Unraveling the AI Banking Frontier: How Perceived Intelligence and Anthropomorphism is Revolutionizing Philippine Mobile Banking?

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ABSTRACT

The cumulative consumer exigence for more powerful self-service technologies around the world unfastens ingresses for artificial intelligence (AI) in transforming the banking industry through proffering personalized and consumer-centric service innovations. This research aims to empirically test how AI features, explicitly avowed intelligence and anthropomorphism, impact task-technology fit (TTF), perceived cost, perceived risk, and trust, which subsequently, influence user adoption of AI in mobile banking applications. The data were collected from 486 respondents through homogeneous purposive sampling. To analyze the latent variables, confirmatory factor analysis, structural equation modeling, and mediation analysis were performed. The outcomes bared that perceived intelligence enhanced the propensity of users to adopt mobile banking apps through TTF, perceived cost, and trust. On the other hand, the professed anthropomorphism exhibited a positive effect on users' perceived cost. Furthermore, the mediation model adjudicated the impact of users' perceived intelligence and anthropomorphism on perceived risk to be statistically insignificant. Anchored on these findings, bank operators can develop user retention strategies by fostering and implementing personalized interactions, transparent communication of AI benefits, and continuous user education and support.

Keywords: artificial intelligence, mobile banking, SOR model, human-AI interaction.

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1. BACKGROUND OF THE STUDY

In contemporary epochs, banks have been disrupted by major technological alteration as fewer consumers visit physical branches. This shift has led to prevalent branch closures, adversely affecting banks' ability to maintain and propagate deposits. However, banks with enhanced online banking capabilities experience a mitigated impact (Pham et al, 2022). Simultaneously, the global market for mobile devices and wireless services in emerging markets like China, Thailand, Indonesia, and the Philippines, has leapfrogged mobile infrastructure over fixed-line maturities. Such developments have impelled mobile banking into a dominant position within the realm of electronic banking (Gupta, Manrai, and Goel, 2019; George, 2018).

Extant literature underscored that user adoption and acceptance are crucial drivers for the successful implementation of mobile banking. The nascent landscape of mobile banking,

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driven by an increased demand for intelligent and personalized services in the banking sector, has underpinned the critical role of artificial intelligence (AI) techniques (Loureiro et al., 2020; Milana and Ashta, 2021). A 2021 McKinsey report conjectures that over the next decade, quintessential technologies such as artificial intelligence (AI) and blockchain will spearhead Fintech development, reshaping the competitive landscape in the finance and banking sector (Fong et al., 2021). AI has emerged as a significant influencer in the adoption of mobile banking services, with its capabilities highlighted in various studies (Darby, 2016; Payne, Peltier, and Barger, 2018).

In the mobile banking sphere, AI refers to the utilization of intelligent machine performance and human-like behavior to enhance users' experiences with banking services (Lu, 2019). AI abets users in completing tasks by twigging their background, addressing inquiries, and providing valuable assistance (Lin et al., 2023). For instance, the Bank of the Philippine Islands (BPI) refurbished its banking app with 'AI-powered insights'. Amid its features, the app abridged the opening process for new customers, permitting them to open a BPI Save Up account with just a single ID. Introducing an AI-powered personal finance management feature provided users with financial advice, payment reminders, and actionable tips (Yu, 2023).

Within AI-enabled mobile banking applications, intelligent service programs dexterously process user requests, analyze emotions, and employ natural language to offer personalized services and facilitate transactions (West, 2019). Further, Blut et al. (2021), in a meta-analysis of more than 11,000 individuals interacting with service robots reported in 108 independent samples, found that AI can postulate anthropomorphic services. That said, in perception the role of AI in mobile banking applications is anchored on two core AI features: intelligence and anthropomorphism (Kin and Im, 2013; Moussawi, Koufaris, and Benbunan-Fich, 2021; Troshani et al., 2021). Intelligence pertains to a system's ability to exhibit proficient and autonomous behavior, abetting users with various financial services or tasks. Conversely, anthropomorphism depicts a system that rivals human behavior when executing a service or task, aiming to provide a more relatable and human-like interaction (Lin et al., 2023).

Gupta et al. (2019) underscored that users predominantly take into account functional and technical factors in using mobile banking applications. The extant literature pinpointed critical factors such as task-technology fit (TTF), perceived cost, and perceived risk implicitly influence the adoption of mobile banking (Zhou et al., 2010; Owusu Kwateng et al., 2019; Priya et al., 2018). Beyond functionality, user trust plays a pivotal role in adoption, with trustworthiness impacting users' willingness to share personal information (Gupta et al., 2019; Malaquias and Hwang, 2019).

The assimilation of AI technology into mobile banking, often unnoticed in current studies, particularly in terms of AI features like intelligence and anthropomorphism, presents an unexplored area (Payne, Peltier, and Barger, 2018). Indulgent how these AI features impact both functional (TTF, perceived cost, risk) and psychological (trust) aspects of mobile banking apps requires further enquiry. Further, the mainstream of the studies had focused on the role of AI in the backend mobile banking services, entailing a dearth of research on how AI can be applied to improve customer interaction in mobile banking applications (Casu et al., 2016). Thus, this study tackled the research question: "How do intelligence and anthropomorphism, positioned as primary AI features, influence functional and

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psychological factors, which in turn, impact user intentions in the adoption of AI-enabled mobile banking apps?”

2. LITERATURE REVIEW, THEORETICAL FRAMEWORK, AND HYPOTHESIS DEVELOPMENT

2.2 AI applications in mobile banking

As mobile technology redevelops to advance, the practical integration of AI and mobile banking has become more stalwart. Researchers emphasized that AI, is a focal element in mobile banking innovation (Huang et al., 2021), it clutches the potential to augment user experiences and upsurge the efficiency of banking services (Jiang, 2018; Huang and Rust, 2020; Lin et al., 2023). When utilizing AI-enabled mobile banking apps, users facing defies can seek timely assistance from artificially intelligent services (Wu et al., 2021). These apps leverage AI to intelligently use natural language and formulate precise queries, offering assistance during interactions and maintaining consistency in addressing similar problems. The intentions are to generate standardized, reliable results (Selley, Baker, and McKay, 1997; Payne, Peltier, and Barger, 2018), enhance efficiency (Lin et al., 2023), and mitigate the risk of subjective judgment errors in human customer service. Additionally, these apps can provide personalized benefits by identifying and matching different user descriptions with similar problems (Wiegard and Breitner, 2019; Payne, Peltier, and Barger, 2018, 2021), fully reflecting anthropomorphism.

2.2 Stimulus-Organism-Repones Theory

To comprehend the adoption of AI-enabled mobile banking by users, this analysis delved into the characteristics of AI technology as perceived by users, influencing their internal states and subsequently shaping their approach and avoidance behaviors. In this context, we aim to employ the Stimulus-Organism-Response (SOR) theory (Mehrabian and Russell, 1974) as a comprehensive theoretical framework to investigate user adoption of AI mobile banking apps. SOR theory proved more apt for elucidating AI-enabled mobile banking than traditional models like the Technology Acceptance Model (TAM) or Unified Theory of Acceptance and Use of Technology (UTAUT), given that user adoption involves exposure to various stimuli, namely AI features (Cho, Lee, and Yang, 2019).

Instigating from environmental psychology, SOR theory has been widely applied in prior studies to reconnoiter user behavior in the mobile app context (Chen and Yao, 2018; Ashraf et al., 2021; Wu et al., 2021). In this theory, stimulus encompasses a collection of attributes impacting user perception, organism denotes the internal processing mechanisms and evaluations of users, and response reflects the outcomes of users' reactions based on their assessment of AI-enabled mobile banking adoption (Mehrabian and Russell, 1974). Building on SOR theory, our exploration focuses on how AI features, specifically perceived intelligence and anthropomorphism, function as stimuli, shaping users' functional evaluations (e.g., Task-Technology Fit (TTF), perceived cost, risk) and psychological evaluations (e.g., trust) (organism). These valuations subsequently influence the intention to adopt mobile banking apps (response) during interactions with AI-enabled mobile banking applications.

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2.3 AI's anthropomorphism and intelligence as stimuli

The assessment of AI features predominantly centers on users' perceptions, distinguishing them from perceptions of other systems due to the personalized, intelligent, and anthropomorphic behavior exhibited by AI applications (Huang and Rust, 2020; Grewal et al., 2021; Mishra et al., 2021). A systematic analysis by Moussawi and Koufaris (2019) acknowledged perceived intelligence and anthropomorphism as two critical characteristics of AI-enabled systems. Specifically, perceived intelligence is defined as the extent to which the behavior of mobile banking apps is perceived as capable of providing effective output through AI to complete tasks and generate and process natural language. AI-enabled systems are designed to exhibit human-like images, and titles, or simulate human emotions and behaviors (Lin et al., 2020; Moussawi and Koufaris, 2019), with these human-like characteristics termed anthropomorphism (Moussawi and Koufaris, 2019; Moussawi et al., 2020). However, perceived intelligence and perceived anthropomorphism are not completely different and unrelated structures. Moussawi et al. (2020) mentioned that when users employ AI-enabled services, their display of intelligent characteristics may also cause users to regard it as caring, loving, respectful, or interesting. The communication of AI services makes people feel that the applications are anthropomorphic and have a deeper understanding (Mishra et al., 2021; Moussawi et al., 2020; Moussawi and Koufaris, 2019) of users' needs. Therefore, an increase in perceived intelligence may also increase perceived anthropomorphism. We hypothesize that:

H_1: Perceived intelligence has a direct relationship with perceived anthropomorphism.

2.4 Functional and psychological factors as organism

Scholars have underscored that resistance to innovation adoption originates primarily from functional and psychological perspectives (Ram and Sheth, 1989; Huang et al., 2021). Following Ram and Sheth's (1989) definitions, functional aspects encompass three main factors: Task-Technology Fit (TTF), perceived cost, and risk. In mobile banking, risk—related to financial loss, privacy, and data misuse—emerges as a major predictor of adoption (Priya et al., 2018). Additionally, research indicates that understanding users' perceptions of cost is pivotal, as it influences the predictive ability to comprehend and adapt to the usage of mobile banking apps (Hanafizadeh et al., 2014; Owusu Kwateng et al., 2019; Merhi et al., 2019). Moreover, the TTF model has been widely adopted in existing studies to explore users' evaluations of mobile banking adoption (Zhou et al., 2010; Baabdullah et al., 2019). Researchers have affirmed that integrating multiple factors enhances the explanatory power of user adoption intention (Zhou et al., 2010; Baabdullah et al., 2019). Therefore, after amalgamating risk, cost, and TTF in this study, functional factors (organismic experiences) are further considered to predict users' intentions to use AI mobile banking apps.

From a psychological perspective, existing literature indicates that the most significant source of psychological resistance lies in the trust issues brought about by mobile banking innovation (Gupta et al., 2019; Malaquias and Hwang, 2019). Sarkar et al. (2020, p. 286) also emphasize that trust is the most influential predictor of m-commerce adoption, strongly determining its success. Additionally, Bedue and Fritzsche (2021) demonstrate that a crucial path toward improved AI-based adoption is trust-building, prompting our choice of trust as a primary psychological factor (organism) in the model.

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Furthermore, existing studies have individually tested various functional and psychological factors influencing users' adoption of mobile banking (Gupta and Arora, 2017), yet none have amalgamated them into a single model. The field of social psychology literature posits that factors influencing adoption and resistance may not only be opposites; they can also be explained by behavioral reasoning theory, allowing simultaneous testing of the impact of adoption and resistance factors in a single model (Gupta and Arora, 2017). In this context, this study investigates the factors (organism) influencing users' adoption of mobile banking apps by integrating both functional and psychological aspects, corresponding to the selection of TTF, perceived cost, risk (functional factors), and trust (psychological factors).

2.4.1 Task-technology fit

In AI-enabled mobile banking apps, leveraging existing AI technologies allows service programs to deliver personalized services to users, enhancing their experience (Payne, Peltier, and Barger, 2018). These apps are designed with anthropomorphic features (Lin et al., 2023). The human-like attributes enable users to engage with mobile banking transactions as if interacting with real individuals, enhancing the overall user experience (Lin et al., 2023). Anthropomorphic features, as highlighted by Mohd Thas Thaker et al. (2019), bring benefits to users by making technology more accessible for task completion. Task-technology fit (TTF) plays a crucial role in user adoption, assuming that users engage with mobile banking for improved performance and efficiency (Baabdullah et al., 2019). If an AI-enabled mobile banking app aligns its technologies effectively with the user's need, creating a highly compatible environment, users perceive the service as useful, thus increasing their adoption intention. This assumption forms the basis for understanding how TTF influences users' perceptions and adoption behavior in the context of AI-enabled mobile banking apps. That said, we pose the following hypotheses:

H_2: Perceived intelligence has a direct relationship with task technology fit.

H_3: Perceived anthropomorphism has a direct relationship with task technology fit.

H_4: Task technology fit enhances user adoption of mobile banking applications.

2.4.2 Perceived cost

The perceived costs, including search, information, bargaining, decision-making, and execution, are crucial determinants of users' willingness to adopt (Lin et al., 2020). Perceived cost represents a cognitive analysis of personal trade-offs in users' adoption of mobile banking applications. When users perceive that the value offered by the service outweighs the associated costs, they are more likely to adopt it (Owusu Kwateng et al., 2019). The intelligent anthropomorphic characteristics of AI-powered mobile banking applications contribute to a reduction in waiting costs for users. By having in-app features that replicate manual customer service, AI provides standardized answers promptly, eliminating the need for users to wait in line in an actual bank for assistance. Moreover, the transition from traditional mobile banking customer service to AI-powered services requires minimal time and effort for users to adapt, as the simulation of manual customer service is user-friendly and efficient. Withal, personalized functions tailored to individual needs further contribute to lowering transaction costs (Lin et al., 2020). Consequently, the perceived cost associated with AI-powered mobile banking apps is effectively reduced, positively impacting their adoption (Singh and Srivastava, 2018).

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H_5: Perceived intelligence has an indirect relationship with perceived cost.

H_6: Perceived anthropomorphism has an indirect relationship with perceived cost.

H_7: Perceived cost curbs user adoption of mobile banking applications.

2.4.3 Perceived risk

Perceived risk pertains to the level of uncertainty users experience regarding their ability to achieve anticipated results, encompassing potential losses due to discrepancies between user expectations and technology performance (Chen & Lai, 2023; Hassan and Wood, 2020). These risks could manifest as financial, performance, and privacy concerns. Financial risk, a core technology-driven concern, often arises from fears of transaction errors leading to losses, which hinder users from adopting mobile banking. The development of AI in mobile banking apps has the potential to enhance users' perception of intelligence, mitigating risks associated with the backend operating system and reducing the likelihood of financial risks. Further, privacy risk, a prominent and frequently discussed concern, revolves around the misuse of user data and the potential for fraud or theft (Darby, 2016). The intelligence embedded in mobile banking apps diminishes the perceived risk associated with sharing personal information, while simultaneously enhancing users' perceptions of data protection during interactions. If there is a misalignment between user needs and the actual performance of mobile banking technology, leading to unexpected results, the perceived risks may surpass user expectations, resulting in potential losses and diminishing users' willingness to adopt mobile banking (Wiegard and Breitner, 2019). That said, we hypothesize:

H_8: Perceived intelligence has an indirect relationship with perceived risk.

H_9: Perceived anthropomorphism has an indirect relationship with perceived risk.

H_{10}: Perceived risk curbs user adoption of mobile banking applications.

2.4.4 Trust

The intelligent anthropomorphism characteristics of AI have become a focal point of study in various fields, including information systems (Moussawi et al., 2020), marketing (Huang and Rust, 2020, 2021), and finance (Belanche et al., 2019; Milana and Ashta, 2021). The integration of intelligence in these apps not only reduces operational errors but also enhances trust in mobile banking (Moussawi and Koufaris, 2019). Trust serves as a foundational element during users' adoption of mobile banking, crucial for establishing successful interactions with AI services (Gupta et al., 2019). It aids individuals overcome the perception of uncertainty and facilitates the development of trust-based relationships, evident in behaviors such as sharing personal information (Moussawi et al., 2020). Lin et al. (2021) highlighted that the intelligence of mobile banking apps, characterized by autonomous efficiency, natural language processing abilities, and user-centric support, fosters a sense of trust among users. The anthropomorphic component further enhances trust during interactions, as users subliminally perceive the mobile banking AI app as a real person (Lin et al., 2023). Consequently, users are more likely to trust mobile banking apps when they perceive the services as intelligent and anthropomorphic.

Research has demonstrated that a lack of trust leads to concerns about the unauthorized transfer of personal information or funds, resulting in user reluctance to engage in mobile banking transactions (Gupta et al., 2019; Owusu Kwateng et al., 2019; Merhi et al., 2019).

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H_{11}: Perceived intelligence has a direct relationship with trust.

H_{12}: Perceived anthropomorphism has a direct relationship with trust.

H_{13}: Trust enhances user adoption of mobile banking applications.

2.5 Mediation effect of functional and psychological factors

The extant literature underlined the potential for user internal evaluation (organism) to serve as a theoretical mediator within the framework of SOR theory (Cho et al., 2019; Chan et al., 2017; Arora, 1982). Anchored on Baron and Kenny's (1986) criteria for mediation, this presents a scenario where an independent variable influences a dependent variable through an additional theoretically relevant variable. As posited in our earlier hypothesis, in the context of AI, the features of intelligence and anthropomorphism may impact users' intentions to adopt AI mobile banking apps by shaping their perceptions and evaluations of TTF, cost, risk, and trust. Essentially, organismal experiences (i.e., the functional and psychological factors proposed in this study) may act as mediators in the relationship between stimuli (AI characteristics) and user response (adoption intention) (Figure 1).

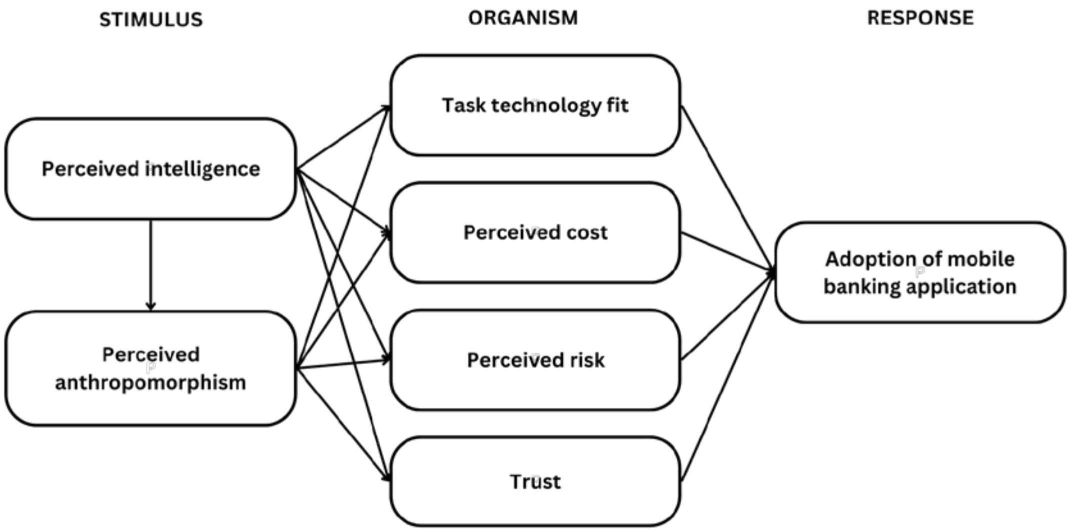

Figure 1. SOR Model

2.6 Research gap

In retort to the emergence of AI services in mobile banking, this study protracted the current perceptive of mobile banking by delving into the AI-powered evolution of mobile banking apps. Despite numerous studies discussing AI''s role in users' adoption or usage of mobile banking, there's a dearth in the literature in light exploring how AI features, specifically intelligence and anthropomorphism, influence users' functional and psychological evaluations within the realm of AI-based mobile banking. To address this gap, we leverage SOR theory, treating intelligence and anthropomorphism as stimuli, and investigate their impacts on Task-Technology Fit (TTF), risk, perceived cost (functional organism), and trust (psychological organism). These factors, in turn, affect users' intentions to adopt AI-enabled mobile banking apps (response).

Likewise, recognizing potential variations in user perceptions and reactions across different countries, we acknowledge the importance of a contextualized investigation at the

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national level. This approach offers unique insights into less-explored contexts, contributing to the creation of new knowledge. Existing AI-enabled financial or banking research predominantly focuses on the USA, UK, or Australia, leaving a void in understanding users' perceptions of AI banking services in the Chinese context. Therefore, this study emphasizes Chinese users, exploring their cognition in adopting AI-enabled mobile banking apps through both functional and psychological aspects. This endeavor aims to enhance country-specific understanding of how AI technology shapes mobile banking services in China.

3. METHODOLOGY

The research design followed a causal quantitative approach to determine the cause-and-effect links of the latent variables. Through homogeneous purposive sampling, the survey data were collected from Filipinos aged 18 to 44 who are users of mobile banking applications. The data collection process was executed through an online survey through Google Forms, which received a total of 486 valid responses. Table 1 describes the research instruments utilized in the study. The validity of measurement scales was assessed through Cronbach's Alpha which generated values between 0.863 and 0.933, implying good reliability and internal consistency.

Table 1. Item Measurement Scales per Latent Variable

Latent Variable	**Item Measurement Scales**	**Cronbach's Alpha**	**Reference**
Perceived intelligence (PI)	PI1: Mobile banking apps can help me complete banking business quickly PI2: Mobile banking apps can understand my instructions PI3: Mobile banking apps can communicate with me in a way that I understand PI4: Mobile banking apps are able to set and pursue tasks autonomously in anticipation of future user needs PI5: Mobile banking apps can adapt their behavior based on prior events	0.863	Lin et al. (2021), Moussawi and Koufaris (2019)
Perceived anthropomorphism (PA)	PA1. Using a mobile banking app to complete a task feels similar to interacting with a real person PA2. The mobile banking app feels friendly PA3. I feel that the mobile banking app respects me PA4. The mobile banking app makes	0.9	Lin et al. (2021), Moussawi and Koufaris (2019)

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	me feel interesting PA5. The mobile banking app makes me feel considerate		
Task technology fit (TTF)	TTF1. The banking functions provided by the mobile banking app are comprehensive TTF2. The services provided by the mobile banking app meet my business needs TTF3. The various banking service functions provided by the mobile banking app are useful TTF4. The functions provided by the mobile banking app are consistent with the banking tasks I need to complete TTF5. The functions provided by the mobile banking app simplify the banking tasks I need to complete	0.912	Lin and Huang (2008)
Perceived cost (COST)	PC1. Adopting mobile banking apps is expensive PC2. I think surfing the Internet using mobile banking apps would be expensive PC3. The main obstacles to using mobile banking apps involve financial or monetary difficulties (such as learning, searching, decision-making, execution costs, etc.)	0.816	Hanafizadeh et al. (2014)
Perceived risk (RISK)	PR1. I feel that using mobile banking apps may expose my bank information to potential fraud PR2. I think the use of mobile banking apps may threaten the privacy of my personal information PR3. I feel that using mobile banking apps may expose my bank account to financial risks PR4. I think that my private information might be hacked when using mobile banking apps PR5. I think that choosing to conduct banking activities	0.933	Hassan and Wood (2020)

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	through mobile banking apps is a risky choice		
Trust (TRUST)	TR1. I believe that mobile banking apps are trustworthy TR2. I believe that mobile banking apps have users' interests at heart TR3. I believe that mobile banking apps provide safe services TR4. I trust mobile banking apps to protect my personal information	0.889	Hassan and Wood (2020)
Adoption intention (ADI)	ADI1. If my bank were to provide a mobile banking app, I would use it immediately ADI2. If mobile banking apps become available, I would adopt them ADI3. I plan to increase my adoption of mobile banking apps in the future ADI4. I would use mobile banking apps because my family and friends do	0.859	Priya et al. (2018)

The research hypotheses underwent empirical investigation through structural equation modeling (SEM), a two-step process involving (1) assessing the reliability and validity of the measurement model through confirmatory factor analysis (CFA) and (2) testing the structural models via path analysis, as outlined by Fan (2016). Structural equation models integrate factor analysis with path analysis and other path modeling techniques, employing a set of linear equations to delineate the hypothesized relationships between latent variables and their multiple indicators, as discussed by Knoke (2005).

Statistical analyses were conducted using the Lavaan package in RStudio. Ancillary, the model evaluation relied on fit indices, namely the Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA). For an acceptable model fit, thresholds were set at values above 0.90 for TLI and CFI (Hu & Bentler, 1999) and 0.08 or less for SRMR and RMSEA (Hu & Bentler, 1999; Fabrigar et al., 1999).

4. RESULTS AND DISCUSSION

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4.2 Descriptive Statistics

The dataset, grounded on 486 observations, displays mean values ranging from 1.38 (STD) to 6.21 (PI1) on a 7-point scale, with standard deviations from 0.501 to 1.780. The sex distribution is 56% female and 44% male. Most participants (68.5%) are aged 18–25, with lesser groups in older age brackets. Educational background shows 70.6% have an undergraduate degree, 20.4% are postgraduates, and 9.1% completed high school. Nearly half of participants (47.5%) earn below PHP 15,000 monthly, while 52.5% earn higher, up to above PHP 100,000.

Table 2. Descriptives

	N	Missing	Mean	Median	SD	Minimum	Maximum
PI1	486	0	6.21	7.00	1.190	1	7
PI2	486	0	5.83	6.00	1.268	1	7
P13	486	0	5.83	6.00	1.222	1	7
PI4	486	0	5.57	6.00	1.432	1	7
PI5	486	0	5.28	5.00	1.522	1	7
PA1	486	0	4.64	5.00	1.758	1	7
PA2	486	0	5.44	6.00	1.443	1	7
PA3	486	0	5.18	5.00	1.545	1	7
PA4	486	0	4.75	5.00	1.780	1	7
PA5	486	0	4.84	5.00	1.689	1	7
TTF1	486	0	5.58	6.00	1.289	1	7
TTF2	486	0	5.79	6.00	1.198	1	7
TTF3	486	0	5.96	6.00	1.133	1	7
TTF4	486	0	5.90	6.00	1.185	1	7
TTF5	486	0	5.94	6.00	1.223	1	7
PCO1	486	0	3.40	3.00	1.802	1	7
PCO2	486	0	3.50	3.00	1.787	1	7
PCO3	486	0	4.40	5.00	1.705	1	7
RI1	486	0	4.99	5.00	1.611	1	7
RI2	486	0	4.95	5.00	1.637	1	7
RI3	486	0	4.88	5.00	1.657	1	7

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RI4	486	0	4.95	5.00	1.713	1	7
RI5	486	0	4.47	5.00	1.731	1	7
TR1	486	0	5.02	5.00	1.260	1	7
TR2	486	0	4.99	5.00	1.378	1	7
TR3	486	0	5.05	5.00	1.326	1	7
TR4	486	0	4.98	5.00	1.446	1	7
ADI1	486	0	5.57	6.00	1.406	1	7
ADI2	486	0	5.65	6.00	1.279	1	7
ADI3	486	0	5.59	6.00	1.371	1	7
ADI4	486	0	5.44	6.00	1.536	1	7

4.3 Normality Check and Common Method Bias

The Mardia's test and the Anderson-Darling test were utilized in evaluating multivariate and univariate normality respectively, exposing a non-normal distribution in the survey data. In response to this deviation from normality and to minimize the influence of outliers, the present study utilized the maximum likelihood robust (MLR) estimator, as proposed by Rosseel (2012). Further, Harman's single-factor test was executed, revealing a 0.34 proportion variance is less than the 0.5 threshold. This confirms that item measurement scales are unaffected by common method bias issues (Rosseel, 2012).

4.4 Measurement Model

Confirmatory factor analysis was utilized to validate the factor structure of the primary research model. Factor loadings equal to or exceeding 0.7 are deemed robust, indicating a substantial relationship between the observed variable and the latent construct. However, to avoid losing data, factor loadings below 0.6 will be eliminated in the structural model. Nonetheless, factor loadings falling within the 0.4 to 0.6 range are considered moderate, suggesting a reasonable association between the observed variable and the latent construct, albeit not as prominent as those with higher loadings. Observably in Table 2, the initial CFA includes model fit indices that were in the acceptable range except for RMSEA. After removing the item measurement scales with factor loadings below 0.6, all model fit indices observably improved and were well within the acceptable range.

Table 3. Comparison of Model of Fit Indices

Model Fit Indices	Acceptable Range	Initial CFA	Final CFA
Tucker Lewis Index (TLI)	Above 0.90 (Weston & Gore, 2006)	0.932	0.944
Comparative Fit Index	Above 0.90 (Hu &	0.924	0.936

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(CFI)	Bentler, 1999)		
Standardized Root Mean Square Residual (SRMR)	Less than 0.08 (Hu & Bentler, 1999)	0.061	0.059
Root Mean Square Error of Approximation (RMSEA)	Less than 0.08 (Fabrigar et al., 1999).	0.057	0.053

4.5 Convergent and Discriminant Validity

To enrich the robustness of the measurement model, we conducted an assessment of both convergent and discriminant validity for the measurement scales. The results presented in Table 3 confirmed the convergent and discriminant validity, with Average Variance Extracted (AVE) values exceeding the recommended threshold of 0.5 for each construct. Further, the Heterotrait-monotrait (HTMT) ratios of correlation, falling below the prescribed 0.90 threshold (ranging between 0.041 to 0.879), further validate the discriminant validity of the scales (Fornell & Larcker, 1981; Henseler, 2015).

Table 4. HTMT Ratios of Correlation

	AVE	**PI**	**PA**	**TTF**	**COST**	**RISK**	**TRUST**	**ADI**
PI	0.620	1						
PA	0.650	0.725	1					
TTF	0.683	0.879	0.649	1				
COST	0.706	0.102	0.091	0.061	1			
RISK	0.740	0.041	0.114	0.073	0.45	1		
TRUST	0.671	0.579	0.533	0.603	0.068	0.335	1	
ADI	0.716	0.643	0.449	0.675	0.12	0.192	0.713	1

PI - perceived intelligence; PA - perceived anthropomorphism; TTF - task technology fit; COST - perceived cost; RISK- perceived risk; TR - trust; ADI - adoption intention

4.6 Structural Model

The examination of the structural model revealed statistical significance in eight of the 13 paths, except for H_3, H_8, H_9, H_10 and H_12 (Table 4). All of the model fit indices except for the SRMR were within the acceptable range. Notwithstanding, three of the four model fit indices showed that the structural model exhibited adequate model fit.

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Table 5. Structural model results

Paths	**Estimates**	**SE**	***p*-value**	**Result**
H_1: PI → PA	1.021	0.101	<0.001	Supported
H_2: PI → TTF	0.906	0.105	<0.001	Supported
H_3: PA → TTF	-0.038	0.063	0.546	Not supported
H_4: TTF → ADI	0.427	0.071	<0.001	Supported
H_5: PI → COST	-0.557	0.179	0.002	Supported
H_6: PA → COST	0.444	0.13	0.001	Supported
H_7: COST → ADI	-0.111	0.034	0.001	Supported
H_8: PI → RISK	0.011	0.14	0.935	Not supported
H_9: PA → RISK	-0.148	0.099	0.136	Not supported
H_{10}: RISK → ADI	0.04	0.03	0.179	Not supported
H_{11}: PI → TRUST	0.556	0.106	<0.001	Supported
H_{12}: PA → TRUST	0.09	0.075	0.227	Not supported
H_{13}: TRUST → ADI	0.561	0.078	<0.001	Supported

CFI = 0.929; TLI = 0.921; RMSEA= 0.066; SRMR = 0.087

PI - perceived intelligence; PA - perceived anthropomorphism; TTF - task technology fit; COST - perceived cost; RISK- perceived risk; TR - trust; ADI - adoption intention

The positive imprint of perceived intelligence on perceived anthropomorphism can be understood through the lens of user interactions with AI-enabled systems. When users perceive high intelligence in AI-enabled mobile banking apps, it often correlates with the system's ability to mimic human-like intelligence. Therefore, this perception creates a natural bridge to anthropomorphism. The positive impact occurs because users tend to associate higher intelligence with human-like characteristics. As the perceived intelligence of the AI system increases, users may project more anthropomorphic traits onto the system, such as friendliness, helpfulness, and the ability to comprehend user emotions.

The findings reveal a notable distinction in the impact of task-technology fit (TTF) on users' adoption of mobile banking concerning the AI features of intelligence and anthropomorphism. At the functional level, the results affirm that a higher degree of TTF

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significantly promotes users' adoption of mobile banking applications, aligning with previous research (Zhou et al., 2010; Baabdullah et al., 2019). TTF, emphasizing the compatibility between users' tasks and the technological capabilities of mobile banking apps, emerges as a crucial factor influencing individuals' willingness to embrace these applications. Nonetheless, the nuanced finding indicates that TTF exerts its influence on adoption intention predominantly in the context of perceived intelligence rather than anthropomorphism. In other words, users are more likely to be incited to adopt mobile banking when they perceive a strong coalition between the technological functionalities of these apps and their specific tasks, focusing predominantly on the intelligent aspects of AI. While the impact of TTF on adoption intention remains vigorous, the role of anthropomorphism seems to play a lesser role in this functional relationship.

On this bedrock, intelligence and anthropomorphism are proven to further enhance users' TTF in using AI mobile banking apps. In other words, mobile banking apps powered by AI technology are more effective in providing personalized services to ease users conduct their tasks by matching their needs and purposes. This study contributes to the existing mobile banking literature with the TTF model in that intelligence and anthropomorphism are important catalysts to strengthen the technical ability of mobile banking apps to accommodate users' goals.

Grippingly, intelligence and anthropomorphism unveiled contrasting effects on the cost of utilizing AI-enabled banking applications, wherein intelligence reduces the cost of adoption and anthropomorphism increases the adoption cost. Users may perceive that the AI system in mobile banking app can swiftly and adeptly address their needs, contributing to a streamlined and user-friendly experience. This enhanced efficiency translates to a decreased perceived cost of adoption as users find the transition to the new technology more seamless and less demanding. However, anthropomorphic features of mobile banking apps can lead to heightened user expectations for personalized and context-aware services, akin to human interactions. If the AI system fails to fully meet these elevated expectations, users may experience a learning curve and increased cognitive effort in adapting to the system's behavior, contributing to a higher perceived cost of adoption. This aligns with the findings of Hanafizadeh et al. (2014), whose research identified perceived cost as a significant explanatory variable in the adoption growth of mobile banking among a sample of over 360 Iranian bank clients.

The lack of statistically significant impact of risk on adoption intention suggests that users' decisions to adopt AI-enabled mobile banking apps are not substantially influenced by perceived risks, deviating from the findings of Owusu Kwateng, Osei-Wusu, and Amanor (2020). This could be attributed to the reassurance provided by the intelligent features and anthropomorphic characteristics present in mobile banking applications. Users might trust that the advanced capabilities of the AI-powered apps adequately address potential risks, making risk perceptions less influential in their adoption decisions. Further, bank operators have undertaken extensive measures to instill a robust sense of security among users. The ongoing efforts in risk management and security protocols contribute to fostering an environment where users feel increasingly secure in their interactions with AI-enabled mobile banking apps.

The study outcomes underscored the role of trust in shaping users' inclination toward adopting mobile banking applications, aligning with prior research (Hassan and Wood, 2020). The results reveal a statistically significant direct link between user trust and the

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perceived intelligence of AI-enabled mobile banking apps. That said, users are more likely to place trust in mobile banking applications when they perceive the intelligence embedded in these systems. However, interestingly, the results did not establish a similar direct relationship between user trust and anthropomorphism. This nuanced finding suggests that while users' trust is influenced by the perceived intelligence of the AI system, anthropomorphic features may not play a direct role in shaping user trust within the mobile banking context.

Table 6. Structural model with mediation analysis results

Paths	Direct effect	Indirect effect	Result
PI → TTF → ADI	0.01	0.444***	Full mediation
PA → TTF → ADI	-0.099	-0.016	No mediation
PI → COST → ADI	0.01	0.05**	Full mediation
PA → COST → ADI	-0.099	-0.04**	Full mediation
PI → RISK → ADI	0.01	<0.001	No mediation
PA → RISK → ADI	-0.099	-0.005	No mediation
PI → TRUST → ADI	0.01	0.319***	Full mediation
PA → TRUST → ADI	-0.099	0.058	Full mediation

CFI = 0.920; TLI = 0.929; RMSEA= 0.066; SRMR = 0.086

PI - perceived intelligence; PA - perceived anthropomorphism; TTF - task technology fit; COST - perceived cost; RISK- perceived risk; TR - trust; ADI - adoption intention

Table 5 displays the results of the structural model with mediation analysis. Observably, we found no evidence that perceived risk has a mediating impact on the link between perceived intelligence and anthropomorphism, and adoption intention. This implied that mobile banking users' adoption may be driven by the positive attributes of AI features, bypassing the need for risk perceptions to mediate this relationship. Further, the mediation effect of TTF illustrated how the impact of perceived intelligence on adoption intention is channeled through users' evaluations of how well the technology fits with the tasks at hand. Essentially, when users perceive the intelligence of AI in mobile banking applications, this recognition influences their assessment of how seamlessly the technology aligns with their specific tasks and needs.

The mediation analysis also disclosed that trust and perceived cost had a full mediating effect on the relationship between adoption intention and AI features. Trust acts as a bridge that facilitates users' propensity to adopt, as it alleviates concerns related to the reliability and security of mobile banking application. Similarly, the perceived cost of adopting AI-enabled mobile banking applications, influenced by both intelligence and anthropomorphism, reflects cognitive trade-off analysis. When users perceive the value

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provided by these applications as higher than the associated costs, it positively affects their adoption intention.

5. CONCLUSION AND RECOMMENDATION

Cultivating on the stimulus-organism-response model, this inquiry looks into how the intelligent and anthropomorphic features of artificial intelligence (stimuli) in mobile banking applications impact functional and psychological factors (organism), and in turn, influence adoption (response) among Filipino users. The organism factors included task technology fit (TTF), perceived risk, perceived cost, and trust.

The brunt of AI features on the cost of adoption, diverges. Perceived intelligence ebbs the adoption cost by augmenting efficiency and crafting a seamless user experience. Contrastingly, anthropomorphism amplifies the adoption cost due to heightened user outlooks for bespoke and context sentient services, leading to a learning curve and amplified cognitive effort. Enigmatically, perceived risk had no statistically significant bearing on adoption intent, denoting that users' decisions to adopt AI-enabled mobile banking apps are not substantially predisposed by perceived risks. This may be ascribed to the reassurance afforded by intelligent edifices and anthropomorphic characteristics, along with the all-encompassing risk management conduits implemented by banks. Likewise, trust surfaced as a crucial factor shaping users' proclivity to adopt mobile banking apps, predominantly induced by perceived intelligence.

Anchored on such findings, banks and other financial institutions may invest further in consumer product enhancement to optimize coalition between AI functionalities. Personalized banking is a prime paradigm of how these results are being applied in practice. Banks currently offer landscape that provide germane and timely succor, such as tailored product proposals based on the user's financial conduct. For exemplar, the Commonwealth Bank of Australia (CBA) uses its CommBank app and NetBank platform to offer a feature called "Benefits Finder." This contrivance helps customers discover and apply for benefits, rebates, and concessions they may be entitled to, concocting the banking experience more user-centric and responsive to individual needs (Commonwealth Bank, 2023).

Operative on these findings, banks are progressively instigating customization options that allow users to personalize their app familiarity. This comprises customizable dashboards, smart investment trackers, savings planners, and notification settings—features that allow users to stencil the platform to their personal preferences, providing a more engaging episode. Banks must likewise invest in developing anthropomorphic topographies that afford context cognizant assistance. For instance, a virtual banking assistant with human-like characteristics can twig and riposte to users' contextual queries, propounding a more innate and personalized user interface. Anthropomorphic AI, such as virtual banking assistants, epitomizes another emergent trend that stalemate bluntly to managerial practices. Bank of America's virtual assistant, Erica, is typical of this. Erica uses advanced AI to interact with customers in a natural, conversational manner, assisting them to manage transactions, review account balances, and even receive financial advice (Bank of America, 2024).

The study conceded several constraints that should be considered in future research endeavors. Given that the study was conducted exclusively in the Philippines, it is recommended for future investigations to gather responses from multiple countries with

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varying customer characteristics to enhance the generalizability of the findings. Imminent research could delve into the exploration of intelligent and anthropomorphic features of AI beyond the realm of mobile banking, ranging their application to diverse sectors. Such as, exploring how these AI attributes manifest and influence user experiences in sectors like fashion retail and consumer goods would provide valuable insights. This comprehensive exploration would interpose to a more exhaustive understanding of the implications and applications of AI features, allowing for the development of bespoke plans and solutions amongst various industries.

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