UNLOCKING GENERATION Z'S MINDS ON STOCK INVESTMENT: DETERMINANTS OF MOBILE STOCK INVESTMENT APPLICATION ADOPTION

Jacquelinda Sandra Sembel

Univeristas Pelita Harapan, Indonesia

e-mail: sandra.sembel@uph.edu

ABSTRACT

Generation Z is the youngest generation entering the stock markets. Their participation may break or make the future of stock investment. This study aims to investigate the determinants of the adoption of mobile stock investment applications by Generation Z. The study provides new insights into the minds of Generation Z on how their perception of financial risks and benefits, their financial literacy, and financial influencers affect their adoption of mobile stock investments applications in the context of Indonesia. The study used survey questionnaires as research instruments with Partial Least Square-Structural Equation Modeling (PLS-SEM) as the quantitative data analysis tool. This study involved 253 Generation Z who are active students at private universities in Java and Sumatra islands (the two most populous islands in Indonesia). The study found that perceived benefits, perceived technology security, and financial literacy affect the adoption of mobile stock investment applications. Finfluencers and Perceived financial risks were not found to have a positive influence on the adoption of mobile stock investment applications among Generation Z.

Keywords: Generation Z, Mobile stock investment applications, Perceived Financial Benefits, Perceived Financial Risk, Financial literacy, Finfluencers

1. INTRODUCTION

Indonesia is home to 212,9 million internet users as of January 2023, making the country the fourth-largest country in terms of digital population (Petrosyan, 2023). Indonesian Gen Z is the biggest generation group with approximately 74,93 million or 27.94% of the total population (BPS, 2024). Approximately half of Gen Z (born between 1997 and 2012) are coming of age to step into the world of work. With their huge number and special attachment to digital technology, Gen Z has started to attract many industries,

In the fast-paced landscape of financial technology, Gen Z has also attracted the financial technology (fintech) industry, as they are beginning to be increasingly attracted to venture into the stock market (Karp, 2023). The accelerated development in mobile application technology has paved the way for easy and wider access to the stock market. Being born digital, Gen Z openly adopts mobile stock investment applications. They have also become a new breed of investors who are personally attached to digital technology (IDN Media, 2024). However, the availability of research in Indonesia about Generation Z's investment mindset is still limited (Yusup & Hongdiyanto, 2023).

There is an increasing interest among Gen Z in adopting mobile stock investment applications. In making their investment decision, Gen Z, who has a high level of digital skills, is greatly influenced by social media and finfluencers (Institute, 2023). With their unique

characteristics of Fear of Missing Out (FOMO), Gen Z's curiosity and tendency to make quick decisions lead them to seek practical advice from finfluencers they encounter in social media (Ahmed, 2023). Their limited financial literacy attracted Gen Z to learn about stock investing and the financial benefits of stock investing. They are also concerned about the potential risks (financial and technology) entailed in mobile technology used as the vehicle for stock investing (Sembel, et al., 2024). Limited research has been conducted to examine how Gen Z's minds work in making investment decisions and what factors influence their stock investment decision, specifically using the mobile technology they are familiar with (Liu, 2023).

This research aims to decode the minds of Gen Z, the new breed of young investors, focusing on how they perceive benefits and risks using mobile stock investment applications. The research also explores the impact of financial literacy and finfluencers on Gen Z's adoption of mobile stock investment applications using the Theory of Planned Behavior (TPB).

2. LITERATURE REVIEW

2.1.Theory of Planned Behavior

The Theory of Planned Behavior (TPB) explains that an individual decision to adopt a certain behavior can be predicted by the intention to form the behavior (Ajzen, 1991). This intention is influenced by attitude, subjective norms, and perceived behavior control influence the shaping of a certain behavior. In the context of the adoption of mobile stock investment applications by Gen Z, the first determinant (attitude) is represented by this theory helps explain how investors' minds perceive something: Perceived financial benefits, perceived financial risks, and perceived technology security. Subjective norms in the context of mobile technology are represented by finfluencers. Finally, Perceived Behavioral Control is represented by investors' Financial Literacy. These three determinants are linked to the Adoption of mobile stock investment applications.

2.2.Generation Z

Generation Z in this study refers to the definition provided by Biro Pusat Statistics (BPS, 2020). This group of population was born between 1997 and 2012. The early Gen Z has reached the age to enter the job market and have the right to have accounts to invest in stocks.

2.3. Benefits, Risks, and Adoption of Mobile Stock Investment Applications

Empirical studies involving the adoption of financial services found that customers tend to weigh the benefits and risks of adopting financial services. One study confirmed that perceived financial benefits positively influence mobile payment adoption. The study also revealed the negative influence of multiple dimensions of risk, including financial risk and technological risk (Bland et al., 2024). Another study on the adoption of mobile payment systems found a positive influence of perceived benefits and trust on adoption behavior (Chin et al., 2020). In the context of mobile stock trading, Tai and Ku (2013) found a positive influence of benefits on the adoption of mobile stock trading. In contrast, risks were found to negatively influence the adoption of mobile stock trading applications (Chong et al., 2021). An increase in perceived risks will discourage retail investors from conducting stock investment transactions using mobile applications. All this leads to the formulation of the following hypotheses:

H1: Perceived financial benefits positively influence the adoption of mobile stock

investment applications.

H2: Perceived financial risks negatively influence the adoption of mobile stock investment applications.

2.4. Perceived technology security and the adoption of mobile stock investment applications.

In addition to perceived financial benefits and perceived financial risks, previous studies also examined the influence of perceived technology security in the adoption of mobile stock investment applications. One study found that a mobile application with secure technology is perceived positively by customers (Aprilia & Amalia, 2023). The study's finding is confirmed by another study that revealed a positive influence of perceived technology security on mobile payment application adoption (Oliveira et al., 2016). Another study also found a positive influence of perceived technology security on the adoption of WeChat, China's mobile payment application (Havidz et al., 2018). To find out the influence of perceived technology security positively in the context of the adoption of mobile stock investment applications, the following hypothesis is formulated.

H3: Perceived technology security positively influences the adoption of mobile stock investment applications.

2.5. Finfluencers and Adoption of Mobile Stock Investment Applications

Financial influencers, or finfluencers, have been found to significantly influence young investors to adopt mobile stock investment applications (Espeute & Preece, 2024). These young investors access the financial information provided by finfluencers over social media platforms. Other studies in the specific context of stock investment in digital platforms found a positive influence of finfluencers on mobile stock investment applications (Nair et al., 2022; Johri et al., 2023). These studies found a significant role of finfluencers on young investors' decision to adopt mobile stock investment applications. These findings led to the formulation of the following hypothesis.

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

2.6. Financial Literacy and Adoption of Mobile Stock Investment Applications.

Several previous studies have found a link between financial literacy and the adoption of digital financial services. A study found that financial literacy (objective and subjective knowledge of investment) has a significant influence on mobile investment decision-making (Fan, 2021). This result is confirmed by another study that found financial literacy as a significant determinant of fintech adoption (Firmansyah et al., 2023). Financial literacy was also found as an important driver of an individual's adoption of risky financial services (Nguyen & Nguyen, 2022). These results led to the formulation of the following hypothesis for this study:

H5: Financial literacy positively influences the adoption of Mobile stock investment applications.

2.7. Research Framework

The research framework of this study, developed from the formulated hypotheses, is presented in Figure 1.

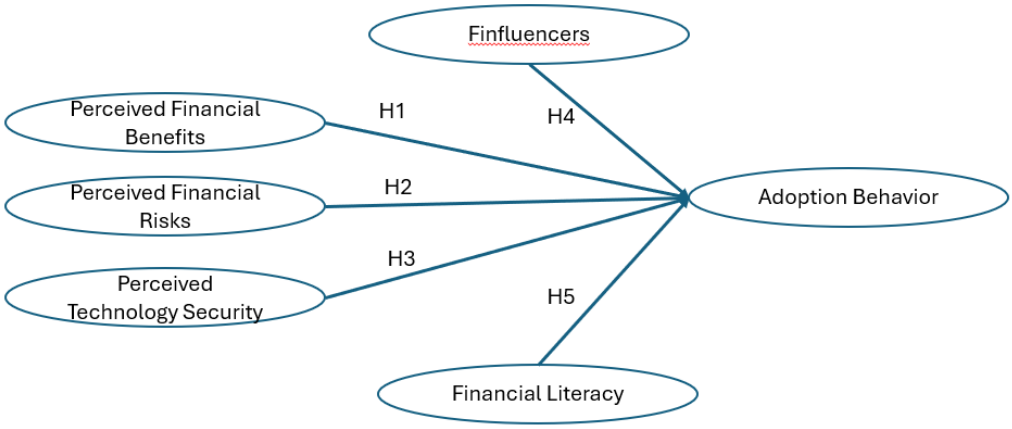

Figure 1. Theoretical Framework of this study
Source: Author's research (2024)

3. RESEARCH METHOD

2.8. Type of research

This study involved a survey questionnaire that was analyzed quantitatively with multi-variate data analysis. The questionnaire was distributed online between July to August 2023.

2.9. Population and Sample

The population of the study involved students studying in a management program at private universities in Jakarta and its surrounding cities. Data was collected using purposive sampling techniques. Special inclusion criteria are management students who have taken basic finance courses and have adopted at least one mobile stock investment application for one year.

Power Analysis with GPower was used to determine the minimum sample size of this study. The Power Analysis was set for a one-tailed test with an effect size (f-square) of 0.15. A minimum of 114 was identified. However, the researchers decided to recruit more respondents to anticipate missing items and invalid answers. A total of 262 respondents were recruited, but, after screening for missing items and conducting validity and reliability tests, only 256 respondents were finally recruited.

2.10. Measures

A five-point Likert scale, ranging from 1 (totally disagree) to 5 (totally agree), was used in this study. Variable measures were adapted from previous literature in the technology adoption context. The perceived financial benefits scale was measured using four indicators from Chong et al. (2021). The perceived financial risk was measured using four indicators from Tai and Ku

(2013). The perceived technology security scale was measured using four indicators from Oliveira et al. (2016). The finfluencers scale was measured using four indicators from Tai and Ku (2013. The financial literacy scale was measured using four indicators from Atkinson and Messy (2012). The adoption behavior scale was measured using four indicators from Tai and Ku (2013) and Chong et al. (2021).

To assess the face validity of the data, the study involved a panel of two academic experts. English was used in the original questionnaire. The study involved Indonesian-speaking respondents; therefore, a backward translation (involving two language experts) and forward translation processes (involving two language experts) were conducted to prevent translation bias. Common method bias was conducted using variance inflection factor (VIF) values (between 3 and 5) to make sure no multicollinearity issues occurred.

2.11. Data Analysis

Structural Equation Modelling (SEM) with Smart PLS 4 software was used for data analysis for at least three reasons. First, the study adopted multivariate analysis with six variables. Another reason is that the variables do not have to be normally distributed. Finally, SEM-PLS can discriminate measurement and structural models and account for error (Henseler, et al., 2009; Ringle, et al., 2015). The measurement model (outer model) was conducted to check the reliability and validity of the data. The structural model (inner model) was conducted to check the robustness of the research model. This phase of analysis consists of Multicollinearity, Coefficient of determination, Effect Size, Predictive Relevance, and Hypothesis test.

4. RESULTS AND DISCUSSION

4.1.Respondents

Most respondents of this study reside in Jakarta and its surrounding areas (83.98%). Female respondents (50.39%) are just slightly higher than male respondents (49.61%). They mostly spend below Indonesian Rupiah (IDR) 10 million monthly for their routine expenses (66%). They mostly make small stock investment transactions, less than IDR. 5 million (51%). Almost half of the respondents conduct their stock trading monthly (49.24%), indicating that they are not traders. 'Bibit' is the preferred mobile application to download (27%) and the most frequently used (17%) by the respondents of this study. Most respondents are active Instagram users (71.75%).

4.2.The Measurement Model

The results of the Reliability and Validity tests are presented in Table 1. Outer loading are all above 0.7. The results of Composite Reliability and Cronbach's alpha are all above 0.7. The results of AVE are above 0.5 (Hair et al., 2021; Chin, 1998). Thus, it can be concluded that the requirements for construct validity and reliability have all been met.

Table 1. Reliability and Validity Test Results

Variable	Indicator	Items	OL > 0.7	CA >0.7	CR >0.7	AVE >0.5
Perceived Financial Benefits	PFB1	Using mobile stock investment applications minimizes stock trading fees	0.713	0.860	0894	0.795
	PFB2	Using mobile stock investment applications increases transaction speed	0.894			
	PFB3	Using mobile stock investment applications provides transparent financial information	0.895			
	PFB4	Using mobile stock investment applications provides free-of-charge investment information	0.842			
Perceived Financial Risks	PFR1	Using mobile stock investment applications entails the risk of paying additional fees	0.729	0.879	0.877	0.644
	PFR2	Using mobile stock investment applications entails the risk of fraud	0.759			
	PFR3	Using mobile stock investment applications entails the risk of fake transactions	0.739			
	PFR4	Using mobile stock investment applications entails the risk of financial loss due to system errors.	0.960			
Perceived Technology Security	PTS1	The technology used is secure	0.874	0.942	0.959	0.853
	PTS2	Financial information stored is secure	0.942			
	PTS3	The investor's identity is securely stored	0.941			
	PTS4	It is safe to keep stock trading information in the applications	0.945			
Adoption behavior	ADP1	I have developed a habit of using mobile stock investment applications	0.925	0.896	0.929	0.766
	ADP2	I continue trading stocks using mobile stock investment applications	0.938			
	ADP3	I have used mobile stock investment applications for stock investment in bigger volume	0.852			
	ADP4	I use this technology to select a variety of stocks to invest in.	0.774			
Finfluencers	FFL1	Flinfluencers serve as important sources of stock investment information	0.868	0.917	0.934	0.781
	FFL2	I refer to the information on the finfluencers' social media accounts.	0.884			
	FFL3	I follow the finfluencers' advice on stock options	0.835			
	FFL4	I pay attention to finfluencers' predictions of stock price movements.	0.925			
Financial Literacy	FL1	I know my stock investment goals	0.818	0.914	0.940	0.797
	FL2	I have the skills to manage my stock investment portfolio,	0.908			
	FL3	I can decide when to invest in stocks.	0.931			
	FL4	I can decide when to invest in stocks	0.910			

OL: Outer Loading, CA: Cronbach Alpha, CR: Composite Reliability, AVE: Average Variance Extracted

Source: Authors' research (2023)

The summary of the measurement model can also be summarized in Figure 2. Measurement Model.

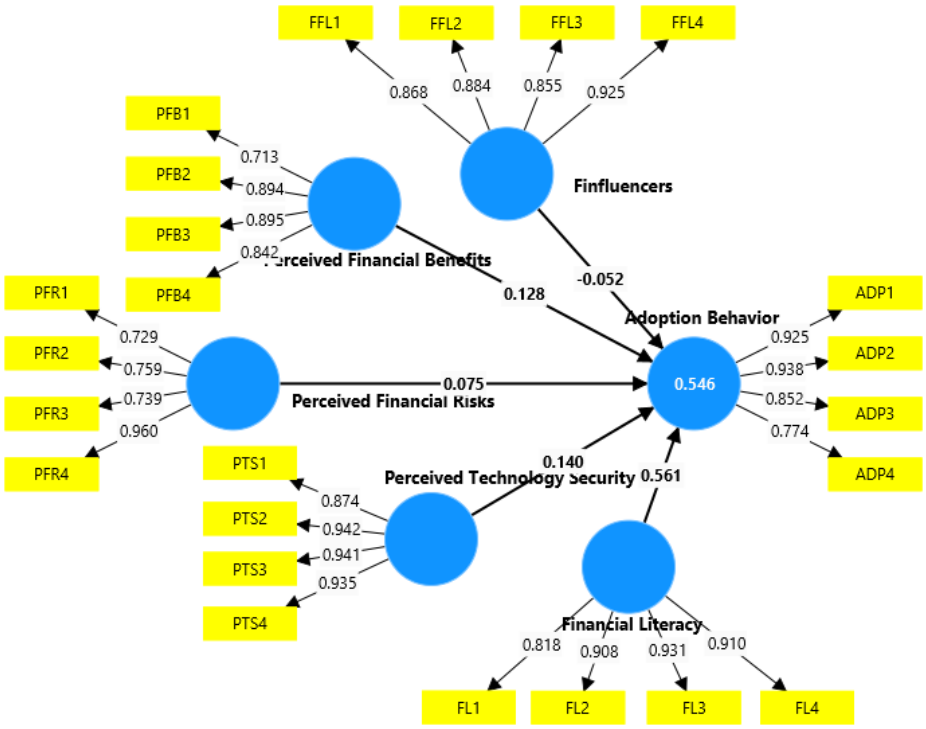

Figure 2. Measurement Model Evaluation (outer model)
Source: Author's research (2023)

Discriminant validity in this study was measured using Heterotrait-Monotrait (HTMT) ratio presented in Table 2. All values have met the criteria of discriminant validity with values < 0.9,

Table 2. Heterotrait-Monotrait ratio (HTMT)

	Heterotrait-monotrait ratio (HTMT)
Financial Literacy <-> Adoption Behavior	0,781
Finfluencers <-> Adoption Behavior	0,119
Finfluencers <-> Financial Literacy	0,133
Perceived Financial Benefits <-> Adoption Behavior	0,596
Perceived Financial Benefits <-> Financial Literacy	0,659
Perceived Financial Benefits <-> Finfluencers	0,296
Perceived Financial Risks <-> Adoption Behavior	0,083
Perceived Financial Risks <-> Financial Literacy	0,052
Perceived Financial Risks <-> Finfluencers	0,259
Perceived Financial Risks <-> Perceived Financial Benefits	0,125
Perceived Technology Security <-> Adoption Behavior	0,578
Perceived Technology Security <-> Financial Literacy	0,628
Perceived Technology Security <-> Finfluencers	0,248
Perceived Technology Security <-> Perceived Financial Benefits	0,667
Perceived Technology Security <-> Perceived Financial Risks	0,059

Source: Author's research (2023)

Since the data set have met the criteria of validity and reliability, the test can proceed to the next phase (Inner Model).

4.3.The Structural Model (Inner Model)

The structural model measurement consists of a multicollinearity test with inner VIF, coefficient of determination (R-square), effect size (F-square), predictive relevance (Q-square), and hypothesis test.

Multicollinearity Test

The multicollinearity test was conducted to identify if the collinearity issue (strong correlations among the independent variables) exists, using the Forner-Larcker criterion. The results of the Forner-Larcker test of this study are presented in Table 3. The Forner-Larcker values confirm no collinearity problem in the research model in this study.

Table 3. Discriminant Validity with Forner Larcker Criterion

	AB	FL	FFL	PFB	PFR	PTS
Adoption Behavior	0,875					
Financial Literacy	0,715	0,893				
Finfluencers	0,119	0,149	0,884			
Perceived Financial Benefits	0,540	0,593	0,283	0,839		
Perceived Financial Risks	0,114	0,058	0,198	0,127	0,802	
Perceived Technology Security	0,531	0,583	0,257	0,606	0,005	0,923

Source: Authors' research (2023)

Coefficient Determination (R-Square)

The value of R^2 (ranging from 0 to 1) describes the explanatory power of a model (Hair et al., 2019). Zero value signifies no explanatory power and 1 signifies strong explanatory power (Hair et al., 2019). The R^2 of Adoption Behavior in this study is 0.546 (moderate). This means that the independent variables in this study have the power to explain the dependent variable (Adoption Behavior) by 54.6%.

Effect Size (F squared/f^2)

Effect size values between 0.02 – 0.15 denote a small effect size. Values of 0.15 – 0.35 signify a medium effect size, and values of more than 0.35 reflect a large effect size (Cohen, 1988). Table 4 summarizes the Effect Size Values of this research.

Table 4. Effect Size Values (f^2)

Path	f-square	Category
Financial Literacy -> Adoption Behavior	0.392	Large effect size
Finfluencers -> Adoption Behavior	0.005	No effect sizes
Perceived Financial_Benefits -> Adoption Behavior	0.019	No effect size
Perceived Financial Risks -> Adoption Behavior	0.012	No effect size
Perceived Technology Security -> Adoption Behavior	0.023	Medium effect sizes

Source: Authors' research (2023)

Financial Literacy on Adoption Behavior has the largest effect size of 0.39. Perceived Technology Security on Adoption Behavior has a medium effect size of 0.23. Finflueners on Adoption Behavior, Perceived Financial Benefits on Adoption Behavior, and Perceived Financial Risks on Adoption Behavior have no effect sizes when used independently (all values are less than 0.15. This means that these variables are suggested to be used in parallel to have a bigger effect size on Adoption Behavior.

Predictive Relevance (Q square predict)

The predictive relevance is measured by looking at Q2_predict in the PLS Predict menu in Smart PLS 4 (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. The predictive relevance of a model is measured by Q2 predict (Sarstedt et al., 2022; Shmueli et al., 2019), which is between -1 and +1. A value below 0 signifies no predictive relevance. On the other hand, a value above 0 indicates predictive power. Table 5 shows that the Q^2 value of Adoption behavior (> 0.5) falls in the category of medium to large predictive relevance.

Table 5. Q^2 Predict

	Q^2predict	**Category**
Adoption Behavior	0.512	Large predictive relevance

Source: Authors' research (2023)

A more accurate measure of predictive relevance is also included in Table 6 using Cross Validated Predictive Abality or CVPAT (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). First, PLS SEM and Indicator Average (IA) are compared. Then, PLS-SEMand the Linear Model (LM) are compared. 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. Cross Validated Predictive Ability Test (CVPAT)

Variable	PLS SEM vs. Indicator Average		Variable	PLS SEM vs. Linear Model	
	Average loss difference	p value		Average loss difference	p value
Adoption Behavior	-0.463	0.000	Adoption Behavior	-0.047	0.05
Overall	-0.463	0.000	Overall	-0.047	0.05

Source: Authors' research (2023)

Table 6 (CVPAT) shows that the Indicator Average (IA) values and Linear Model (LM) Values are both negative, which signifies the existence of a strong predictive ability of the model. This means that the research model can be recommended to be adopted for future studies.

Hypothesis Test

The hypothesis tests in this study were conducted using the bootstrapping process, with resampling data of 15,000 and a significance level of 0.05. The test involved a one-tailed test, with complete bias-corrected features conducted in Smart PLS 4 (Hair et al., 2022). A supported hypothesis should meet three requirements. First, the direction of the standardized coefficient should be in line with the direction indicated in the hypothesis. Second, the p-value should be less than 0.05 or α = 0.05 because the confidence level is set at 95% (Hair et al., 2022). Finally, the bootstrap confidence interval (CI) should not contain a zero value. The summary of the hypothesis test in this study is presented in Table 7 below.

Table 7. Hypothesis Test

Hypothesis	Standardized Coefficient	p-Values < 0.05	95% Confidence Interval		Results
			5%	**95%**	
H1: Perceived Financial Benefits →Adoption Behavior	0.128	0.046	0.010	0.260	Supported
H2: Perceived Financial_Risks → Adoption Behavior	0.075	0.201	-0.114	0.177	Not supported
H3: Perceived _Technology Security - → Adoption Behavior	0.140	0.027	0.011	0.249	Supported
H4: Finfluencers → Adoption Behavior	-0.052	0.173	-0.114	0.177	Not Supported
H5: Financial Literacy → Adoption Behavior	0.561	0.000	0.443	0.663	Supported

Source: Authors' research (2023)

The Hypothesis Table (Table 7) reveals three supported hypotheses (H1, H3, H5) and two unsupported hypotheses (H2 and H4). Hypothesis 1 is supported by the standardized coefficients of 0.128, p-value (0.046 < 0.05), and a Confidence Interval containing no zero value. Hypothesis 2 is not supported as the path coefficient shows a negative direction which doesn't support the positive direction in the formulated hypothesis; the p-value of 0.201 > 0.05 and the confidence interval contains zero value. Hypothesis 3 is supported by the standardized coefficient of 0.140, p-value of 0.027 < 0.05, and the Confidence Interval does not contain a zero value. Hypothesis 4 is not supported as the standardized coefficient shows a negative direction, which doesn't support the positive direction in the formulated hypothesis. In addition, the Confidence Interval contains a zero value and a p-value of 0.173 > 0.05. The final hypothesis (H5) is supported by the biggest standardized coefficient of 0.581, a p-value of 0.000 < 0.05, and the Confidence Interval does not contain a zero value.

The summary of the hypothesis results can also be graphically depicted in Figure 3 below.

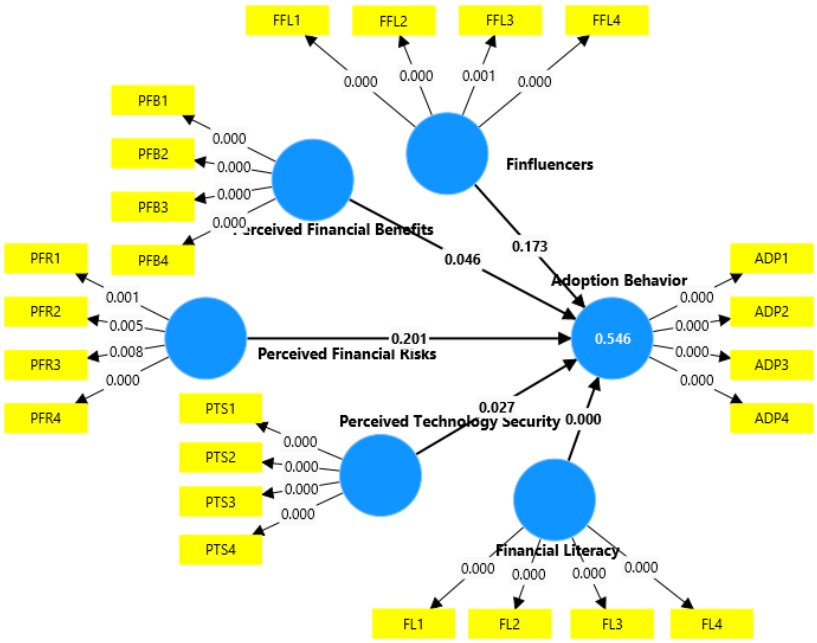

Figure 3. Structural Model Results of this study
Source: Authors' research (2023)

Hypothesis 1 (Perceived Financial Benefits positively influence Adoption Behavior) is supported. This result uncovers the mindset of the respondents (Gen Z) who seek to adopt a mobile stock investment application when the application is perceived to offer a lot of financial benefits. Previous studies (Chong et al., 2021; Nair et al., 2022) also supported this result, highlighting the importance of mobile applications to attract investors by offering financial benefits (e.g. low starting capital, low commission fee, and potentially higher returns).

Hypothesis 2 (Perceived Financial Risks negatively influence Adoption Behavior) is not supported. This result unlocks the risk-taking mindset of the respondents (Gen Z). Since they are born with a digital silver spoon, they are familiar with the risks and may also have the ability to maneuver a way to minimize the risks. Previous studies involving older generations revealed the opposite result. Older investors consider financial risks to be negatively linked to their decision to adopt a mobile application for their stock investment transactions (Tai & Ku, 2013; Chin et al, 2020; Chong et al, 2021).

Hypothesis 3 (Perceived Technology Security positively influences the adoption of mobile stock investment applications) is found to be supported. As tech-savvy, younger investors seem to understand that trouble with technology security is a critical issue to consider when adopting a mobile application for financial services, including for stock transactions. The same result applied to mobile payment applications (Aprilia & Amalia, 2023), and mobile banking applications (Oliveira et al., 2016).

Hypothesis 4 (Finfluencers positively influence the adoption of mobile stock investment applications) is found to be unsupported. Even though the younger investors in this study are active social media users, and they follow social influencers, they do not base their decision to adopt a mobile stock investment application on the finfluencers. This is perhaps because there is still a limited number of social influencers in the financial

services that reach out to Gen Z. A study found very little influence of finfluencers on the adoption of mobile stock investment applications (Sembel et al., 2024). In the context of older investors, finfluencers play some role in influencing the older investors to adopt mobile stock investment applications (Nair et al., 2022; Johri et al., 2023; Espeute & Preece, 2024).

The last hypothesis, Hypothesis 5 (Financial Literacy influences the adoption of mobile stock investment applications) is supported. This result is also confirmed by many previous studies involving older and younger generations (Fan, 2021; Nguyen & Nguyen, 2022). Investors with strong financial literacy tend to have more confidence in adopting mobile applications in financial services (Firmansyah et al., 2023).

5. CONCLUSION

This study aims at unlocking the mindsets of Gen Z as a new breed of investors: what influences them in adopting mobile stock investment applications. The data analysis results of the study uncovered three supported hypotheses. Perceived financial benefits, perceived technology security, and financial literacy were found to have a positive influence on Gen Z's adoption of mobile stock investment applications. The study found two unsupported hypotheses: Perceived financial risks were not found to have a negative influence on adoption of mobile stock investment applications. In addition, the results of this study found that Finfluncers were not considered a deciding factor in the adoption of mobile stock investment applications.

The supported results have led to recommendations to application providers to design strategies to attract younger investors by offering financial benefits. They can provide low starting investment and low commission fees. They can also engage younger investors through financial games that offer financial literacy as well as financial rewards.

This moderate R-square, and the large predictive power (Q-square and CVPAT values) revealed the robustness of the research model to be used in this study. Thus, the research framework can be recommended to future researchers to use in future studies. within a similar financial service or stock investment context.

The study has some limitations. First is the absence of emotional factors in the analysis. Future researchers can include First of Missing Out (FOMO) variable which is a unique characteristic of Generation Z (Institute, 2023), which provides useful insights to stakeholders in financial services. Finally,this study didn't perform advanced analysis, such as Important Performance Map Analysis for managerial Implications.

ACKNOWLEDGEMENTS

The author sincerely extends her gratitude to Universitas Pelita Harapan for giving the opportunity to submit this article and for providing constant support for the completion of this article.

REFERENCES

Ahmed, K. (2023, September 14). Unlocking the Investor's Mind: A Deep Dive into Stock Investment App Usage in Indonesia. TGM Research. https://tgmresearch.com/stock-investment-app-usage-case-study-in-indonesia.html

Aprilia, C., & Amalia, R. (2023). Perceived Security and Technology Continuance Theory: An Analysis Of Mobile Wallet Users' Continuance Intention. Global Business Review, 0(0). https://doi.org/10.1177/09721509221145831

Bland, E., Changchit, C., Changchit, C., Cutshall, R., & Pham, L. (2024). Investigating the components of perceived risk factors affecting mobile payment adoption. Journal of Risk and Financial Management, 17(6), 216. https://doi.org/10.3390/jrfm17060216

Biro Pusat Statistik. (2024). *Jumlah Penduduk Menurut Wilayah, Klasifikasi Generasi, Dan Jenis Kelamin, Di Indonesia - dataset - sensus penduduk 2020 - Badan Pusat Statistik*. WEB SENSUS BPS - Badan Pusat Statistik Republik Indonesia. https://sensus.bps.go.id/topik/tabular/sp2020/2

Chin, A. G., Harris, M. L., & Brookshire, R. G. (2020). An empirical investigation of intent to adopt mobile payment systems using a trust-based extended valence framework. Information Systems Frontiers, 24(1), 329-347. https://doi.org/10.1007/s10796-020-10080-x

Chong, L., Ong, H., and Tan, S. (2021). Acceptability of mobile stock trading application: A study of young investors in Malaysia. TechnologyIn Society, 64, 101497. https://doi.org/10.1016/j.techsoc.2020.101497

Espeute, S., & Preece, R. (2024). *The Finfluencer Appeal: Investing in the Age of Social Media Industry Future*. https://rpc.cfainstitute.org/-/media/documents/article/industry-research/finfluencer-report.pdf

Fan, L. (2021). Mobile investment technology adoption among investors. International Journal of Bank Marketing, 40(1), 50-67. https://doi.org/10.1108/ijbm-11-2020-0551

Firmansyah, E.A.; Masri, M.; Anshari, M.; Besar, M.H.A. (2023). Factors Affecting Fintech Adoption: A Systematic Literature Review. FinTech, 2, 21–33. https://doi.org/10.3390/fintech2010002

Havidz, I, L, H., Aima, M, H., Wiratih, H, W, R. (2018). Determinants of Intention to Recommend WeChat Mobile Payment Innovation in China to be Implemented in Indonesia. International Journal of Advanced Engineering Research and Science (IJAERS), 5(7),https://dx.doi.org/10.22161/ijaers.5.7.38

Hair, H.F., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2022). A Primer on Partial Least Squares StructuralEquation Modelling (PLS-SEM) (3rd ed.). Thousand Oaks, CA: Sage

Henseler, J., **Ringle,** C. M., & **Sarstedt,** M. (2015)**. A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135.** https://doi.org/10.1007/s11747-014-0403-8

IDN Media (2024). *Indonesia Gen Z Report 2024.* IDN Research Institute. https://cdn.Idntimes.com/content-documents/Indonesia-gen-z-report-2024.pdf

Institute, N. C. (2023). Gen Z and Investing: Social Media, Crypto, FOMO, and Family. https://doi.org/10.56227/23.1.15

Johri, A., Wasiq, M., Kaur, H., Asif, M. (2023). Assessment of users' adoption behaviour for stock market investment through online applications, *Heliyon 9* (2023), https://doi.org/10.1016/j.heliyon.2023.e19524

Karp, E. (2023, September 21). A Crucial Challenge For Manufacturers: Attracting—And Retaining—Generation Z. *Forbes*. https://www.forbes.com/sites/ethankarp/2023/09/19/a-crucial-challenge-for-manufacturers-attracting-and-retaining-generation-z/?sh=14a72f231ce8

Liu, Y. (2023). The Impact of Social Media Influencers on Generation Z Online Consumer Behavior (Take the Social Media Platform Douyin as an Example). *Advances in Economics, Management and Political Sciences*, *41*(1), 19–24. https://doi.org/10.54254/2754-1169/41/20232026

Nair, P. S., Shiva, A., Yadav, N., & Tandon, P. (2022). Determinants of mobile apps adoption by retail investors for online trading in emerging financial markets. Benchmarking: An International Journal, 30(5), 1623-1648. https://doi.org/10.1108/bij-01-2022-0019

Nguyen, Y. T. H., Tapanainen, T., & Nguyen, H. T. T. (2022). Reputation and its consequences in fintech services: the case of mobile banking. International Journal of Bank Marketing, 40(7), 1364-1397. https://doi.org/10.1108/ijbm-08-2021-0371

Oliveira, T., Thomas, M., Baptista, G., and Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. Computers inHuman Behavior, 61, 404-414. doi: 10.1016/j.chb.2016.03.030

Pašiušienė, I., Podviezko, A., Malakaitė, D., Žarskienė, L., Liučvaitienė, A., & Martišienė, R. (2023). Exploring Generation Z's investment patterns and attitudes towards greenness. *Sustainability*, 16(1), 352. https://doi.org/10.3390/su16010352

Petrosyan, A. (2023, August 30). *Countries with the largest digital populations in the world as of January 2023.* Statista; Statista. https://www.statista.com/statistics/262966/number-of-internet-users-in-selected-countries/

Sembel, J. S., Widjaja, A. W., & Antonio, F. (2024). An Empirical Analysis of Financial Literacy As Mediator For Stock Investment Intention Among University Students. *ijbs.ipmi.ac.id*. https://doi.org/10.32924/ijbs.v8i1.307

Shmueli, G., Sarstedt, M., Hair, J.F., Cheah, J.-H., Ting, H., Vaithilingam, S. and Ringle, C.M. (2019), "Predictive model assessment in PLS-SEM: guidelines for using PLSpredict", *European Journal of Marketing*, Vol. 53 No. 11, pp. 2322-2347. https://doi.org/10.1108/EJM-02-2019-0189

Tai, Y. and Ku, Y. (2013) Will Stock Investors Use Mobile Stock Trading? A Benefit-Risk Assessment Based on a Modified UTAUT Model. Journal of Electronic Commerce Research, 14, 67-84.

Yusup, A. K., Hangdiyanto, C. (2023). Unlocking Financial Literacy in Generation Z: Are Sociodemographic Factors the Key? *Petra International Journal of Business Studies, 6*(2), 193-200. https://doi.org/10.9744/petraijbs.6.2.193-200