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Determinants of Adoption Intention and Attitude Toward AI-Powered Mobile Payment Applications: Evidence from Yangon, Myanmar

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Abstract

Purpose: This study investigates the determinants of customers' attitudes and adoption intentions towards artificial intelligence (AI) in mobile payment applications in Yangon, Myanmar. The proposed conceptual framework examines relationships among eight key constructs: perceived intelligence, perceived anthropomorphism, trust, perceived risk, adoption intention, attitude, perceived usefulness, and perceived ease of use. **Research design, data and methodology:** The study applied a quantitative research design, collecting survey data from 500 users of leading mobile payment applications in Yangon. Data were analyzed using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to evaluate model fit and assess the construct validity and reliability. **Results:** Seven out of ten hypotheses were supported. Trust ($\beta = 0.169$, $p < 0.05$) and attitude ($\beta = 0.826$, $p < 0.05$) were the strongest predictors of adoption intention ($R^2 = 0.735$). Perceived usefulness ($\beta = 0.578$, $p < 0.05$) and perceived ease of use ($\beta = 0.604$, $p < 0.05$) influenced attitude ($R^2 = 0.698$). Perceived anthropomorphism ($R^2 = 0.881$) strongly affected trust ($\beta = 0.938$, $p < 0.05$) and perceived risk ($\beta = 1.136$, $p < 0.05$). **Conclusions:** This study offers evidence for financial institutions on how AI features can improve customer experience and encourage adoption.

Keywords: Adoption Intention, Artificial Intelligence, Attitude, Mobile Payment Applications, Myanmar

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Financial technology (FinTech) represents the convergence of banking expertise, management science, and computing innovations (Bettinger, 1972). It broadly refers to the application of technology in delivering financial products and services that surpass traditional offerings in sophistication and accessibility (Knewtson & Rosenbaum, 2020). Among its many innovations, artificial intelligence (AI) has emerged as one of the most transformative. AI is commonly defined as the ability of machines to replicate human cognitive functions (Jarrahi, 2018), with the ultimate goal of simulating human thought processes as closely as possible (Shubhendu & Vijay, 2013). AI encompasses replicating human thought, mimicking human actions, enabling logical reasoning, and demonstrating rational behavior (Russell & Norvig, 1995), while also performing perception, learning, interaction, and problem-solving, and even creative tasks (Dobrev, 2005). These capabilities make AI a versatile and powerful tool across diverse domains, including financial services.

In recent years, the integration of AI into digital financial platforms has accelerated, with banks and financial institutions increasingly employing AI-powered solutions to enhance operational efficiency and deliver personalized services. Mobile payment technologies, in particular, enable the collection, storage, and analysis of consumer data to support customized financial services (Khrais & Shidwan, 2020). Studies highlight the importance of AI in responding to rising consumer demand for intelligent and personalized banking solutions (Loureiro et al., 2020; Milana & Ashta, 2021). Alongside these developments, mobile banking has also become a cornerstone of modern financial ecosystems. Traditional banks provide mobile platforms that allow users to transact directly with banks or through third parties (Upadhyay & Jahanyan, 2016). Distinct from these, mobile wallets function as digital applications that store monetary value, enabling payments, transfers, and transaction management—often without requiring a traditional bank

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account (Kudo et al., 2023).

Akhila (2018) categorizes mobile wallets into three main types. Open wallets act as flexible instruments, providing access to a wide range of products and services, including financial offerings such as insurance and mutual funds, while also enabling cash withdrawals and fund transfers at ATMs and point-of-sale terminals. Semi-closed wallets facilitate online shopping, bill payments, and mobile recharges but restrict cash withdrawals, limiting transactions to affiliated merchants partnered with the wallet provider. In contrast, closed wallets are issued by a single company and are restricted to transactions within that company's ecosystem, often serving as a repository for refunds or balances related to purchases and cancellations. This classification highlights the diversity of mobile payment applications and the varying levels of flexibility and accessibility they provide to consumers.

These developments reflect a global shift toward digital and cashless payments. Conventional paper-based instruments such as cash and cheques are declining in use, while electronic payment solutions—including bank cards, QR codes, cryptocurrencies, and mobile applications—continue to expand (Hayashi et al., 2003). Mobile services, in particular, are gaining traction due to their convenience, portability, and efficiency in meeting everyday payment needs (Singh et al., 2017).

Despite the rapid growth of FinTech and the increasing adoption of AI in financial services, most existing studies focus on developed markets characterized by strong digital infrastructure, high financial literacy, and institutional trust. As a result, consumer attitudes toward AI-powered mobile payment applications in emerging economies remain underexplored, even though these contexts face challenges such as limited banking penetration and cultural reliance on cash. Consequently, findings from developed settings may not fully generalized. There is limited empirical evidence on how perceived intelligence, perceived anthropomorphism, trust, and perceived risk collectively shape customers' attitudes and adoption intentions in such environments. This gap is especially relevant in Yangon, Myanmar's commercial hub, where rapid digital growth coexists with infrastructural limitations and cash-based practices, creating a distinctive environment for AI-enabled financial services.

This study addresses this gap by examining the determinants of customers' attitudes and adoption intentions toward AI-powered mobile payment applications, offering insights to guide banks, financial service providers, and FinTech companies in enhancing digital payment ecosystems. Accordingly, this study investigates:

1. How perceived intelligence and perceived anthropomorphism influence perceived risk and trust in AI-powered mobile payment applications.
2. How perceived intelligence affects perceived anthropomorphism.
3. How trust and perceived risk shape adoption intention.
4. How perceived usefulness, ease of use, and attitude influence adoption intention.

2. Literature Review

2.1 Perceived Intelligence

AI intelligence is often defined by its capacity for goal achievement, problem-solving, adaptability, learning, and environmental awareness (Legg & Hutter, 2007). In mobile payment applications, perceived intelligence refers to users' belief that AI-powered features can effectively perform tasks and understand natural language to deliver reliable outcomes (Lee & Chen, 2022).

Perceived intelligence is closely tied to both risks and benefits. While mobile payment systems face persistent concerns such as privacy violations, fraud, and misuse of user data (Darby, 2016), intelligent technologies can mitigate these risks by improving security and enhancing user confidence (Wiegard & Breitner, 2019). Trust also emerges as a critical outcome: perceptions of intelligence influence whether users view AI systems as competent and reliable (Glikson & Woolley, 2020), and prior evidence suggests that users' trust is shaped by their initial assessments of system intelligence (Moussawi, 2016).

Beyond trust, perceived intelligence has been linked to anthropomorphism. AI services often engage users in ways that mimic human-like understanding (Mishra et al., 2021), a view supported by Moussawi and Koufaris (2019) and Moussawi et al. (2020). Empirical evidence further shows that higher perceived intelligence enhances anthropomorphism in mobile payment applications (Lee & Chen, 2022). Based on these insights, the following hypotheses are proposed:

H1: Perceived Intelligence has a significant influence on Perceived Risk.

H2: Perceived Intelligence has a significant influence on Trust.

H3: Perceived Intelligence has a significant influence on Perceived Anthropomorphism.

2.2 Perceived Anthropomorphism

Anthropomorphism refers to the human tendency to attribute human-like traits, emotions, or motivations to non-human entities (Kim et al., 2019; Chen & Park, 2021). In the context of machine-human interaction, perceived anthropomorphism is the assignment of human-like characteristics, intentions, and behaviors to technological

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systems. Such perceptions can shape how users relate to and interact with AI-powered services.

Research highlights several outcomes of anthropomorphism in technology use. Interacting with anthropomorphized systems can fulfill users' social needs and alter future interaction patterns (Mourey et al., 2017). In mobile services, anthropomorphic interactions give users the impression that AI applications understand their needs (Moussawi et al., 2020). Perceived anthropomorphism is also linked to perceived risk; while it may help users manage uncertainty (Cui, 2022), its influence on risk evaluations can vary depending on customers' social expectations (Kim & McGill, 2011).

Trust is another important outcome. Morana et al. (2020) showed that anthropomorphized chatbots foster greater trust, while Lee and Chen (2022) found that, within mobile payment applications, perceived anthropomorphism directly enhances trust. In mobile banking, users tend to trust AI more when its design incorporates human-like characteristics, leading them to subconsciously associate the application with a human (Lin et al., 2023). These findings indicate that attributing human-like qualities to AI not only affects perceived risk but also reinforces trust in technology. This study accordingly hypothesizes that:

H4: Perceived Anthropomorphism has a significant influence on Perceived Risk.

H5: Perceived Anthropomorphism has a significant influence on Trust.

2.3 Perceived Risk

Perceived risk reflects uncertainty about potential negative outcomes and their consequences (Cox & Rich, 1964; Oentoro, 2020). It can arise from doubts about product performance, complex purchase processes, economic or psychosocial impacts, or cognitive ambiguity. In the context of technological products, technological risk—the fear of sophisticated advances—adds an additional dimension, particularly for internet-based and high-tech services (Dekimpe et al., 2000). Similarly, Peter and Ryan (1976) describe it as the combination of uncertainty, consequence severity, and the anticipation of losses, all of which may inhibit consumer behavior. In technology adoption, perceived risk specifically refers to users' doubts about a technology's ability to meet expectations, including concerns over potential losses resulting from discrepancies between anticipated and actual performance (Chen & Lai, 2023).

Perceived risk plays a critical role in shaping users' attitudes and intentions toward adopting mobile payment applications. Prior research indicates that uncertainty surrounding security, privacy, and system reliability significantly influences adoption decisions (Deventer et al., 2017; Purwanegara et al., 2014; Wessels & Drennan, 2010). More generally, innovation adoption studies highlight perceived risk as a key factor consumers use when evaluating new technologies (Hoeffler, 2003; Ostlund, 1974). This leads to the following hypothesis:

H6: Perceived Risk has a significant influence on Adoption Intention.

2.4 Trust

Trust is defined as the belief in the reliability and integrity of another party (Morgan & Hunt, 1994). It can be motivated by cognitive reasoning, affective intuition, or a combination of both (Lewis & Weigert, 1985). Similarly, Luhmann (1979) describes trust as the conviction that others will act in predictable and expected ways. In technology adoption, trust reduces uncertainty by assuring users of safety and security, which in turn encourages usage (Zhou, 2011).

Trust plays a pivotal role in human-technology interactions. It influences how people perceive and engage with technological systems, shaping both confidence and willingness to rely on them (Siau & Wang, 2018). Prior studies confirm its importance in financial technologies: trust has been found to significantly impact customers' adoption intentions in both online banking (Bashir & Madhavaiah, 2014) and mobile banking (Kumar et al., 2017). These findings highlight that trust is not only a relational factor but also a key determinant of user acceptance in digital financial services. Thus, this study proposes the following hypothesis:

H7: Trust has a significant influence on Adoption Intention.

2.5 Perceived Usefulness

Perceived usefulness refers to the extent to which individuals believe that a system will enhance their performance and help them accomplish tasks more effectively (Davis, 1989; Saade & Bahli, 2005). In the Technology Acceptance Model (TAM), Davis (1989) identified perceived usefulness as a central determinant of technology adoption, focusing on whether users expect performance improvement from system use. Building on this, Venkatesh and Davis (2000) described it as consumers' conviction that technology enhances their capabilities, while Thokchom (2012) emphasized its role in shaping how populations adapt to technological change. Individuals are more likely to adopt new technologies when they perceive them as useful in their daily lives (Alalwan et al., 2017; Davis, 1989; Kleijnen et al., 2004).

Within TAM-based research, perceived usefulness has been consistently linked to attitudes toward technology

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adoption. Studies show that users' perceptions of usefulness directly influence both their attitudes and behavioral intentions toward mobile payment applications (Alalwan et al., 2017; Chen, 2013; Koenig-Lewis & Moll, 2010; Muñoz-Leiva et al., 2017). These findings confirm its critical role as a predictor of adoption in digital financial services. Based on this review, the following hypothesis is proposed:

H8: Perceived Usefulness has a significant influence on Attitude.

2.6 Perceived Ease of Use

Perceived ease of use refers to the degree to which an individual believes that using a technology will require minimal effort (Venkatesh & Davis, 2000). It reflects the extent to which users find a system user-friendly and intuitive, shaping their willingness to adopt it across different applications. As Morosan (2014) observed, individuals are more likely to embrace new technologies when they perceive them as easy to understand and operate.

Within TAM, Davis (1989) highlighted perceived ease of use as a key determinant of technology adoption, influencing both learning and effective usage. This relationship underscores that technologies perceived as simple and intuitive are more likely to be considered useful, thereby enhancing adoption (Ali & Arshad, 2016). Moreover, perceived ease of use has been shown to shape attitudes toward adoption, particularly in contexts requiring specific skills and knowledge, such as mobile payment applications (Makanyeza, 2017). Users' perceptions of a system's ease of implementation can therefore significantly influence their attitudes (Elliott & Fu, 2008). Drawing on TAM and prior empirical findings, this study proposes the following hypothesis:

H9: Perceived Ease of Use has a significant influence on Attitude.

2.7 Attitude

Attitude refers to an individual's overall evaluation of a behavior as favorable or unfavorable (Davis, 1989). It reflects one's psychological readiness to adopt or reject new technologies (Alsajjan & Dennis, 2010; O'Cass & Fenech, 2003). In technology adoption contexts, attitude represents users' feelings toward a system and influences whether they incorporate it into daily routines (Shanmugam et al., 2014; Lee, 2010).

Empirical studies consistently highlight the central role of attitude in predicting adoption behavior. Akurtan and Tezcan (2012) identified it as the most critical factor influencing the intention to adopt mobile payment applications. Similarly, Deb and David (2014) and Chawla and Joshi (2019) confirmed a strong positive association between attitude and adoption intention in mobile banking. Based on these findings, the following hypothesis is proposed:

H10: Attitude has a significant influence on Adoption Intention.

2.8 Adoption Intention

Adoption reflects an individual's willingness to accept and continue using a new concept or technology, shaped by various personal and contextual factors (Rogers, 2003). Within the Theory of Reasoned Action (TRA), intention is defined as the perceived likelihood of carrying out a specific behavior (Fishbein & Ajzen, 1975). Similarly, TAM emphasizes intention as the critical determinant of technology utilization (Davis, 1989). Adoption intention therefore represents the deliberate mindset individuals form when deciding whether to engage with a system, serving as a self-fulfilling driver of behavior (Bagozzi et al., 1992).

In digital finance, adoption intention captures the user's evaluation of mobile payment services and their likelihood of integrating them into daily use. Successful implementation of bank-led mobile payment applications depends on user adoption (Shumaila, 2012), making it vital to understand the drivers that shape this intention. Prior studies have highlighted trust, risk, and perceived value as key influences in the decision to adopt such services (Cao & Liu, 2018; Cao et al., 2014; Tam & Oliveira, 2017).

3. Research Methods and Materials

3.1 Research Framework

This study develops a conceptual model to examine customer attitudes and adoption intentions toward AI-powered mobile payment applications by drawing on TAM and the Stimulus-Organism-Response (SOR) framework. TAM emphasizes the influence of perceived usefulness and perceived ease of use in shaping user attitudes toward technology, while the SOR framework, originally proposed by Woodworth (1929), explains how external stimuli shape internal psychological states, which in turn drive behavioral intentions. In this study, perceived intelligence and perceived anthropomorphism are conceptualized as stimuli, with perceived risk and trust representing the organism, and adoption intention serving as the response. Together, these theories provide a robust foundation for examining both cognitive and emotional factors that drive the adoption of mobile payment applications.

As depicted in Figure 1, the framework incorporates eight constructs—perceived intelligence (PI), perceived anthropomorphism (PA), perceived risk (PR), trust (T),

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adoption intention (ADI), attitude (A), perceived usefulness (PU), and perceived ease of use (PEOU)—adapted from prior research (Lee & Chen, 2022; Rafdinal & Senalasari, 2021; Rahman et al., 2021). The framework illustrates how cognitive appraisals (PI, PU, PEOU), affective and relational dimensions (PA, PR, T), and attitudinal responses (A) collectively shape adoption intention, thereby clarifying the causal mechanisms driving consumers' acceptance of AI-powered mobile payment applications in Yangon, Myanmar.

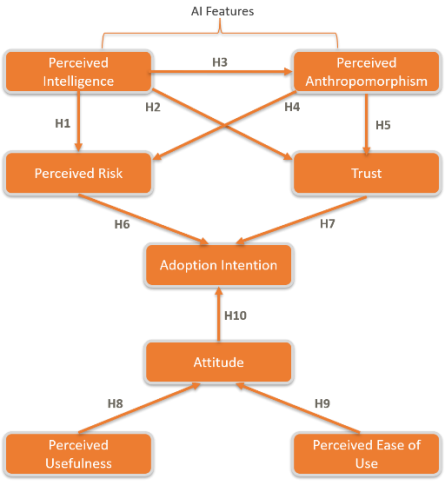

Figure 1: Conceptual Framework

3.2 Methodology

The study employed a quantitative research design, using a structured questionnaire as the primary instrument for data collection. The questionnaire was organized into three sections: (i) three screening questions to confirm respondents' residency in Yangon and experience with the top three bank-led mobile payment applications; (ii) five demographic items capturing gender, age, education, occupation, and income; and (iii) 35 five-point Likert scale items (1 = strongly disagree, 5 = strongly agree) assessing eight latent constructs—perceived intelligence, perceived anthropomorphism, trust, perceived risk, adoption intention, attitude, perceived usefulness, and perceived ease of use. All items were adapted from previously validated instruments (Lee & Chen, 2022; Rafdinal & Senalasari, 2021; Rahman et al., 2021) and carefully contextualized for this study.

To ensure content validity, the questionnaire items were evaluated by a panel of three experts using the Index of Item-Objective Congruence (IOC), with all items demonstrating acceptable validity (IOC values ranging from 0.67 to 1.00), confirming that each item effectively measured its intended construct. Following Turner et al. (2002), IOC values within the range of 0.5 to 1.0 were considered acceptable, and items scoring 0.5 or higher were retained (Turner & Carlson, 2003). A pilot test with 50 participants further demonstrated strong internal consistency, with Cronbach's alpha values exceeding 0.70, indicating reliable measurement and minimal error (Mujis, 2011). To reduce potential common method bias, procedural remedies were implemented, including assuring respondents of anonymity, emphasizing that there were no right or wrong answers, and separating items from different constructs across multiple sections to minimize response patterning.

Following data cleaning, descriptive statistics were calculated to summarize the sample characteristics. Confirmatory Factor Analysis (CFA) was employed to assess the adequacy of the measurement model, evaluating convergent validity through factor loadings (> 0.70) and Average Variance Extracted (AVE > 0.50), and discriminant validity using the Fornell-Larcker criterion. Structural Equation Modeling (SEM) was conducted in Jamovi 2.4 using maximum likelihood estimation to simultaneously test all ten hypotheses. Model fit was assessed with multiple indices, including $\chi^2/df < 5$ (Al-Mamary & Shamsuddin, 2015; Awang, 2012), Goodness-of-Fit Index (GFI ≥ 0.85; Sica & Ghisi, 2007), Root Mean Square Error of Approximation (RMSEA < 0.08; Pedroso et al., 2016), Normed Fit Index (NFI ≥ 0.80; Wu & Wang, 2006), Comparative Fit Index (CFI ≥ 0.80; Bentler, 1990), and Tucker-Lewis Index (TLI ≥ 0.80; Sharma et al., 2005).

3.3 Population and Sample Size

The target population of this study consisted of individuals aged 18 years and above, residing in Yangon, Myanmar, who have prior experience using widely adopted mobile payment applications in the country. To determine the appropriate sample size, the recommendation of Soper (2006) was followed, which suggests a minimum of 444 participants for structural equation modeling. Accordingly, the study set a target of 500 respondents to ensure sufficient statistical power and robustness of the findings.

3.4 Sampling Technique

This study employed a combination of judgmental, quota, and convenience sampling techniques. Judgmental sampling was first used to ensure that respondents met the inclusion criteria: (1) age 18 years or older, (2) currently residing in Yangon, and (3) having experience using at lease one of the top three bank-led mobile payment applications in Myanmar that have integrated AI-supported features.

Quota sampling was then applied to achieve balanced representation across these applications. The target distribution was 80%, 13.4%, and 6.6%, respectively, and the final sample closely matched these proportions, helping ensure representativeness of the major service providers.

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In addition, convenience sampling facilitated the online distribution of the questionnaire through email and social media platforms, including Facebook and LinkedIn. Data were collected over a period of approximately four months, from December 2023 to March 2024. During data screening, responses were verified to ensure they originated from the intended target group. Respondents were also encouraged to share the survey link with their peers to enhance reach and participation.

The use of multiple sampling methods aligns with Sullivan et al. (2012), who highlight that combining approaches allows for more comprehensive data collection, and with Clark-Carter (2010), who notes that practical considerations such as time, cost, and accuracy often guide the choice of sampling strategies.

4. Results and Discussion

4.1 Population and Sample Size

The collection of demographic data allows for meaningful comparisons across different characteristics, attitudes, and intentions (Polonsky & Waller, 2015). A total of 500 valid responses were analyzed, as shown in Table 1.

Most respondents were female (77.8%), with 22.2% male. The largest age group was 26-45 years (69.2%), followed by 18-25 years (17.2%) and 46-60 years (13.6%). Educational backgrounds included high school/vocational (3.6%), bachelor's (44%), master's (44%), doctoral (4.8%), and other (3.6%). Occupations were primarily company employees (57.8%), self-employed (15.6%), other (8%), non-government (7%), government (5.8%), students (3.4%), and unemployed (2.4%). The largest income group earned MMK 5,000,001 and above monthly (24.4%), with the remainder distributed across lower brackets.

Table 1: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	111	22.2%
	Female	389	77.8%
Age	18-25 years old	86	17.2%
	26-45 years old	346	69.2%
	46-60 years old	68	13.6%
Education Level	High School / Vocational	18	3.6%
	Bachelor's Degree	220	44.0%
	Master's Degree	220	44.0%
	Doctoral Degree	24	4.8%
	Other	18	3.6%
Occupation	Student	17	3.4%
	Government Employee	29	5.8%
	Company Employee	289	57.8%
	Non-government Employee	35	7.0%
	Self-employee	78	15.6%
	Unemployed	12	2.4%
	Other	40	8.0%
Income Level	MMK 500,000 or less	73	14.6%
	MMK 500,001 - 1,000,000	113	22.6%
	MMK 1,000,001 - 2,000,000	110	22.0%
	MMK 2,000,001 - 3,500,000	57	11.4%
	MMK 3,500,001 - 5,000,000	25	5.0%
	MMK 5,000,001 and above	122	24.4%

Source: Constructed by the researcher

4.2 Confirmatory Factor Analysis (CFA)

Prior to testing the structural relationships, the measurement model was evaluated through a rigorous CFA to assess the psychometric properties of all eight constructs. The analysis was conducted using maximum-likelihood estimation in Jamovi 2.4, with 35 observed indicators loading on their respective latent constructs: perceived intelligence (PI), perceived anthropomorphism (PA), trust (T), perceived risk (PR), adoption intention (ADI), attitude (A), perceived usefulness (PU), and perceived ease of use (PEOU

Table 2: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Intelligence (PI)	Lee and Chen (2022)	5	0.913	0.764 - 0.824	0.898	0.637
Perceived Anthropomorphism (PA)	Lee and Chen (2022)	5	0.841	0.664 - 0.735	0.827	0.489
Trust (T)	Lee and Chen (2022)	4	0.779	0.632 - 0.690	0.757	0.438
Perceived Risk (PR)	Lee and Chen (2022)	5	0.845	0.585 - 0.839	0.828	0.495
Adoption Intention (ADI)	Lee and Chen (2022)	4	0.769	0.642 - 0.734	0.792	0.489
Attitude (A)	Rafdinal and Senalasari (2021)	4	0.837	0.592 - 0.816	0.777	0.471
Perceived Usefulness	Rafdinal and Senalasari (2021)	3	0.794	0.736 - 0.910	0.849	0.653
Perceived Ease of Use	Rafdinal and Senalasari (2021)	5	0.905	0.558 - 0.757	0.803	0.452

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As shown in Table 2, all standardized factor loadings were statistically significant ($p < 0.001$) and exceeded the conservative threshold of 0.50 recommended by Hair et al. (1998), with the lowest loading being 0.558 (PEOU5) and the highest 0.91 (PU1), demonstrating strong convergent validity. Reliability and convergent validity were further confirmed through composite reliability (CR) values ranging from 0.757 (T) to 0.898 (PI), surpassing the recommended threshold of 0.70 (Fornell & Larcker, 1981). Average Variance Extracted (AVE) values ranged from 0.438 (T) to 0.653 (PU), exceeding the 0.40 benchmark, indicating that the indicators accounted for a substantial portion of the variance in their respective constructs (Fornell & Larcker, 1981).

Discriminant validity was assessed using the Fornell-Larcker criterion, which requires that the square root of each construct's AVE be greater than its correlations with other constructs (Hair et al., 2010). As shown in Table 3, this condition was satisfied for all constructs. For example, the square root of AVE for perceived anthropomorphism (√AVE = 0.699) exceeded its highest inter-construct correlation (0.416), thereby confirming discriminant validity.

Table 3: Discriminant Validity

	PI	PA	T	PR	ADI	A	PU	PEOU
PI	**.798**							
PA	.796	**.699**						
T	.394	.391	**.662**					
PR	.368	.416	.376	**.704**				
ADI	.226	.203	.271	.238	**.699**			
A	.140	.107	.156	.145	.687	**.686**		
PU	.134	.133	.172	.182	.644	.478	**.808**	
PEOU	.042	.024	.025	.008	.298	.595	.171	**.672**

Note: The diagonally listed value is the AVE square roots of the variables.
Source: Constructed by the researcher

Model fit was evaluated using multiple goodness-of-fit indices, as presented in Table 4. The results indicated that the measurement model demonstrated satisfactory fit. All indices fell within recommended threshold values, confirming that the model provided a robust representation of the data.

The CFA results indicated that all items loaded significantly on their intended constructs ($\lambda > 0.70$) with no cross-loadings, demonstrating strong convergent and discriminant validity. The analysis confirmed a clear and theoretically consistent measurement structure, providing robust support for the reliability, validity, and subsequent structural equation modeling (SEM).

Table 4: Goodness of Fit for Confirmatory Factor Analysis (CFA)

Index	Acceptable Values	Statistical Values of CFA
CMIN/DF	< 5.00 (Wheaton et al., 1977)	2.227
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.884
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.863
NFI	≥ 0.80 (Wu & Wang, 2006)	0.864
CFI	≥ 0.80 (Bentler, 1990)	0.919
TLI	≥ 0.80 (Sharma et al., 2005)	0.910
RMSEA	< 0.08 (Pedroso et al., 2016)	0.050
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI= Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation.
Source: Constructed by the researcher

4.3 Structural Equation Model (SEM)

The structural model was assessed to examine the proposed relationships among eight constructs. The analysis confirmed that both the measurement and structural models fit the data well, indicating that the conceptual framework reliably captures the interconnections among perceived intelligence, perceived anthropomorphism, perceived risk, trust, perceived usefulness, perceived ease of use, attitude, and adoption intention. Goodness-of-fit indices for both models are presented in Table 5, demonstrating that the model provides a solid foundation for testing hypotheses and interpreting the structural relationships among the latent variables.

Table 5: Goodness of Fit for Structural Equation Model (SEM)

Index	Acceptable Values	Statistical Values of SEM
CMIN/DF	< 5.00 (Wheaton et al., 1977)	2.509
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.868
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.849
NFI	≥ 0.80 (Wu & Wang, 2006)	0.841
CFI	≥ 0.80 (Bentler, 1990)	0.897
TLI	≥ 0.80 (Sharma et al., 2005)	0.889
RMSEA	< 0.08 (Pedroso et al., 2016)	0.055
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI= Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation.
Source: Constructed by the researcher

4.4 Research Hypothesis Testing Result

Table 6 presents the results of the ten hypothesized paths. Seven hypotheses were supported, confirming the proposed model. Perceived Intelligence (PI) influenced Perceived Anthropomorphism (PA), which affected Trust (T) and

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Perceived Risk (PR). Trust and Attitude (A) emerged as key predictors of Adoption Intention (ADI), with Attitude shaped by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PI did not directly impact T or PR, and PR did not significantly affect ADI. Overall, the findings highlight the central roles of trust and attitude in driving adoption intention and the mediating effect of perceived anthropomorphism.

Table 6: Hypotheses Testing Result of the Structural Model

Hypothesis	Standardized β	t-value	Result
H1: PI → PR	-0.660	-2.391	Not Supported
H2: PI → T	-0.417	-1.634	Not Supported
H3: PI → PA	0.939	15.926*	Supported
H4: PA → PR	1.136	3.969*	Supported
H5: PA → T	0.938	3.533*	Supported
H6: PR → ADI	0.112	2.546	Not Supported
H7: T → ADI	0.169	3.567*	Supported
H8: PU → A	0.578	9.708*	Supported
H9: PEOU → A	0.604	8.492*	Supported
H10: A → ADI	0.826	9.502*	Supported

Note: *p<0.05
Source: Constructed by the researcher

H1 - Perceived Intelligence → Perceived Risk: Not supported (β = -0.660, t = -2.391). Consistent with Smith and Jones (2020), users' perceptions of AI intelligence did not significantly influence their assessment of associated risks.

H2 - Perceived Intelligence → Trust: Not supported (β = -0.417, t = -1.634). In line with Ahn et al. (2021), perceived intelligence did not significantly enhance trust.

H3 - Perceived Intelligence → Perceived Anthropomorphism: Supported (β = 0.939, t = 15.926). Echoing Waytz et al. (2014) and Lee and Chen (2022), higher perceived intelligence encourages users to attribute humanlike qualities to technology, fostering anthropomorphic perceptions.

H4 - Perceived Anthropomorphism → Perceived Risk: Supported (β = 1.136, t = 3.969). This aligns with Mori's (2012) uncanny valley theory, suggesting that highly humanlike entities may evoke discomfort and perceived threat.

H5 - Perceived Anthropomorphism → Trust: Supported (β = 0.938, t = 3.533). The finding supports prior research indicating that humanlike traits in technology enhance relational trust, as users feel more comfortable with systems exhibiting humanlike cues (Lee & Chen, 2022; Nass & Moon, 2000).

H6 - Perceived Risk → Adoption Intention: Not supported (β = 0.112, t = 2.546). Consistent with Lee and Chen (2022), perceived risk did not significantly affect adoption intention.

H7 - Trust → Adoption Intention: Supported (β = 0.169, t = 3.567). As predicted by the Technology Acceptance Model (TAM), trust is a critical determinant of users' intention to adopt new technologies (Gefen, 2000).

H8 - Perceived usefulness → Attitude: Supported (β = 0.578, t = 9.708). This supports TAM's premise that perceived usefulness strongly shapes favorable user attitudes toward technology (Davis, 1989).

H9 - Perceived Ease of Use → Attitude: Supported (β = 0.604, t = 8.492). Aligning with TAM, systems perceived as easy to use positively influence users' attitudes (Davis, 1989).

H10 - Attitude → Adoption Intention: Supported (β = 0.826, t = 9.502). This reinforces TAM's assertion that positive user attitudes are strong predictors of technology adoption (Davis, 1989; Venkatesh & Davis, 2000).

Taken together, these results highlight the pivotal roles of trust and attitude in driving users' adoption intentions for AI-powered mobile payment applications.

As presented in Table 7, the model demonstrated strong explanatory power, accounting for 73.5% of the variance in adoption intention (R^2 = 0.735) and 69.8% of the variance in attitude (R^2 = 0.698). Perceived anthropomorphism, trust, and perceived risk were explained at 88.1%, 32.0%, and 31.9% respectively.

Table 7: Explained Variance (R^2) of Endogenous Variables

Dependent Variable	R^2
Adoption Intention (ADI)	0.735
Attitude (A)	0.698
Perceived Anthropomorphism (PA)	0.881
Trust (T)	0.320
Perceived Risk (PR)	0.319

Source: Constructed by the researcher

5. Conclusions

5.1 Conclusion

This study examined the determinants of users' attitudes and adoption intentions toward AI-powered mobile payment applications in Yangon, Myanmar. Perceived intelligence did not directly influence trust or perceived risk; however, it strongly predicted perceived anthropomorphism, suggesting that intelligent systems are more likely to be viewed as humanlike. This indicates that perceived intelligence may exert its influence indirectly through relational or experiential factors rather than directly through risk or trust assessments.

Perceived anthropomorphism significantly shaped both trust and perceived risk, demonstrating that humanlike cues can foster emotional comfort while also introducing uncertainty. Contrary to expectations, perceived risk did not significantly predict adoption intention, suggesting that users may prioritize trust and practical benefits over risk evaluations when considering AI-enabled mobile payment

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services.

Trust and attitude emerged as the strongest predictors of adoption intention, highlighting their central roles in supporting mobile payment use. Perceived usefulness and ease of use were important antecedents of attitude, which subsequently contributed to adoption intention, indicating that positive evaluations are formed when services are seen as beneficial and easy to navigate.

Overall, the findings show that fostering trust, shaping positive attitudes, and carefully designing humanlike features are critical to improving acceptance. By clarifying how intelligence, anthropomorphism, usefulness, ease of use, trust, and perceived risk interact to influence adoption intention, the study provides evidence for financial institutions on how AI features can improve customer experience and encourage adoption in Yangon and other emerging markets.

5.2 Recommendation

To enhance the adoption of AI-powered mobile payment applications in Yangon and similar emerging markets, several strategic actions are recommended.

Mobile payment service providers should prioritize strengthening users' attitudes and trust by communicating clear value propositions, ensuring reliable system performance, and applying user-centered design principles. Robust security measures—such as biometric authentication, real-time fraud detection, and transparent privacy practices—should be visibly demonstrated, supported by recognizable trust signals to reinforce user confidence. Providers may further improve engagement by integrating AI-driven personalization, conversational interfaces, and responsive chatbots to increase perceived intelligence, anthropomorphism, and overall satisfaction.

Policymakers can facilitate adoption by establishing clear regulatory frameworks on data protection, cybersecurity, and consumer rights while promoting financial literacy and digital education to reduce perceived risks and improve user understanding.

Technology developers should integrate advanced AI capabilities, such as predictive spending insights and personalized financial recommendations, supported by intuitive interface designs, streamlined onboarding, and multilingual options to enhance usability and accessibility. Continuous innovation and iterative refinement of features and interface designs remain essential to ensuring sustained user adoption and engagement.

5.3 Limitation and Further Study

This study focused on users of the top three mobile payment applications in Yangon, Myanmar, which may limit generalizability. Future research could explore diverse populations, additional platforms, and cross-cultural contexts, including urban-rural differences, to better understand adoption patterns. Comparative studies across bank-led, telecom-led, and independent applications are also recommended. Using a quantitative survey design, this study could be complemented by mixed-method approaches, such as interviews or focus groups, to capture richer insights into user perceptions and motivations. The conceptual framework may be expanded by integrating models like the Unified Theory of Acceptance and Use of Technology (UTAUT), the Expectation-Confirmation Theory of Information System Continuance (ECT-IS), or Information Systems Success Model (ISSM), which consider moderating factors, post-adoption behavior, and system quality dimensions. Finally, the strong link between perceived intelligence and anthropomorphism warrants further investigation, including potential moderators such as personality, culture, or prior AI experience, to clarify how cognitive and affective perceptions jointly influence attitudes and adoption.

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