Determinants of mobile stock investment application adoption and its impact on intention to recommend the applications in emerging countries: a case study of Indonesia

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Abstract. *Commonly used research models analysing technological adoption, such as the Technology Adoption Model, Theory of Planned Behaviour, and Unified Theory of Acceptance and Use of Technology, mostly emphasise technology-related variables. In the context of mobile stock investment application adoption, this study extends the existing technological adoption models by adding digital financial service-related variables. The purpose of this study is to investigate the main determinants of mobile stock investment application adoption in emerging countries, specifically in Indonesia. The study deployed a quantitative type of research with an online survey questionnaire by recruiting 256 respondents of stock investors who have used mobile applications for a minimum of one year. Data was analysed using partial least squares structural equation modelling (PLS-SEM) with advanced analysis tests. The results confirm the significant influence of performance expectancy, finfluencers, perceived financial risks, perceived financial benefits, perceived technology security, financial literacy, and e-reputation on adoption behaviour. The results also find a significant influence of adoption behaviour on the intention to recommend. Meanwhile, effort expectancy and facilitating conditions were insignificant toward adoption behaviour. These findings signify that the comprehensive research model could contribute to enriching studies on adoption of the mobile technology by extending TPB and UTAUT with specific variables related to stock investment and its impact on the intention to recommend the applications. Finally, the implications of the proposed new model for future research and FinTech practice are discussed.*

Keywords: mobile application adoption, stock investment, intention to recommend, finfluencers, perceived financial benefits, financial literacy.

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Introduction

Mobile technology has had a significant impact on the stock investment sector both in developed as well as in emerging countries (Lee & Hsieh, 2013). In Malaysia, mobile technology provides easy access to the stock market, convenience, and zero commissions to retail investors (Chong et al., 2021). Mobile technology has also significantly increased stock market participation among retail investors in China (Gao & Li, 2018). In Hong Kong, mobile technology has increased the participation of retail investors by providing ease of trading and speed of decision (Chong & Chan, 2012). In Indonesia, mobile technology has sharply increased the number of retail stock investors by 275% from 1.2 million in 2020 to 10.31 million in 2022 (OJK, 2022; Nair et al., 2022. The COVID-19 outbreak in 2020 and the advancement in mobile technology have been the drivers of the sharp increase in interest and popularity of stock investment (Ahmed, 2022).

The rapid rise of retail stock investors has attracted many new startups in mobile stock investment applications to enter the stock investment sector. These companies compete to offer time, financial services, and financial benefits, such as free commission, quick withdrawal, expert assistants (EA), or Robot Trading (BIS, 2021; Putra et al., 2022). Major banks and asset managers also join in alongside their internal financial services, causing intense rivalry in the market for mobile stock investment applications. The tight competition in this market is reflected in the investment media reviews with none of the players consistently remaining at the top rank (Prasidya, 2020). This creates an urgent need for these startups to expand their customer base, such as by encouraging their existing users to recommend the mobile technology to their family and friends. As there are still limited studies in stock investment investigating the influence of intention to recommend (Oliveira et al., 2016; Octavius & Antonio, 2021), this study includes this variable in the research model.

The rise of mobile stock investing apps attracts more young people with limited knowledge of stock investing (Yulius et al., 2023). They mostly follow the advice of experts in financial matters and stock investing (Tai & Ku, 2013). As these young investors (Generations Y and Z) are digital natives, they look for financial advice online, from social media and online news media (Rose, 2023). Financial advisers followed by young people can be professional experts or just anyone who claims to have experience in stock investing. They drive the adoption of mobile stock investment applications. This study also examines the influence of finfluencers and financial literacy on the adoption of mobile stock investment applications.

Stock investing is a complex matter that is affected by many factors including non-technological factors (Nadeem et al., 2020), for example, the reputation of the organisation running the technology. Mobile stock investment application platforms need to win the trust of new users to adopt their apps by using reputation-gaining strategies (Soleimani, 2022). The increasing number of investment scams on the news lately (Santia, 2022) has made it critical to carefully manage this issue of reputation to build trust. This research will investigate e-reputation of the application providers which hasn't been well-addressed in previous studies (Oliveira et al., 2016; Maziriri et al., 2019).

Considering all the issues discussed, this research proposes an integrated conceptual model that has not been tested before in stock investing using mobile technology. This study involves analysis of the antecedents related stock investment using mobile application that may be used to predict the adoption of a mobile stock investment application and its impact on the intention to recommend the application, using financial service variable of finfluencers, financial literacy, e-reputation and a marketing variable of intention to recommend.

Literature review

UTAUT and UTAUT 2

Unified Theory of Acceptance and Use of Technology (UTAUT) is a technology acceptance model involving performance expectancy, effort expectancy, social influence, facilitating conditions, intention to use, and actual use (Venkatesh et al., 2003). The model is updated in the consumer context by adding three variables: hedonic motivation, price value, and habit (Venkatesh et al., 2012). Finally, Venkatesh et al. (2012) included age, gender, experience, and habit as moderating variables. As this research involves the adoption of new technology, UTAUT 2 is used due to its improved ability to explain the adoption of new technology (Tam & Oliveira, 2018). However, hedonic motivation is not included in this study, as stock investing is more driven by a rational motif rather than a hedonic one (George, 2019). This existing study breaks up the Price value of UTAUT 2 into two variables related to stock investing: perceived financial risks and perceived financial benefits that are more relevantly used in the stock investing context. Habit is not included in this existing research because this research examined the new users of mobile stock investment applications who have not reached the habitual process.

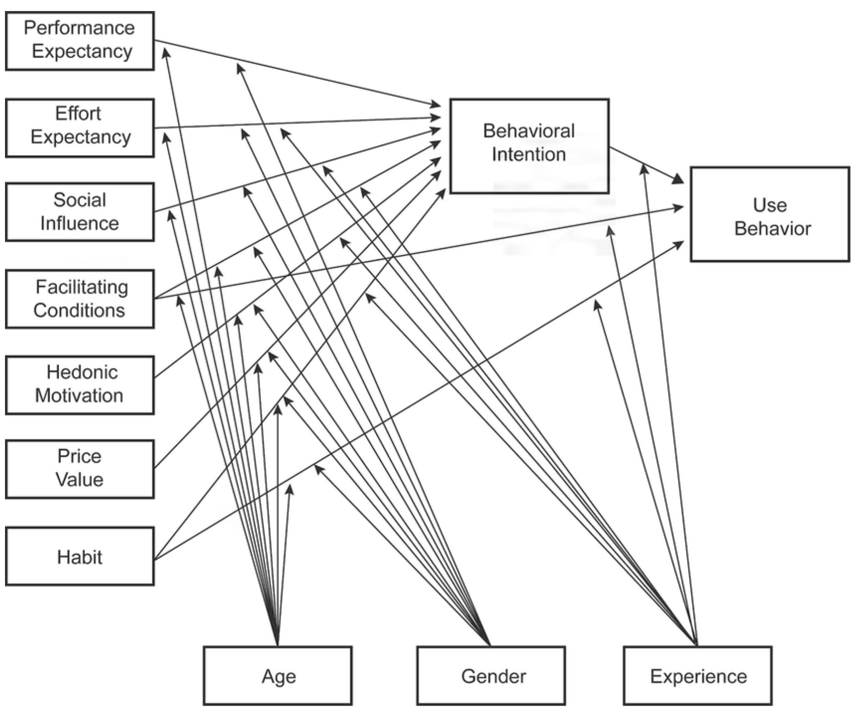

Figure 1. UTAUT 2

Source: Venkatesh et al. (2012).

Performance expectancy, effort expectancy, and the adoption of mobile stock investment applications

Previous empirical studies confirmed the significant influence of performance expectancy on the adoption of new technology in various contexts. Performance Expectancy (PE), Effort

Expectancy (EE), and satisfaction have crucial effects on the adoption of mobile learning among university students (Chao et al., 2019). Another study investigated PE and EE as determinants of the adoption of mobile banking with a sample of 441 respondents (Yu, 2012), In this study, PE and social influence (SI) are the major determinants of consumers' adoption of mobile banking. Similar results were revealed by Sair and Danish (2018) who revealed the existence of a significant influence of PE and EE on adopting mobile commerce. This is in line with the results of another study with three positive determinants of mobile stock trading adoption, namely: PE, EE, and SI (Tai & Ku, 2013). The complexity of Mobile applications in previous studies is very much like that of mobile technology in stock investing analysed in this research. Therefore, it is interesting to examine if PE and EE also have a positive effect on the actual adoption of mobile stock investment applications. Therefore, the following hypothesis is formulated:

H1: Performance expectancy positively influences the adoption of mobile stock investment applications.
H2: Effort expectancy positively influences the adoption of the mobile stock investment application.

Facilitating conditions and the adoption of mobile stock investment application

A study by Susana and Prabhu (2020) employing the UTAUT model found that facilitating conditions (FC) significantly influence technology adoption. FC was also found to be a significant influence on the adoption of e-banking applications (Gladys & Daka, 2016). A similar result in mobile banking adoption was revealed by Oliveira et al. (2016). In the context of mobile payment applications, Linge et al. (2023) found a significant influence of facilitating conditions on adoption behaviour. Tusyanah et al. (2021) also supported the positive influence of FC on the adoption of cashless applications. The findings of previous studies about the influence of Facilitating conditions on adoption behaviour led to the formulation of the third hypothesis of this study.

H3: Facilitating conditions positively influence the adoption of mobile stock investment applications.

Finfluencers and the adoption of mobile stock investment application

Previous studies found a positive influence of social influence on the adoption of new technology (Hong et al., 2008). In the context of e-wallet, Tusyanah et al. (2021) identified a positive influence of social influence on technology adoption. A similar result was found by Yu (2012) who involved 440 respondents in the adoption of mobile banking applications. Hoque and Sorwar (2017) also found a positive effect of social influence on the adoption of m-health in the elderly. The role of social networks has also been empirically found significant in influencing the adoption behaviour of mobile stock trading applications (Chong et al., 2015; Tai & Ku, 2013). In the digital technology landscape, social influence strongly exists in digital society through the role of influencers (Jimenez-Castillo & Sanchez-Fernandez, 2019). In the digital landscape, the financial influencers (finfluencers) are the powerful drive behind the change in consumer behaviour. This study formulates the fourth hypothesis involving finfluencers as follows.

H4: Finfluencers positively influence the adoption of a mobile stock investment application.

Perceived financial risks and the adoption of mobile stock investment application

Perceived financial risk is the perceived financial loss attributed to fraud, identity theft, or errors when using mobile applications. Investors' perceptions of financial risks are critical in the process of financial transactions. Retail investors tend to avoid mistakes rather than maximise utility in purchasing decisions (Adam et al., 2023). Thus, when the perceived financial risk increases, it will discourage retail investors from using the mobile application for their stock investment transactions. A previous study found that perceived financial risk negatively influences adoption behaviour (Chin et al., 2022). Another study also revealed a similar result of the negative effect of financial risks on mobile stock trading applications (Chong et al., 2021). It is interesting to examine if a similar result is also applicable to the adoption of mobile stock investment applications in Indonesia. Thus, the fifth hypothesis is formulated as follows.

H5: Perceived financial risk negatively influences the adoption of Mobile stock investment applications.

Perceived financial benefits and the adoption of mobile stock investment applications

A study revealed a significant effect of perceived benefits, attitudes, and perceived behavioural controls on the adoption of mobile stock trading among young people in Malaysia (Chong et al., 2021). Their study found that Perceived benefits, perceived attitude, and perceived behavioural control positively influence the adoption of mobile stock trading among the younger generations. Other studies also revealed similar results in the context of internet adoption (Mehrtens et al., 2001) and adoption of e-business (Zheng et al., 2006). Jung et al. (2016) found that perceived benefits positively affect attitude and positively impact use behaviour. The results of previous studies concerning the role of perceived financial benefits in the adoption of new technology led to the formulation of the following hypothesis.

H6: Perceived financial benefits positively influence the adoption of a mobile stock investment application.

Perceived technology security and the adoption of mobile stock investment applications

Security in technology adoption gets serious attention from technology adopters or users (Salisbury et al., 2001). Havidz et al. (2018) found a significant effect of perceived technology security on the adoption of WeChat mobile payment. Oliveira et al. (2016) empirically supported this finding of the significant role of technology security and the adoption of new technology in the mobile banking sector. This leads to the formulation of the following hypothesis in this study.

H7: Perceived technology security positively influences the adoption of Mobile stock investment applications.

Financial literacy and the adoption of mobile stock investment application

Financial literacy is found to have a positive effect on fintech adoption in Japan (Yoshino et al., 2020). Similar results were also confirmed by Nguyen & Nguyen (2020) and Das et al. (2020). They found that individuals with high financial literacy are more open to participating in risky financial activities, such as stock investing. Van Rooij et al. (2011) also found a positive impact of financial literacy on stock investment behaviour. Based on the empirical results of the previous studies in the financial services context, the following hypothesis is formulated.

H8: Financial literacy positively influences the adoption of mobile stock investment applications.

E-Reputation and adoption of mobile stock investment applications

Corporate reputation plays an important role in the decision to adopt a new technology (Naveed et al., 2020). Other studies found e-reputation as a critical determinant of consumer behaviour to fintech adoption (Irimia-Diéguez et al., 2023). In the digital landscape, corporate reputation is shaped by various aspects such as consumers' reviews and ratings of the products or services offered (Alwi et al., 2020). Previous empirical findings conclude the critical role of e-reputation in the adoption of a new technology. To investigate if the same result is applicable in this context of mobile applications for stock investment, the next hypothesis is formulated.

H9: E-reputation positively influences intention to adopt mobile stock investment applications.

Adoption of mobile stock trading application and Intention to recommend

Behavioural intention to recommend is a result of a high intention to adopt a particular innovative technology (Oliveira et al., 2016). Marketing new technology-based products requires specifically tailored marketing strategies (Cham et al., 2022), one of which is a recommendation of the satisfied early users (the innovators). These new users who are satisfied using the new technology will most likely recommend the technology to other people in their social network. (Zhang et al., 2015; Xu et al., 2015; Oliveira et al., 2016). Based on the findings of several prior studies, this study posits the following hypothesis.

H10: Adoption of a mobile stock investment application positively influences intention to recommend the adoption of a mobile stock trading application.

Below is the Mobile Application Technology Adoption Model in stock investment proposed as the novelty of this research. This is a comprehensive model using constructs from technology adoption (Performance Expectancy, Effort Expectancy, Financial Conditions), Perceived values in the financial and technology contexts (Perceived Financial Risks, Perceived Financial benefits, Perceived technology security), Financial Literacy as the internal capacity of investors derived from self-determination theory (Ryan & Deci, 1980), Social influence in digital financial society (finfluencers), and e-reputation derived from signaling theory (Spence, 1973).

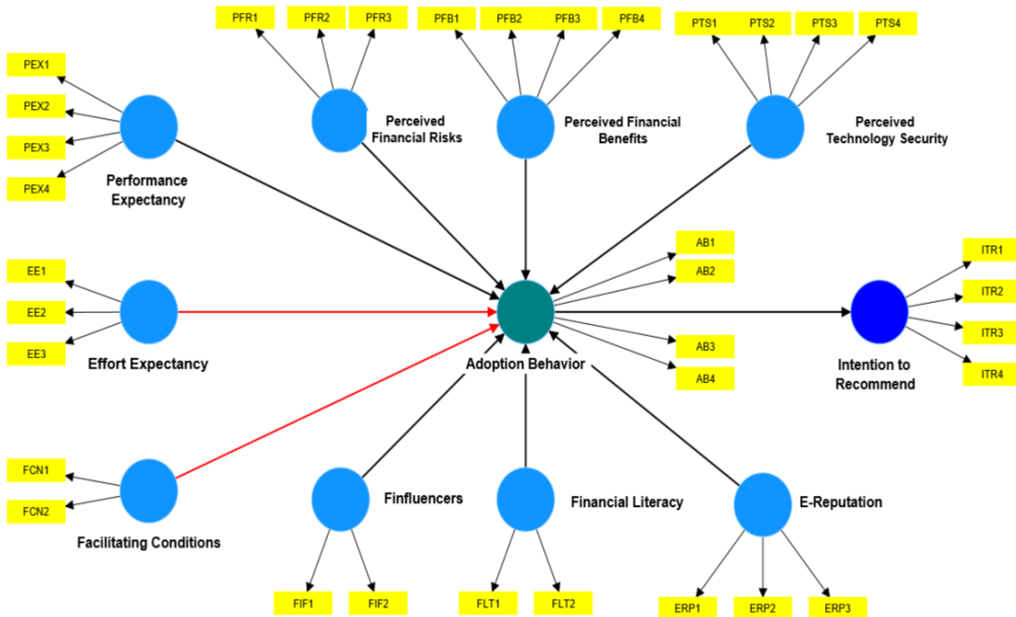

Figure 2. Mobile Application Technology Adoption (MATA) Model in Stock Investment

Source: Author's proposed research model, {2023}.

Research methodology

The existing research is a quantitative type with an online survey questionnaire as a data collecting instrument. The questionnaire was distributed to retail stock investors in Indonesia who have downloaded and used mobile stock investment applications for at least the last year. Data was gathered using non-probability, judgmental sampling, from May to June 2023. A total of 256 respondents were recruited. The minimum sample size was calculated using Power Analysis for a one-tailed test, with an effect size (f-square) of 0.15. Measures of constructs for the online survey were developed based on previous literature. This study adopted a five-point Likert scale, ranging from 1 (totally disagree) to 5 (totally agree) to measure each variable. The indicators in the questionnaire were originally in English. Since the study involved Indonesian-speaking respondents, the questionnaire went through backward and forward translation processes and a review by a panel of experts to minimise bias. Respondents' demographic profile, and stock investment behaviour questions were included in the online survey.

Table 1. Measurement of Constructs

Research Variable	Conceptual definition	Operational definition	Source
Performance Expectancy (PE)	The degree of an individual's confidence in the benefits of using the system to facilitate his or her technology-enhanced activities. (Venkatesh et al., 2003)	Using Mobile stock investment applications enhances: PE1: efficiency in conducting stock investment transactions. PE2: effectiveness in conducting stock investment transactions. PE3: time convenience of stock investment transactions. PE4: place convenience in stock trading. PE5: speed of stock investment transaction	Adapted from: Tai & Ku (2013)

Research Variable	Conceptual definition	Operational definition	Source
Effort Expectancy (EE)	The degree to which an individual believes that using the system is easy. (Venkatesh et al., 2003)	EE1: Learning to use a mobile stock investment application is easy for me. EE2: Stock investment using a mobile application is easy to understand. EE3: The features of a mobile stock investment application are easy to use. EE4 – Becoming skillful in trading using a mobile stock investment application is fast.	Adapted from: Oliveira et al. (2016)
Facilitating Conditions (FC)	The degree to which an individual believes that organisational and technical infrastructures exist to support the use of the system. (Venkatesh et al., 2003)	The following conditions make it easy for me to use this application. FC 1: Reliable smartphone to run the application. FC 2: Internet connection speed to run the application.	Adapted from: Oliveira et al. (2016); Havidz et al. (2018)
Financial Influencers (Finfluencers)	The degree to which an individual perceives the message given by financial experts (financial influencers) on social media is worth following (Cowen & Gillson, 2023))	FII1: Financial influencers (finfluencers) serve as important sources of stock information. FII2: I refer to the information on the finfluencers' social media accounts.	Adapted from: Tai and Ku, (2013); Oliveira et al. (2016)
Perceived Financial Benefits (PFB)	Stock investor's perception of the possibility of financial gains derived from lower brokerage fees, faster execution, and more transparency when stock transactions are conducted using smartphone apps (Chong et al., 2021)	Using mobile stock investment applications provides the following benefits: PFB1: minimises stock trading fees. PFB 2: increases transaction speed. PFB 3: provides transparent financial information. PFB 4: provides free-of-charge investment information.	Adapted from: Mehrens, (2001); Chong et al. (2021)
Perceived Financial Risks (PFR)	Stock investors' perception of the possibility of economic loss due to transaction errors or incorrect operations when using the technology (Lee, 2009)	Using Mobile stock investment applications entails the following risks: PFR 1: Additional fees (e.g. currency conversion fee, account management fee, withdrawal fee) PFR 2: fraud by mobile application staff PFR 3: fake transactions by hackers	Adapted from: Nguyen and Huyuh (2018); Grabneur-Krauter and Faullant (2008); Tai and Ku (2013)
Perceived Technology Security (PTS)	The feeling of security perceived by an individual in conducting financial transactions with mobile technology (Salisbury et al., 2001)	PTS1: The technology used in this mobile application is secure. PTS2: Financial information stored (e.g. bank account, transaction cash value) in this mobile application is secure. PTS3: Information about the investor's identity saved in this application is secure. PTS4: Overall, this mobile application technology is a safe	Adapted from: Rahi et al. (2018),), Oliveira et al. (2016)

Research Variable	Conceptual definition	Operational definition	Source
		place to keep my stock trading information.	
Financial Literacy	Knowledge of financial concepts and ability to manage stock investment to make effective stock investment choices (adapted from Foster et al., 2022)	FL 1: I know my stock investment goals. FL 2: I have the skills to manage my stock investment portfolio	Adapted from: Atkinson & Messy (2012)
E-reputation (ER)	The perception of customers about the good image of a company providing e-service (Maryam, et al., 2021)	ER 1: This mobile stock investment application is run by a company that everyone recognises. ER 2: This mobile stock investment application is reputable as a secure platform. ER 3: This mobile stock investment application has an excellent reputation in stock trading.	Adapted from: Lee and Tan (2003),
Adoption of a mobile stock trading application	The effective use of a technological product or service (Venkatesh et al., 2003)	AD1: I have developed a habit of using Mobile stock investment applications. AD2: I continue trading stocks using this type of application. AD3: I have used this technology in a bigger volume AD4: I use this technology to select a variety of stocks	Adapted from: Tai and Ku (2013); Chong et al. (2021)
Intention to recommend	The intention of users to suggest to others the use of the technology (Oliveira et al., 2016)	IR 1: I would inform others about this application. IR 2: I will tell others that this application is a reliable investment tool. IR 3: I will recommend others adopt this technology over other ways of stock trading. IR 4: I am willing to share with others the benefits of using this application.	Adapted from: Oliveira (2016); Havidz et al. (2018); Octavius and Antonio (2021)

Source: From Various Sources.

Results

Profile of respondents

The respondents recruited in this study mostly reside in the capital city of Jakarta and its surrounding areas (83.98%). Male and Female respondents are almost equal in percentage with Female respondents slightly higher (50.39%) than male respondents (49.61%). The majority of the respondents belong to the younger generation segments (Generation Y and Z) or 78.5%, They are mostly bachelor's degree holders (39.06%) and work in private companies (33.20%). The detailed profile of respondents is presented below.

Respondents mostly spend below Rp. 10 million monthly for their routine expenses, which indicates their lower-middle income class (66%). They also make small stock investment transactions below Rp. 5 million (51%) and they don't conduct stock transactions daily but mostly monthly (49.24%), indicating that they are not traders. Around half of them (59%) have previous trading experience. They mostly use the stock analysis feature of the mobile application downloaded (55.72%). They spread their risks by investing in mutual funds (52.7%). The mobile application 'Bibit' is the most downloaded (27%) and the most frequently used (17%) by respondents. Bisnis.com (33.96%) and Investor Daily (33.20%) are the favourite news media of the respondents. Most of them also use Instagram actively (71.75%).

The measurement model

The study used Structural Equation Modelling (SEM) with Smart PLS 4 software for data analysis for several reasons. First, the study adopted multiple variables with 11 variables and not all items may be normally distributed. SEM-PLS is also considered as having the ability to discriminate measurement and structural models and account for error (Henseler et al., 2009; Ringle et al., 2015).

The measurement model evaluated the reliability (construct reliability, indicator reliability) and validity (convergent validity and discriminant validity) of the indicators and variables. Construct reliability was tested using composite reliability and Cronbach's alpha, which should be above 0.7. Indicator Reliability was tested using outer loadings > 0.7 (Henseler et al., 2009). Convergent Validity was tested using Average Variance Extracted (AVE) that must be more than 0.5 (Fornell & Larcker, 1981; Henseler et al., 2009; Hair et al., 2012). Finally, discriminant validity was tested with HTMT, which should be below 0.9 (Henseler et al, 2022).

The summary result of the measurement model tests is presented in the following figure. Construct Reliability and Validity give the results of Cronbach's Alpha and Composite Reliability: all above 0.7. The figure also reveals the results of AVE > 0.5 (Hair et al., 2021; Chin, 1998). This indicates that all requirements for construct validity and reliability have been met.

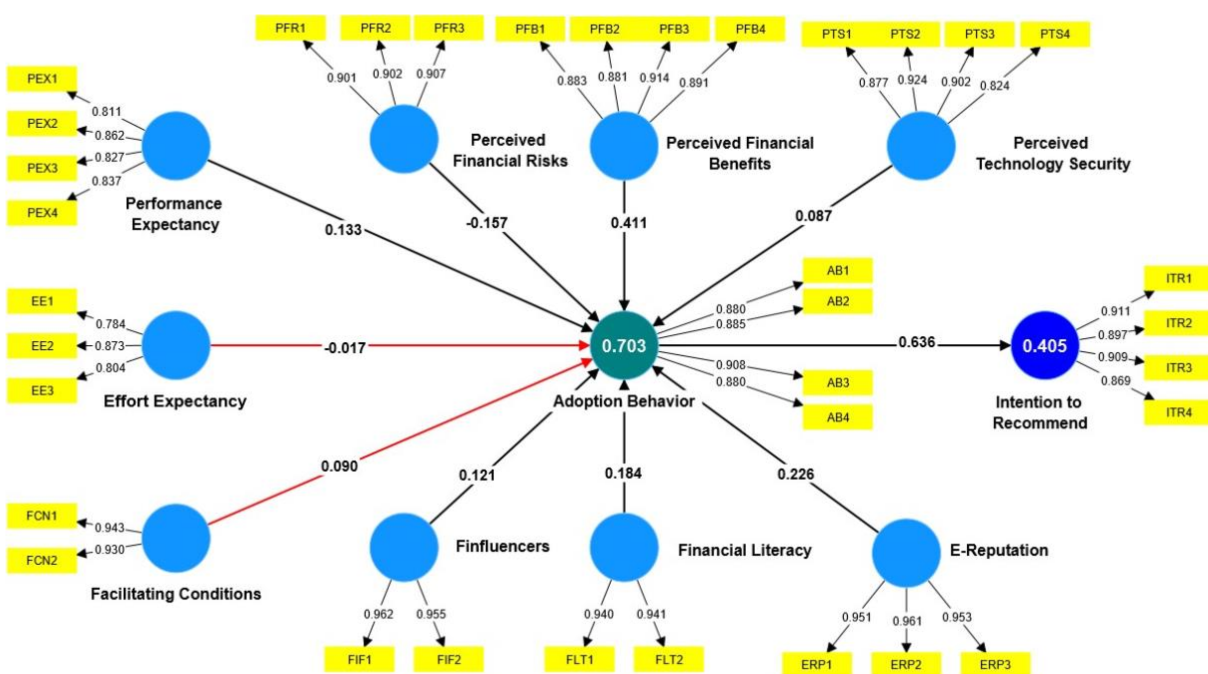

Figure 2. Measurement model outputs

Source: Smart PLS 4 Data Processing Outputs, (2023).

The structural model

The structural model covers the multicollinearity test with inner VIF, coefficient of determination, effect size, predictive relevance, and hypothesis test. An advanced analysis was also conducted including Importance Performance Map Analysis and PLS-POS Analysis.

Multicollinearity Test with Inner VIF

This test aims to identify the collinearity issue (strong correlations among the independent variables) by interpreting the values of the Inner Variance Inflation Factor (Inner VIF). The value of VIF should ideally be less than 3. However Inner VIF values between 3 to 5 are still considered acceptable. After processing the data set with the PLS Algorithm, the inner VIF values are retrieved as follows (Table 3). The Inner VIF values in the table suggest no collinearity problem in the research model in this study.

Table 2. Inner VIF Values

Variables	VIF
Adoption Behaviour -> Intention to _Recommend	1.000
E-Reputation -> Adoption Behaviour	3.092
Effort Expectancy -> Adoption Behaviour	1.360
Facilitating Conditions -> Adoption Behaviour	1.862
Financial Literacy -> Adoption Behaviour	2.819
Finfluencers -> Adoption Behaviour	3.230
Perceived Financial_Benefits -> Adoption Behaviour	2.403
Perceived _Financial Risks -> Adoption Behaviour	2.327
Perceived _Technology Security -> Adoption Behaviour	1.851
Performance _Expectancy -> Adoption Behaviour	1.636

Source: Smart PLS 4 Data Processing Outputs, (2023).

Coefficient of Determination (R-squared)

The value of R^2 signifies the explanatory power of a model (Hair et al., 2019). The R^2 values range from 0 (no explanatory power) to 1 (strong explanatory power). The closer it is to 1 the higher the explanatory power (Hair et al., 2019). The R^2 of Adoption Behaviour (0.703) is categorised as 'moderate to strong', and the R^2 of Intention to Recommend (0.405) is weak to moderate.

Effect Size (F squared/f^2)

Effect Size (f^2) is calculated by running the PLS SEM Bootstrapping. The values of effect size fall into three categories (Cohen, 1988). As a rule of thumb, values between 0.02 – 0.15 suggest a small effect size. Values of 0.15 – 0.35 reveal a medium effect size, and values of more than 0.35 show a large effect size.

Table 4. Effect Size Values (f^2)

Path	f-square	Category
Adoption Behaviour -> Intention to _Recommend	0.680	Large effect size
E-Reputation -> Adoption Behaviour	0.056	Medium effect size
Effort Expectancy -> Adoption Behaviour	0.001	No effect sizes
Facilitating Conditions -> Adoption Behaviour	0.015	No effect sizes
Financial Literacy -> Adoption Behaviour	0.040	Small effect size
Finfluencers -> Adoption Behaviour	0.015	No effect sizes
Perceived Financial_Benefits -> Adoption Behaviour	0.237	Medium effect size
Perceived Financial Risks -> Adoption Behaviour	0.036	Small effect size
Perceived Technology Security -> Adoption Behaviour	0.014	No effect sizes
Performance Expectancy -> Adoption Behaviour	0.036	Small effect size

Source: Smart PLS 4 Data Processing Outputs, (2023).

Adoption Behaviour has the largest effect size (68%) on the variance of Intention to Recommend. E-Reputation and Perceived Financial Benefits have medium effect sizes with f^2 values of 0.056, and 0.237. The rest of the variables have either small or almost no effect when used independently to measure the target construct, which means that they cannot be used independently to measure the dependent variable. It is suggested to use the variables with small or no effect sizes in parallel to have a bigger effect size on Adoption Behaviour.

Predictive Relevance (Q square predict)

The predictive relevance of the research model should also be reported (Shamueli et al., 2019). In PLS-SEM, the predictive relevance is measured by looking at Q2_predict, which can be obtained in the PLS Predict menu in the newest version of smart PLS (Sarstedt et al., 2022; Shmueli et al., 2019). The values of Q2 predict are between -1 and +1. A value below 0 suggests no predictive relevance. A value above 0 indicates the existence of predictive power. A value between 0 and 0.25 signifies small predictive relevance. A value between 0.25 and 0,5 signifies medium predictive relevance. A value bigger than 0.5 signifies large predictive relevance. The Q^2 value of Adoption behaviour falls in the category of large predictive relevance, while Intention to recommend falls in the category of medium predictive relevance. These results of medium and large predictive power mean the model can be replicated in future studies.

Table 5. Q^2 Predict

	Q^2predict	Category
Adoption Behaviour	0.671	Large predictive relevance
Intention to Recommend	0.485	Medium predictive relevance

Source: Smart PLS 4 Data Processing Outputs, (2023).

The analysis also included the Cross-validated Predictive Ability Test (CVPAT), which is considered a more accurate measure of predictive relevance (Liengaard et al., 2021; Hair et al., 2022; Sharma et al., 2022). The data is split into the training set (to build the research model) and the test set (to assess the predictive relevance). The first step is done by comparing the PLS SEM and Indicator Average (IA). The next step is to compare the PLS-SEM and the Linear Model (LM). If the value of the error as the result of bootstrapping is smaller, the average loss will be negative. The negative value of the Overall value suggests the existence of a predictive ability.

Table 6. CVPAT

Variable	PLS-SEM vs. Indicator Average		Variable	PLS-SEM vs. Linear Model	
	Average loss difference	**p-value**		**Average loss difference**	**p-value**
Adoption Behaviour	-0.522	0.000	Adoption Behaviour	-0.057	0.003
Intention to Recommend	-0.471	0.000	Intention to Recommend	0.051	0.307
Overall	-0.496	0.000	Overall	-0.003	0.913

Source: Smart PLS 4 Data Processing Outputs, (2023).

The output of CVPAT in the table shows that the Indicator Average (IA) values and Linear Model (LM) Values are negative, which suggests that the model has a strong predictive ability confirming the result of the Q2 predict.

Hypothesis test

This test aims to find out whether the results confirm the hypothesis of the study. The results of the hypothesis tests in this study are retrieved from the bootstrapping process, with resampling data of 15,000, a significance level of 0.05, a one-tailed test, and complete bias-corrected features done in Smart PLS 4 (Hair et al., 2022). A hypothesis is supported if it meets three criteria. First, the direction of the path coefficient should be in line with the direction stated in the hypothesis. Second, the p-value should be less than 0.05 as the significance level selected is 0.05 or α = 0.05, and the confidence level is set at 95% (Hair et al., 2022). Finally, the bootstrap confidence interval (CI) should not include zero (Hair et al., 2022).

Table 7. Hypothesis Test

Hypothesis	Standardized Coefficient	p-Values < 0.05	95% Confidence Interval		Results
			5%	**95%**	
H1: Performance _Expectancy -> Adoption Behaviour	0.133	0.004	0.053	0.216	Supported
H2: Effort Expectancy -> Adoption Behaviour	-0.017	0.347	-0.089	0.050	Not supported
H3: Facilitating Conditions -> Adoption Behaviour	0.090	0.073	-0.018	0.186	Not Supported
H4: Finfluencers -> Adoption Behaviour	0.121	0.040	0.001	0.227	Supported
H5: Perceived _Financial Risks -> Adoption Behaviour	-0.157	0.004	-0.245	-0.050	Supported
H6: Perceived Financial_Benefits -> Adoption Behaviour	0.411	0.000	0.294	0.523	Supported
H7: Perceived _Technology Security -> Adoption Behaviour	0.087	0.025	0.020	0.167	Supported

Hypothesis	Standardized Coefficient	p-Values < 0.05	95% Confidence Interval		Results
			5%	95%	
H8: Financial Literacy -> Adoption Behaviour	0.184	0.004	0.079	0.307	Supported
H9: E-Reputation -> Adoption Behaviour	0.226	0.002	0.095	0.347	Supported
H10: Adoption Behaviour -> Intention to _Recommend	0.636	0.000	0.550	0.716	Supported

Source: Smart PLS 4 Data Processing Outputs, (2023).

The results revealed two unsupported hypotheses (Hypotheses 2 and 3). The remaining eight hypotheses are supported.

Importance-Performance Map Analysis (IPMA)

IPMA is performed to identify critical points of importance and performance of the analysed constructs (Hair et al., 2022). IPMA is conducted both at construct and indicator levels. The results are presented in the table and graphical outputs. The outputs are categorised into four quadrants in an importance-performance map: (1) High importance, low performance; (2) High importance, high performance; (3) low importance, low performance; and (4) low importance, high performance.

Table 8. Importance-Performance Map Analysis (IPMA) at Indicator Level

Variable	Indicator	performance	Importance
E-reputation	ERP1	59.783	0.053
	ERP2	58.992	0.049
	ERP3	60.178	0.052
Facilitating Conditions	FCN1	67.062	0.030
	FCN2	75.296	0.027
Finfluencers	FIF1	54.447	0.047
	FIF2	54.447	0.044
Financial Literacy	FLT1	58.992	0.113
	FLT2	62.055	0.113
Performance Expectancy	PEX1	65.086	0.050
	PEX2	70.487	0.045
	PEX3	70.883	0.040
	PEX4	73.254	0.043
Perceived Financial Benefits	PFB1	62.352	0.140
	PFB2	69.170	0.118
	PFB3	67.292	0.116
	PFB4	70.059	0.106
Perceived Technology Security	PTS1	66.502	0.020
	PTS2	63.142	0.024
	PTS3	62.747	0.023
	PTS4	62.846	0.015
Mean		**64.527**	**0.060**

Source: Smart PLS 4 Data Processing Outputs, (2023).

At the Indicator Levels (Table 8 and Figure 3), the constructs that have low importance (not important) and high performance are all performance expectancy indicators (PEX1, PEX2, PEX3, and PEX4), all facilitating condition indicators (FCN1, FCN2), one Perceived Technology Security indicator (PTS1), and one Perceived Financial Benefits indicator (PFB2). The constructs that are in low priority quadrant (Low importance and low performance): Three indicators of Perceived Technology Security (PTS 2, 3, 4), two indicators of Finfluencers (FIF1, FIF2), and all E-reputation indicators (ERP1, ERP2, and ERP3). The indicators in the category of high importance and high performance are three variables of Perceived Financial Benefits (PFB2, PFB3, and PFB4). Finally, the category that needs to be concentrated on are two indicators of Financial Literacy (FLT1, FLT2) and one indicator of Perceived Financial Benefits 1 (PFB1).

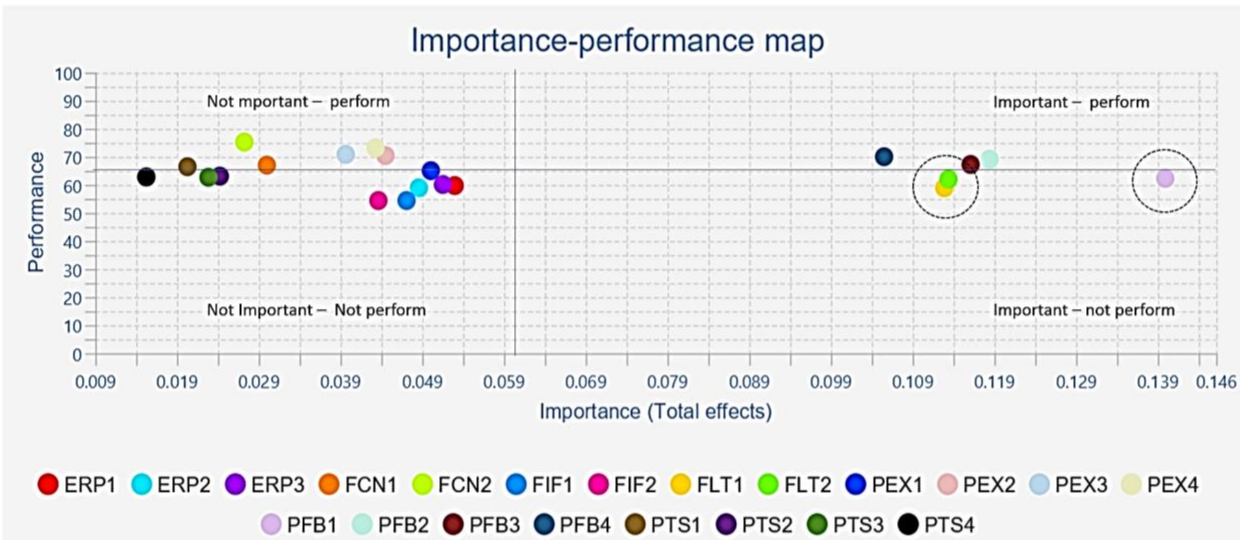

Figure 3. Importance-Performance Map Analysis at the Indicator Level

Source: Smart PLS 4 Data Processing Outputs, (2023).

The result of IPMA at the indicator level suggests a focus on improving all indicators of financial literacy and perceived financial benefits 1.

Table 9. IPMA at the Construct Level

Variable	Performance	Importance
E-Reputation	59.656	0.146
Facilitating Conditions	70.897	0.054
Financial Literacy	60.573	0.213
Finfluencers	54.447	0.087
Perceived Financial_Benefits	67.036	0.428
Perceived _Technology Security	63.810	0.074
Performance Expectancy	69.720	0.148
Mean	63.734	0.164

Source: Smart PLS 4 Data Processing Outputs, (2023).

At the construct level, Facilitating Conditions, Perceived Technology Security, and Performance Expectancy are in the High Performance-Low Importance Quadrant. Finfluencers and E-Reputation are in the Low Performance-Low Importance Quadrant (Low Priority). Perceived Financial Benefits are in the High Performance-High Importance Quadrant. The construct that needs to be prioritised for improvement is Financial Literacy, as it is still low-performing but of high importance.

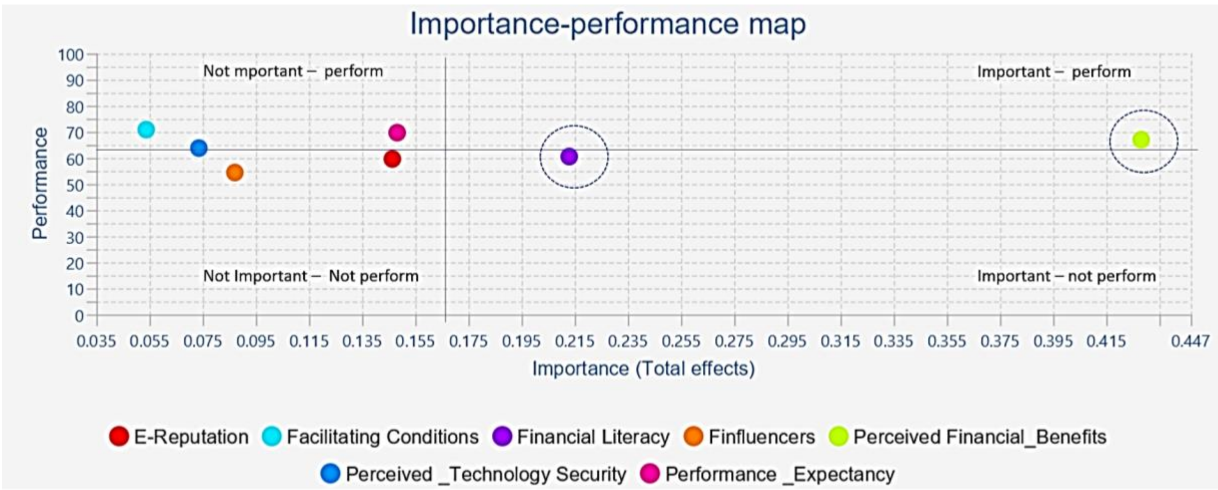

Figure 4. Importance-Performance Map Analysis at the Construct Level

Source: Smart PLS 4 Data Processing Outputs, (2023).

PLS-Prediction Oriented Segmentation (PLS-POS) Analysis

PLS-POS analysis aims to identify the segment in the data set that has a higher R^2 (higher explanatory and prediction power) compared to the R^2 from the bootstrapping result. This information will be useful for researchers as well as mobile application providers to investigate further the characteristics of the samples in the segment with higher R^2. The target constructs are Adoption Behaviour and Intention to Recommend. PLS-POS analysis reveals 43 samples in Segment 1 and 213 samples in Segment 2. Segment 1 has a higher R^2 for adoption behaviour and intention to recommend, both with strong explanatory and predictive power.

Table 10. PLS-POS Results

Variables	Original sample R-squares (n=256)	Weighted average R-squares (n=256)	Segment1 (n=43) or 17%	Segment2 (n=213) or 83%
Adoption Behaviour	0.703	0.780	0.980	0.738
Intention to _Recommend	0.405	0.407	0.679	0.351

Source: Smart PLS 4 Data Processing Outputs, (2023).

The next analysis is to compare the path coefficient values of the two segments. Segment 1 shows that the path coefficient with the highest value belongs to the path of E-Reputation to Adoption Behaviour (0.969). In Segment 2, the path coefficient of Adoption Behaviour to Intention to Recommend has the highest value of 0.493.

Table 12. Comparison table of the coefficient values of the two segments

Path	Original path coefficients (n=256)	Segment1 (n=43) or 17%	Segment2 (n=213) or 83%
Adoption Behaviour -> Intention to _Recommend	0.636	0.824	0.593
E-Reputation -> Adoption Behaviour	0.226	0.969	0.040
Effort Expectancy -> Adoption Behaviour	-0.017	0.283	-0.095
Facilitating Conditions -> Adoption Behaviour	0.090	0.268	0.029
Financial Literacy -> Adoption Behaviour	0.184	0.275	0.296
Finfluencers -> Adoption Behaviour	0.121	-0.195	0.199
Perceived Financial_Benefits -> Adoption Behaviour	0.411	0.183	0.400
Perceived _Financial Risks -> Adoption Behaviour	-0.157	-0.856	-0.061
Perceived _Technology Security -> Adoption Behaviour	0.087	0.252	0.093
Performance _Expectancy -> Adoption Behaviour	0.133	0.469	0.063

Source: Smart PLS 4 Data Processing Outputs, (2023).

The results of the PLS-POS Analysis of the two segments are also visually presented in Figure 5 and Figure 6. Figure 5 shows the PLS POS Results of Segment 1 with a strong R^2 of Adoption Behaviour (0.980) and a moderate to strong R^2 of Intention to Recommend (0.679). The independent variable with the highest influence is E-Reputation (0.969). All outputs have much higher values than the ones in the original model: R^2 of Adoption Behaviour is 0.703 (strong), and R^2 of Intention to Recommend is 0.405 (towards moderate). In the original sample, E-Reputation is also found to have the highest path coefficient of 0.226 (lower than the path coefficient of E-Reputation in Segment 1).

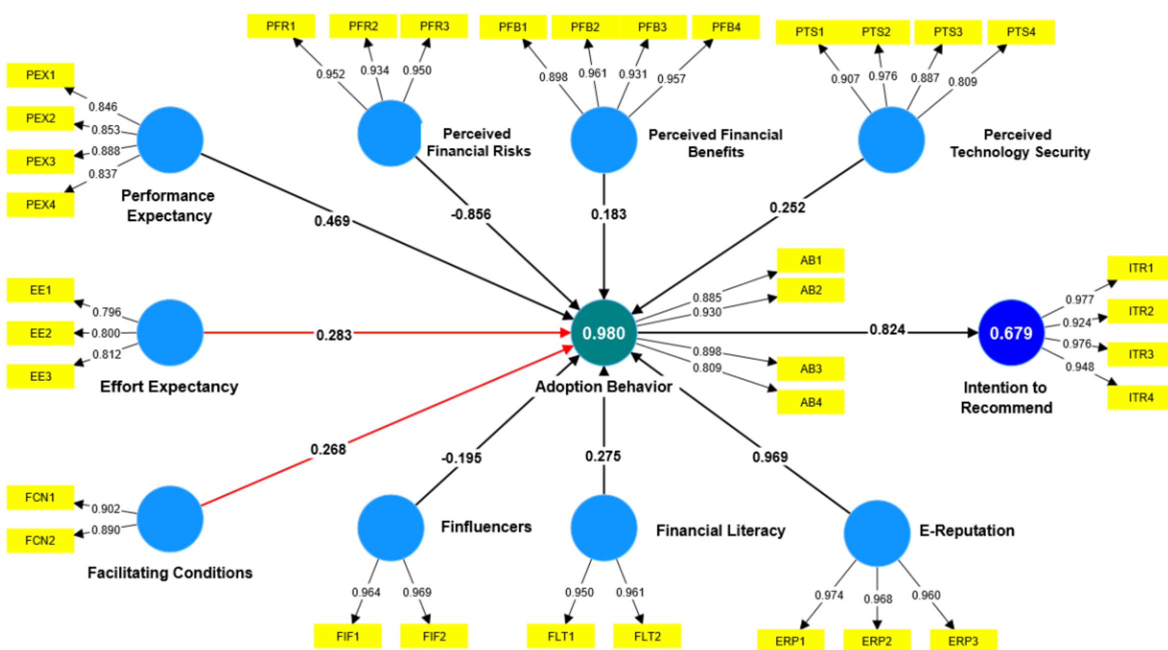

Figure 5. PLS POS Segment 1

Source: Smart PLS 4 Data Processing Outputs, (2023).

The results of Segment 2 show lower values than those in Segment 1. The R^2 of Adoption Behaviour (0.738) is still in the category of strong, only with a lower R^2 value of Adoption Behaviour in Segment 1, but higher than R^2 in the original model. The R^2 of Intention to Recommend in Segment 2 is 0.351 < 0.679 in Segment 1. The independent variable with the highest influence in Segment 2 is Financial Literacy (0.296), followed by Finfluencers (0.199).

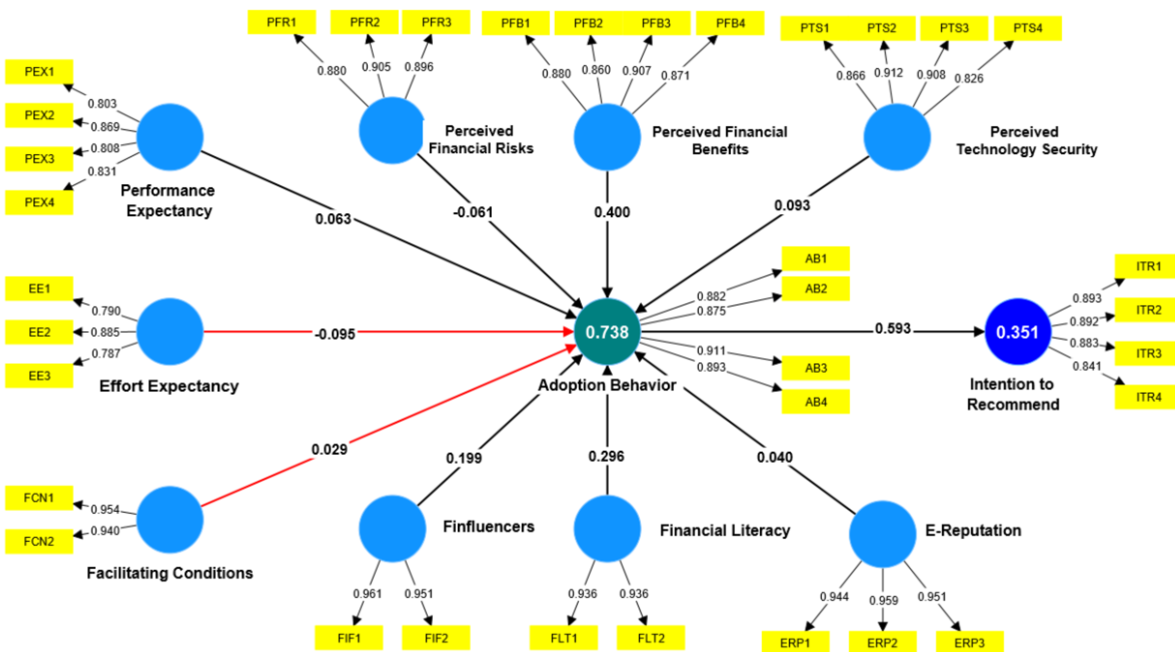

Figure 6. PLS-POS Segment 2 (n=256)

Source: Smart PLS 4 Data Processing Outputs, (2023).

PLS-POS analysis confirmed the existence of heterogeneity, with Segment 1 showing stronger prediction and explanatory ability (higher R^2) compared to the moderate prediction power of the model in Segment 2. With these results, the researcher can investigate further (post-hoc analysis) to identify the characters of samples that differentiate the two segments.

Discussion

The study confirmed the insignificant influence of Effort Expectancy on the adoption of the mobile application. This is probably due to the respondents who are mostly young people (more than 80%) who are familiar with using mobile technology including in the stock investment context (Bohnert & Gracia, 2021). The study also found an insignificant influence of Facilitating conditions on adoption behaviour. This can be explained by the fact that most respondents (more than 80%) reside in Jakarta with advanced 4G and 5G internet connections and easily accessible Wi-Fi services (World Bank, 2021). The remaining eight hypotheses are supported.

The top three variables with the strongest influence on adoption behaviour are Perceived financial benefits (0.411), e-reputation (0.226), and financial literacy (0.181). This means that retail investors in this study depend on the financial benefits offered by the mobile application when deciding to adopt it. Financial literacy as the internal capacity of investors also plays an important role in adoption decisions. Another factor that is considered important is the e-reputation of the application providers. An interesting finding is that finfluencers only have a small influence on adoption behaviour. This is probably because retail investors focus more on perceived returns and the fact that there are no finfluencers with an outstanding reputation yet in Indonesia (Nair et al., 2022).

The overall results of the analysis show that the research model has moderate to strong explanatory power (R2) of the independent variables to explain adoption behaviour (0.703), and weak to moderate explanatory power of adoption behaviour to intention to recommend (0.405). The research model offers the value of Q^2 predict of Adoption behaviour that falls in the category of large predictive relevance, and Intention to recommend that falls in the category of medium predictive relevance. The CVPAT result also suggests strong predictive power. This means that the model examined in this study can be replicated in future studies in similar contexts.

This study also presented the effect size analysis of each independent variable on adoption behaviour. The top three variables with the most effect size values are Perceived Financial Benefits with a medium effect size of 0.237, E-reputation with a medium effect size of 0.056, and Financial Literacy with a small effect size of 0, 040. The results of the effect size suggest using all variables together (not separately) to have a bigger effect on the adoption of mobile stock investment applications.

The study included IPMA Analysis to find indicators and variables that need to be focused on for further improvement. These indicators and variables are those that fall in the quadrant of high importance-low performance. The IPMA analysis at the indicator level shows that all financial literacy indicators and indicator 1 of perceived financial benefit need to be improved further. The IPMA analysis at the construct level reveals financial literacy as the construct to concentrate on for further improvement.

The study also included an advanced analysis of PLS-POS to identify the presence of heterogeneity. The results show there is unobserved heterogeneity with Segment 1 (n=43) having a stronger R2 value of Adoption Behaviour (0.98) and Intention to Recommend (0.679), compared to Segment 2 (n=213) with an R2 value of Adoption Behaviour of 0.738 and Intention to Recommend of 0.351. The results suggest further studies to be conducted to identify the characteristics of samples in Segment 1 as the target market of the mobile stock investment application providers to match their corporate and marketing strategies.

Conclusion and recommendations

The analysis results of this study revealed two unsupported hypotheses (Effort Expectancy to Adoption Behaviour and Facilitating Conditions to Adoption Behaviour). These variables are derived from the UTAUT 2 model. This result suggests that the UTAUT 2 model is not sufficient to predict adoption behaviour in the context of mobile stock investment applications. Additional variables that are more relevant in the context of financial services need to be added. The remaining eight hypotheses are supported. Six of eight hypotheses involve specific variables in financial services (finfluencers, perceived financial risks, perceived financial benefits, perceived technology security, financial literacy, and e-reputation), and one relates to marketing strategy (intention to recommend). This suggests the extension of the UTAUT 2 model to include variables related to financial services and marketing when used in the context of mobile stock investment applications to attract new users.

This study also confirmed the good quality of the model to be used in future studies within a similar financial service or stock investment context. This is evident from the results of moderate to strong R2, the strong predictive relevance of the model (Q2 and CVPAT), and the effect size of the independent variables that suggest using all variables in combination (not separately) to have stronger effect sizes on adoption behaviour.

The study found a strong impact of Adoption behaviour on intention to recommend, financial literacy on adoption behaviour, and e-reputation on adoption behaviour. Mobile application providers should identify the profiles of their existing users to reach out to them and motivate them to recommend the application to their circle of friends. Existing users can be encouraged to share their positive feedback and a review of satisfaction on social media by financially rewarding them. Mobile application providers can 'gamify' the financial services (e.g. fun quizzes or polling related to financial analysis features in the application) to attract younger users. Application providers are also recommended to give credible, attractive, and useful financial education on their various platforms in the form of short anime movies with avatars. To establish a positive e-reputation, providers can collaborate with experienced stock traders, financial influencers, or successful stock investors.

Government regulators in emerging countries can also benefit from this study. When dealing with finfluencers, the government is recommended to conduct active surveillance of the finfluencers' activities to ensure the circulation of accurate information and avoid misleading ones. Education and training for both finfluencers and retail investors can be conducted to certify professional financial influencers in the digital landscape to protect society from getting false advice. Government regulators are also recommended to organise financial literacy sessions (seminars, workshops, training programs) regularly for prospective investors and new investors to help these retail investors make the best investment decisions. The regulators can collaborate with government-certified mobile application providers, Stock Exchange market organisers, and higher education institutions to organise these financial literacy programs for interested parties.

This study is not free from limitations. The first is the absence of investigating psychological variables in the analysis. The psychological traits of investors can provide useful insights to application providers as well as government regulators. Future research can include the types of personality of investors (e.g. risk averse and risk takers) as moderating variables. This study does not include mediating and moderating variables. Therefore, future studies are recommended to add moderating variables (e.g. age, gender, and income), which may provide useful insights to stakeholders in financial services. Finally, this study has not performed a follow-up PLS-POS analysis. Therefore, future researchers are strongly recommended to conduct this post-hoc analysis to get valuable insights into how unobserved heterogeneity influences the adoption of mobile stock investment applications.

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