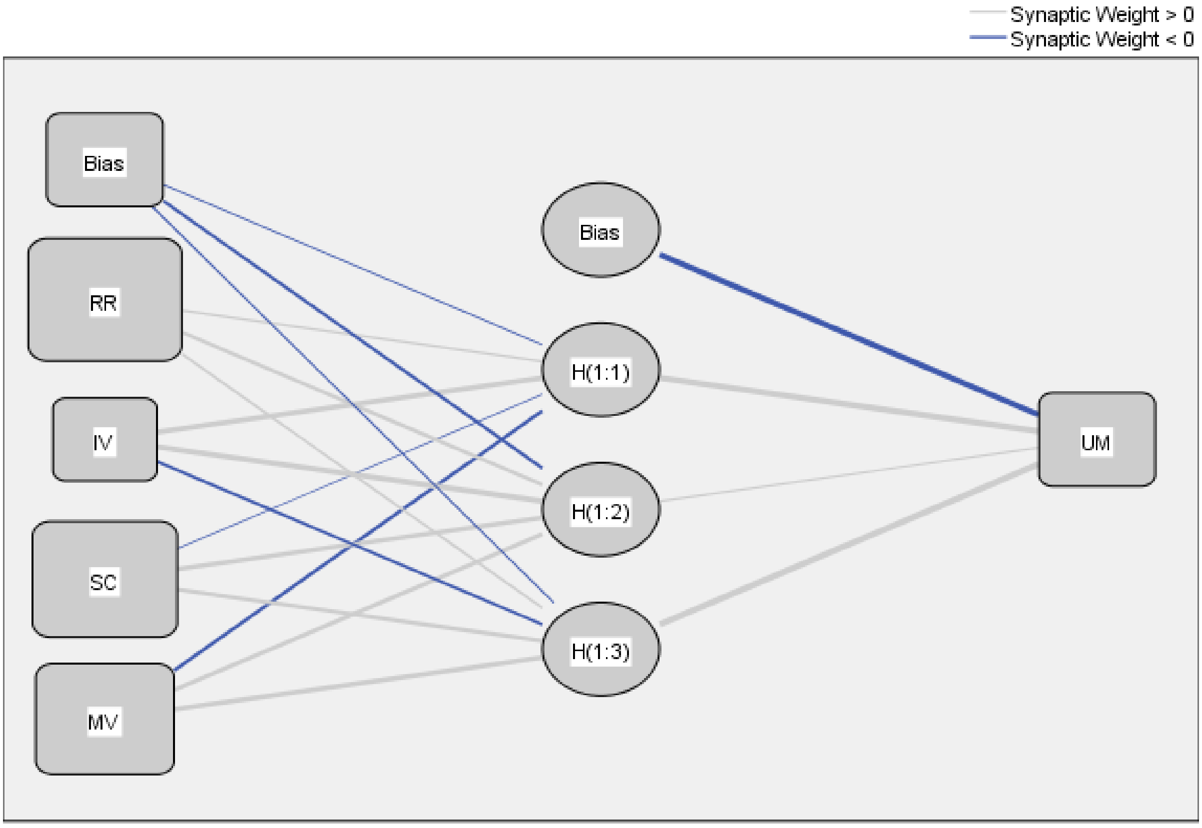
Figure 3: ANN Model A



Hidden layer activation function: Sigmoid

Output layer activation function: Sigmoid

Figure 4: ANN Model B



Hidden layer activation function: Sigmoid

Output layer activation function: Sigmoid

Figure 5: ANN Model C

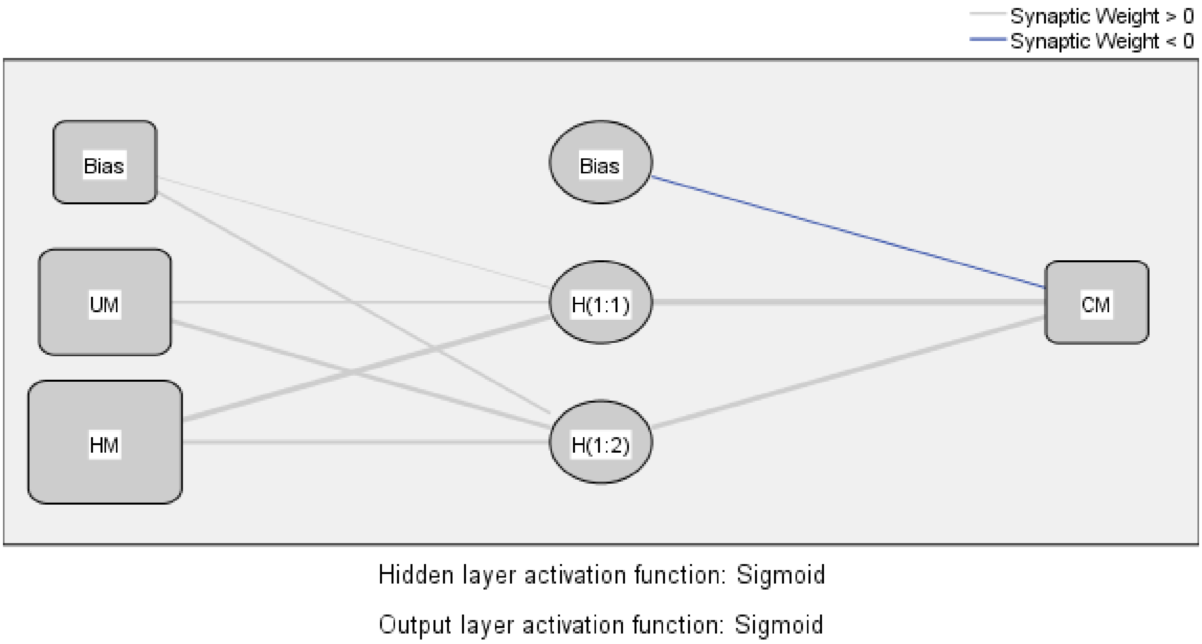


Figure 6: ANN Model D

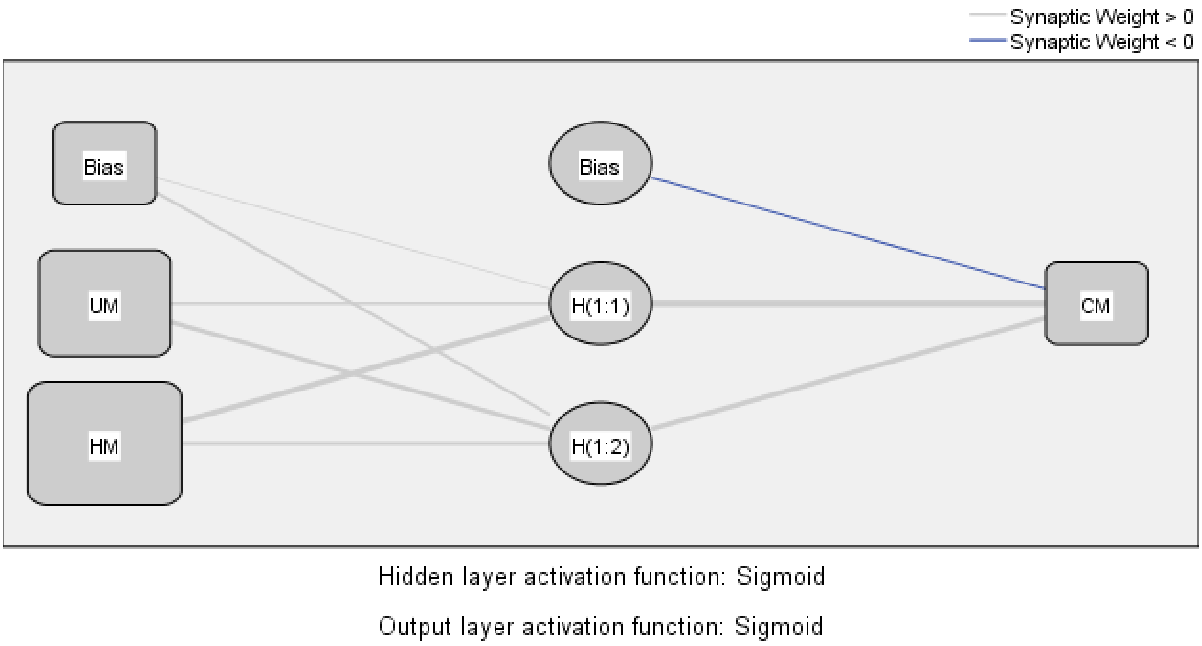


Table 1: Respondent Profile

Demographic Characteristics		Frequency	Percentage
Gender	Male	137	45.20%
	Female	166	54.80%
Age	20 years old and below	19	6.27%
	21-35 years old	198	65.35%
	36-50 years old	77	25.41%
	51 years old and above	9	2.97%
Educational Level	Bachelor's Degree	255	84.16%
	Master's Degree	41	13.53%
	PhD Degree	7	2.31%
Occupation	Student	79	26.07%
	Part-time job	69	22.77%
	Self employed	39	12.87%
	Private employed	116	38.28%
Monthly Income	Below or equal to VND 10,000,000 ($420)	181	59.74%
	VND 10,100,000 to VND 20,000,000 ($840)	72	23.76%
	VND 20,100,000 to VND 30,000,000 ($1,250)	27	8.91%
	VND 30,000,000 and above	23	7.59%
Usage Experience in M-Payment in Past 12 Months	1-10 times	131	43.23%
	11-20 times	109	35.97%
	21-30 times	63	20.79%

Table 2: Loading, Composite Reliability, Dijkstra Henseler and Average Variance Extracted

Latent Constructs	Items	Loadings	Dijkstra-Henseler's (Rho_A)	Composite Reliability (CR)	Average Variance Extracted (AVE)
CM	CM1	0.938			
	CM2	0.938	0.919	0.948	0.858
	CM3	0.902			
CV	CV1	0.770			
	CV2	0.856	0.858	0.900	0.693
	CV3	0.860			
	CV4	0.840			
HM	HM1	0.902			
	HM2	0.904			
	HM3	0.921	0.939	0.951	0.797
	HM4	0.920			
	HM5	0.813			
IV	IV1	0.880			
	IV2	0.868	0.883	0.919	0.740
	IV3	0.872			
	IV4	0.819			
MV	MV1	0.889			
	MV2	0.900	0.838	0.898	0.746
	MV3	0.797			
RO	RO1	0.894			
	RO2	0.893	0.866	0.915	0.783
	RO3	0.867			
RR	RR1	0.838			
	RR2	0.831	0.813	0.888	0.725
	RR3	0.884			
SA	SA1	0.932			
	SA2	0.881	0.900	0.932	0.821
	SA3	0.905			
SC	SC1	0.845			
	SC2	0.895	0.831	0.899	0.748
	SC3	0.853			
UM	UM1	0.858			
	UM2	0.831	0.841	0.893	0.676
	UM3	0.837			
	UM4	0.759			

Table 3: Hetero-Trait-Mono-Trait Assessment

	CM	CV	HM	IV	MV	RO	RR	SA	SC	UM
CM										
CV	0.522 [0.385, 0.635]									
HM	0.808 [0.729, 0.868]	0.463 [0.288, 0.612]								
IV	0.715 [0.607, 0.806]	0.580 [0.387, 0.735]	0.722 [0.618, 0.812]							
MV	0.858 [0.783, 0.913]	0.526 [0.326, 0.682]	0.852 [0.778, 0.909]	0.772 [0.656, 0.860]						
RO	0.566 [0.428, 0.686]	0.609 [0.426, 0.751]	0.560 [0.452, 0.656]	0.662 [0.534, 0.773]	0.626 [0.494, 0.742]					
RR	0.766 [0.659, 0.850]	0.539 [0.371, 0.678]	0.809 [0.725, 0.886]	0.778 [0.653, 0.876]	0.814 [0.720, 0.894]	0.655 [0.525, 0.764]				
SA	0.841 [0.768, 0.897]	0.548 [0.368, 0.698]	0.786 [0.711, 0.851]	0.810 [0.727, 0.878]	0.824 [0.751, 0.884]	0.754 [0.661, 0.834]	0.763 [0.660, 0.846]			
SC	0.828 [0.744, 0.897]	0.565 [0.363, 0.716]	0.752 [0.649, 0.841]	0.831 [0.744, 0.900]	0.840 [0.738, 0.926]	0.633 [0.516, 0.733]	0.801 [0.706, 0.885]	0.732 [0.619, 0.827]		
UM	0.836 [0.768, 0.895]	0.556 [0.374, 0.702]	0.860 [0.787, 0.922]	0.803 [0.712, 0.877]	0.830 [0.746, 0.896]	0.631 [0.532, 0.723]	0.832 [0.729, 0.912]	0.885 [0.804, 0.951]	0.845 [0.759, 0.917]	

Table 4: Outcome of the Structural Model Examination

PLS Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	2.50%	97.50%	Remarks
CV □ HM^{NS}	**-0.008**	**-0.004**	**0.044**	**0.184**	**0.854**	-0.089	0.088	**Unsupported**
CV □ UM^{NS}	**0.051**	**0.054**	**0.045**	**1.139**	**0.255**	-0.030	0.150	**Unsupported**
RO □ HM^{NS}	**0.011**	**0.011**	**0.054**	**0.198**	**0.843**	-0.093	0.121	**Unsupported**
RO □ UM^{NS}	**0.045**	**0.046**	**0.054**	**0.820**	**0.412**	-0.054	0.155	**Unsupported**

RR → HM***	0.271	0.271	0.061	4.475	0.000	0.158	0.393	Supported
RR → UM**	0.218	0.217	0.072	3.027	0.002	0.081	0.358	Supported
IV → HM^{NS}	**0.141**	**0.138**	**0.073**	**1.937**	**0.053**	-0.039	0.327	**Unsupported**
IV → UM**	0.193	0.188	0.072	2.687	0.007	0.003	0.365	Supported
SC → HM^{NS}	**0.101**	**0.102**	**0.070**	**1.440**	**0.150**	-0.080	0.281	**Unsupported**
SC → UM**	0.225	0.225	0.068	3.281	0.001	0.052	0.393	Supported
MV → HM***	0.404	0.403	0.062	6.464	0.000	0.276	0.517	Supported
MV → UM***	0.219	0.221	0.058	3.798	0.000	0.108	0.329	Supported
UM → CM***	0.388	0.390	0.074	5.246	0.000	0.246	0.534	Supported
UM → SA***	0.521	0.525	0.081	6.439	0.000	0.361	0.682	Supported
HM → CM***	0.455	0.455	0.074	6.115	0.000	0.308	0.599	Supported
HM → SA***	0.326	0.323	0.078	4.169	0.000	0.170	0.480	Supported

Note: **<0.05, **<0.01, ***<0.001*

Table 5: PLS Predict

	Q^2_predict	PLS-SEM RMSE	MAE	Linear Model Benchmark RMSE	MAE
CM3	0.512	0.856	0.635	0.863	0.619
CM1	0.550	0.821	0.612	0.859	0.626
CM2	0.530	0.914	0.685	0.944	0.687
SA2	0.431	0.835	0.639	0.835	0.578
SA3	0.545	0.722	0.558	0.728	0.528
SA1	0.498	0.717	0.550	0.726	0.530

Table 6: Predictive Relevance (Q^2) and Predictive Accuracy (R^2)

Endogenous Constructs	SSO	SSE	Q^2 (=1-SSE/SSO)	R Square
CM	903	424.301	0.530	0.627
HM	1505	727.337	0.517	0.657
SA	903	441.375	0.511	0.636
UM	1204	695.756	0.422	0.643

Table 7: Effect size (f^2)

Predictor Construct/ Dependent Construct	CM	HM	SA	UM
CV		0.00		0.005
HM	0.233		0.122	
IQ		0.022		0.040
MV		0.193		0.055
RO		0.000		0.003
RR		0.092		0.057
SC		0.011		0.053
UM	0.169		0.312	

Table 8: Importance Performance Map Analysis

	CM		SA	
Latent Variables	**Importance (Total Effect)**	**Performance (Index Value)**	**Importance (Total Effect)**	**Performance (Index Value)**
CV	0.022	86.85	0.027	86.85
HM	0.482	77.17	0.284	77.17
IV	0.163	79.18	0.141	79.18
MV	0.283	77.06	0.213	77.06
RO	0.027	84.12	0.026	84.12
RR	0.214	76.11	0.171	76.11
SC	0.145	79.10	0.134	79.10
UM	0.445	77.90	0.492	77.90
Mean value	**0.223**	**79.68**	**0.186**	**79.68**

Table 9: RMSE Values for HM, UM, SA, and CM

	Model A		**Model B**		**Model C**		**Model D**	
	Input: RR, MV		Input: RR, IV, SC, MV		Input: UM, HM		Input: UM, HM	
	Output: HM		Output: UM		Output: SA		Output: CM	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Neural network	RMSE	RMSE	RMSE	RMSE	RMSE	RMSE	RMSE	RMSE
ANN1	0.085	0.101	0.094	0.083	0.092	0.070	0.085	0.106
ANN2	0.090	0.082	0.091	0.094	0.085	0.083	0.081	0.104
ANN3	0.091	0.065	0.094	0.079	0.103	0.084	0.086	0.071
ANN4	0.089	0.074	0.093	0.083	0.096	0.064	0.081	0.102
ANN5	0.089	0.072	0.094	0.070	0.093	0.059	0.086	0.106
ANN6	0.093	0.076	0.094	0.080	0.087	0.063	0.086	0.054
ANN7	0.088	0.077	0.094	0.109	0.088	0.091	0.087	0.073
ANN8	0.088	0.083	0.097	0.069	0.092	0.062	0.094	0.077
ANN9	0.095	0.132	0.101	0.094	0.116	0.081	0.084	0.081
ANN10	0.090	0.052	0.095	0.128	0.092	0.064	0.093	0.099
Mean	0.090	0.081	0.095	0.089	0.094	0.072	0.086	0.087
SD	0.003	0.022	0.003	0.018	0.009	0.012	0.004	0.018

Table 10: Sensitivity Analysis

	Model A (Output: HM)		**Model B** (Output: UM)				**Model C** (Output: SA)		**Model D** (Output: CM)	
Neural network	**RR**	**MV**	**RR**	**IV**	**SC**	**MV**	**UM**	**HM**	**UM**	**HM**
ANN1	0.418	0.582	0.332	0.107	0.295	0.266	0.744	0.256	0.441	0.559
ANN2	0.453	0.547	0.307	0.230	0.207	0.257	0.606	0.394	0.461	0.539
ANN3	0.494	0.506	0.319	0.186	0.266	0.229	0.537	0.463	0.394	0.606
ANN4	0.472	0.528	0.388	0.234	0.205	0.172	0.542	0.458	0.438	0.562
ANN5	0.385	0.615	0.353	0.188	0.288	0.171	0.606	0.394	0.436	0.564
ANN6	0.473	0.527	0.323	0.134	0.301	0.242	0.552	0.448	0.438	0.562
ANN7	0.382	0.618	0.262	0.246	0.227	0.266	0.581	0.419	0.417	0.583

ANN8	0.460	0.540	0.395	0.184	0.143	0.278	0.758	0.242	0.142	0.858
ANN9	0.420	0.580	0.179	0.302	0.207	0.311	0.582	0.418	0.377	0.623
ANN10	0.458	0.542	0.189	0.314	0.267	0.229	0.520	0.480	0.527	0.473
Average relative importance	0.442	0.559	0.305	0.213	0.241	0.242	0.603	0.397	0.407	0.593
Normalized relative importance (%)	79.051	100.000	100.000	69.741	78.963	79.455	100.000	65.893	68.663	100.000

Table 11: Comparison Between PLS-SEM and ANN Results

PLS Path	**Original Sample (O)/ Path Coefficient**	**ANN Results: Normalised Relative Importance (%)**	**Ranking (PLS-SEM) [Based On Path Coefficient]**	**Ranking (ANN) [Based On Normalised Relative Importance**	**Remark**
Model A (Output: HM)					
RR □ HM	0.271	79.051	2	2	Match
MV □ HM	0.404	100.000	1	1	Match
Model B (Output: UM)					
RR □ UM	0.218	100.000	3	1	Not Match
IV □ UM	0.193	69.741	4	4	Match
SC □ UM	0.225	78.963	1	3	Not Match
MV □ UM	0.219	79.4552	2	2	Match
Model C (Output: SA)					
UM □ SA	0.521	100.000	1	1	Match
HM □ SA	0.326	65.893	2	2	Not Match
Model D (Output: CM)					
UM □ CM	0.388	68.663	2	2	Not Match
HM □ CM	0.455	100.000	1	1	Not Match