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Understanding Fintech Usage Behavior among Generation Z

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ABSTRACT

This study adopts a quantitative approach and applies the Partial Least Squares-Structural Equation Modeling (PLS-SEM) method to examine the factors influencing behavioral intention and usage behavior regarding Financial Technology (FinTech) services among Generation Z. The research framework integrates variables sourced from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), such as perceived usefulness (PU), perceived ease of use (PEOU), social influence (SI), and facilitating conditions (FC). Data were gathered via a questionnaire given to Generation Z participants who had utilized FinTech services. The results indicate that perceived usefulness (PU), social influence (SI), and facilitating conditions (FC) positively and significantly affect behavioral intention (BI). Conversely, perceived ease of use (PEOU) does not have a significant impact on behavioral intention (BI). Moreover, behavioral intention (BI) is observed to exert a positive and significant influence on use behavior (UB). The findings further suggest that behavioral intention (BI) serves as a mediator between perceived usefulness (PU), social influence (SI), facilitating conditions (FC), and the actual utilization of FinTech services. In general, these results indicate that the perceived advantages, social pressure, and access to technological assistance are significant factors that motivate Generation Z to embrace FinTech solutions. This research adds to the current body of literature on FinTech adoption by combining the TAM and UTAUT frameworks regarding Generation Z in the post-pandemic period.

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1. Introduction

Recent developments in digital technology have led to major transformations in many areas of life, particularly in finance. Digitalization has not only changed the way people communicate and interact but also transformed financial service systems to become faster, more efficient, and more accessible (Fadhilah, 2025). This transformation has driven the emergence of various technological innovations that enable people to conduct a range of financial activities digitally (Tarigan and Muharam, 2025). However, the success of technology implementation is determined not only by the sophistication of the system developed, but also by the level of acceptance and willingness of users to use the technology effectively. One tangible manifestation of information technology advancement is Financial Technology (FinTech). FinTech is a financial service that utilizes digital technology to facilitate transactions and manage finances more efficiently (Bajunaied *et al*., 2023).

FinTech has expanded public access to previously limited financial services, including investment, financing, and digital payments, thereby promoting financial inclusion and market efficiency (Cuandra and Susanto, 2024). The swift advancement of FinTech started following the worldwide financial crisis in 2008. This crisis eroded public trust in the conventional banking system and fostered the emergence of more efficient, faster, and more transparent financial services (Durak *et al*., 2024).

In Indonesia, FinTech development continues to show an upward trend. As per the information from Bank Indonesia (BI), electronic money transaction values in 2022 were around IDR 399.6 trillion, with expectations to rise to IDR 495.2 trillion in 2023. Furthermore, the value of digital banking transactions in 2022 reached IDR 52,545.8 trillion and is projected to increase to IDR 64,175.1 trillion in 2023 (Bank Indonesia, 2023). In the digital financing sector, the Financial Services Authority (OJK) noted that outstanding FinTech peer-to-peer (P2P) lending also increased to approximately IDR 59.64 trillion, representing an annual growth rate of 16.67% (OJK, 2024). The development of digital transactions continues, with Bank Indonesia reporting that the volume of digital payment transactions will reach approximately 4.66 billion transactions, with an annual growth of 41.12% by 2025, indicating the increasing use of digital financial services by the public (Bank Indonesia, 2025a). In addition, the electronic payment framework grounded in the Quick Response Code Indonesian Standard (QRIS) is experiencing remarkable expansion. By 2025, the number of QRIS users will have reached more than 57 million users with more than 39 million merchants, indicating the increasing adoption of digital payments in Indonesia (Bank Indonesia, 2025b). Various FinTech innovations, such as online payments, mobile banking, investments, financial planning, peer-to-peer lending, and crowdfunding, are creating a more open, efficient, and low-cost financial system (Bajunaied *et al*., 2023; Galeone *et al*., 2024). Nonetheless, the accessibility of these Digital services does not ensure that the public will consistently adopt and utilize them. FinTech services are shaped by how much technology is used, which is affected by user experiences and perceptions, along with societal factors that influence the embrace of technology.

Demographically, Generation Z has been exposed to digital technology from a young age, encompassing the utilization of the internet, mobile gadgets, and digital software. This knowledge of technology positions Generation Z as one of the demographics with significant capability to embrace Financial technology (FinTech) solutions. Based on information from the Central Statistics Agency (BPS), the number of individuals in Indonesia within the adolescent and young adult age brackets continues to be quite significant. According to data from the Central Statistics Agency (BPS), the population of teens and young adults in Indonesia remains notably large. By the year 2025, it is projected that the group aged 10 to 14 will consist of around 22 million people, the 15 to 19 age group will also have about 22 million individuals, and the 20 to 24 age range will similarly encompass around 22 million. The large population in these age groups indicates that young people, including Generation Z, have great potential to drive the development of the digital economy in the future (BPS, 2025). Young people also play a significant role in modern financial activities, such as saving, investing, and utilizing various digital financial services as part of more effective financial management. However, challenges remain related to the financial literacy gap that can affect individual financial behavior, including the utilization of digital financial services such as FinTech (Candy and Vira, 2024). Despite the increase in FinTech transactions, not all individuals who intend to use the services actually do so. This underscores the need for additional insight into the factors shaping FinTech usage intentions and actions among Generation Z, particularly in the period following the pandemic.

Numerous research efforts have examined the factors affecting the uptake of FinTech. However, most studies still focus more on behavioral intention (BI) than actual use behavior (UB). Some studies have not even examined actual use, or still equate intention with use behavior (Zhao *et al*., 2024; Egi Arvian Firmansyah, Masri, and Anshari, 2023). However, in the context of technology adoption, the intention to use a service does not necessarily translate directly into actual usage behavior. This discrepancy between intention and actual behavior indicates that our understanding of the FinTech adoption process is still incomplete. Consequently, additional studies

are required on the connection between BI and UB to obtain a deeper insight into the processes driving FinTech adoption. Furthermore, several studies have examined FinTech adoption in various contexts and periods, including during the pandemic and post-pandemic periods (Daragmeh, Lentner, and Sági, 2021; Setiawan *et al*., 2024; Almashhadani *et al*., 2023). However, most of these studies focus on specific respondent groups or contexts, so the results do not fully reflect FinTech usage behavior among other generational groups, which have different characteristics in utilizing digital technology. Therefore, research on FinTech usage behavior among Generation Z is crucial. Even though this generation shows a strong enthusiasm for digital advancements, it remains essential to investigate the elements that influence their motivations and behaviors concerning FinTech services, particularly in the environment following the pandemic.

On the other hand, previous studies have generally used the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT) separately to explain the adoption of FinTech. In fact, some studies further developed the model by adding various external variables such as trust (T), perceived risk (PR), government support (GS), and other psychological factors (Bajunaied *et al*., 2023; Akhtar *et al*., 2024; Hassan *et al*., 2024). Although these approaches provide a broader perspective in explaining technology acceptance, research specifically integrating core variables from both models such as perceived usefulness (PU), perceived ease of use (PEOU), social influence (SI), and facilitating conditions (FC) within a single structured model framework to explain the relationship between behavioral intention (BI) and use behavior (UB) in the context of FinTech is still relatively limited (Bajunaied *et al*., 2023; Idrees and Ullah, 2024). Consequently, merging the key variables from both models is crucial for delivering a more thorough insight into the elements affecting the intention and behavior related to FinTech adoption.

Drawing from the preceding discussion, a research gap persists in fully grasping the FinTech adoption process, especially concerning the connection between BI and UB. Furthermore, there are limitations in studies that integrate core variables from the TAM and the UTAUT within a single analytical framework. Moreover, there are constraints in research that combine essential variables from the TAM and the UTAUT in a unified analytical framework. Thus, this research presents multiple significant contributions. Initially, this research combines the essential variables of the TAM and UTAUT frameworks, including PU, PEOU, SI, and FC, to clarify motivations and actions regarding the use of FinTech services. Second, this study specifically examines UB as the actual use of FinTech services. Secondly, this research particularly focuses on UB as the real utilization of FinTech services. Third, this research focuses on Generation Z in the post-pandemic period, offering a more pertinent view of the adoption patterns of digital financial services within a generational group that has a strong preference for technology. Consequently, this research intends to examine the impact of PU, PEOU, SI, and FC on BI, along with the effect of BI on UB regarding FinTech services within Generation Z.

2. Literature Reviews

The TAM, developed by Fred Davis (1989), is a model used to explain the factors influencing technology acceptance. This model emphasizes two main variables: PU and PEOU, which play a crucial role in shaping a person's intention to use a technology (Igamo et al., 2024). PU indicates how much users think a technology will enhance performance or efficiency, whereas PEOU describes the ease of utilizing the technology. TAM is often employed in research about the adoption of digital technologies, like FinTech services, since it explains how perceived usefulness and ease of use influence intentions and behaviors regarding usage. Another study on mobile FinTech adoption in Sub-Saharan Africa also found that variables in TAM and UTAUT, particularly PU and PEOU, consistently influence FinTech adoption (Hornuf, Safari, and Voshaar, 2025).

In addition to TAM as the main theory, this study also uses the concept of the UTAUT developed by Venkatesh (2003) as a supporting theory. According to Galeone *et al*. (2024), UTAUT is a combination of eight previous theories, including the Theory of Reasoned Action

(Ajzen & Fishbein, 1980), the Theory of Planned Behavior (Ajzen, 1985), and the Technology Acceptance Model (Davis, 1989). In addition, there are also combined models such as the Combination of TAM and TPB (Taylor & Todd, 1995), as well as several other theories such as the Model of PC Utilization (Triandis, 1979), Innovation Diffusion Theory (Rogers, 1983), the Motivational Model (Deci & Ryan, 1985), and the Social Cognitive Theory (Compeau, 1999). UTAUT introduces four main components: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). In this study, two components of UTAUT, SI and FC, were adopted to strengthen the TAM model (Bajunaied *et al*., 2023). FC refers to an individual's belief that they possess sufficient resources and support for utilizing technology, including appropriate devices, internet connectivity, or technical help. In the meantime, SI refers to how much the views of others, such as friends, family, and colleagues, affect an individual's choice to adopt a specific technology. In the FinTech realm, social factors play a crucial role as suggestions from the environment and societal trends frequently influence the degree of uptake of digital financial services.

In addition to TAM and UTAUT, other theories such as Innovation Diffusion Theory, Technology Readiness, and Individual Innovativeness Theory (IIT) are also used to explain technology acceptance. However, various studies show that TAM and UTAUT are the most widely used models because they can explain the main factors that influence technology acceptance, such as perceived usefulness, ease of use, social influence, and support facilities in technology use (Setiawan *et al*., 2024). Therefore, this study combines several variables from TAM and UTAUT to examine the effect of PU, PEOU, SI, and FC on BI and its impact on UB of FinTech services (Almashhadani *et al*., 2023).

In the contemporary digital era of today, how individuals view a technology's utility plays a crucial role in influencing user acceptance levels. PU refers to the degree to which a technology is thought to improve user performance and effectiveness. This factor plays a crucial role in driving the continued adoption of FinTech services because users value tangible benefits such as time savings and ease of transactions (Igamo et al., 2024). In the context of FinTech services, perceived usefulness drives user intention to adopt the technology because it provides benefits such as convenience, time efficiency, and transaction effectiveness (Almashhadani *et al*., 2023). Based on the TAM, a higher perceived usefulness of a technology will increase usage intention. This means that individuals are more inclined to adopt technology that is perceived as useful and can increase their productivity (Shahzad *et al*., 2022). Furthermore, the use of FinTech is considered to help improve financial activities, such as saving and making transactions, thus strengthening individuals' intention to adopt it (Jena, 2025). Overall, the greater the perceived usefulness of a FinTech service, the higher the individual's intention to use it continuously, as perceived usefulness plays a key role in technology acceptance (Dawood *et al*., 2022). H1: PU has a positive effect on BI in using FinTech services.

During technology adoption, social elements significantly influence personal choices and actions. SI describes the extent to which the views and encouragement of significant others, such as family, friends, or social circles, can influence a person's intention to use FinTech services (Bajunaied *et al*., 2023). This factor also reflects the influence of culture and customs that drive individuals in making technology adoption decisions, especially for those in environments with high financial literacy and technology acceptance (Idrees and Ullah, 2024). Social support and cultural norms have been shown to play a positive and significant role in an individual's intention to adopt digital financial services such as FinTech (Sharma *et al*., 2024). Because the concept of FinTech is still relatively new, individuals tend to consider the views of those around them before using it (Almashhadani *et al*., 2023). Several studies have also confirmed that social influence plays a significant role in an individual's intention to adopt technology, including in developing countries (Hassan *et al*., 2023). In general, social influence greatly impacts an individual's intention to utilize FinTech services, as the opinions of others and societal norms can strengthen beliefs and promote the choice to embrace the technology. H2: SI has a positive effect on BI in using FinTech services.

FC refers to how much individuals feel that the existing technical assistance, infrastructure, and resources can enable them to utilize FinTech services efficiently. This factor is a key determinant in increasing users' intention to adopt the technology, as ease of access and the availability of adequate facilities foster confidence in using digital services. Consistent with the views of Venkatesh (2003) and Oliveira (2016), FC reflects the belief that technological infrastructure and organizational support can support efficient system use and influence individual behavioral intentions (Bajunaied *et al*., 2023; Ghose *et al*., 2025). Several studies have shown that technical support, training, and the availability of devices and internet networks positively contribute to individuals' intention to utilize FinTech services (Tariq *et al*., 2024; Hassan *et al*., 2022). Furthermore, the readiness of infrastructure and human resources within an organization contributes to a better user experience, thereby strengthening their intention to switch to digital services (Idrees and Ullah, 2024; Marhadi *et al*., 2024). Overall, conditions that facilitate technology use, such as organizational support, adequate resources, and infrastructure readiness, play a significant role in increasing individuals' confidence and intention to use FinTech services (Hassan *et al*., 2024). Therefore, the better the supporting conditions are, the more likely these individuals are to intend to adopt and utilize digital financial technologies. H3: FC has a positive effect on BI in using FinTech services.

PEOU crucial element affecting users' intention to embrace FinTech services. This concept reflects the extent to which a service is perceived as easy to use, both in terms of interface, navigation, and access across devices, and has been shown to positively influence FinTech adoption (Igamo et al., 2024). The easier a service is to use, the greater a person's intention to use it (Daragmeh *et al*., 2021). Ease of navigation and an intuitive interface also increase user intention (Zhao *et al*., 2024), as do user-friendly and clear FinTech services (Almashhadani et al., 2023). Based on the TAM, ease of use influences user attitudes and drives their intention to adopt technology (Shahzad *et al*., 2022). Similar findings are seen in digital investment and payment services, where ease and convenience of use increase user intention (Kasemharuethaisuk and Samanchuen, 2023). Consequently, the perception of user-friendliness is vital in influencing people's intention to embrace FinTech services, since users usually show greater interest in technologies that are simple to use and enhance digital financial transactions. H4: PEOU has a positive effect on BI to use FinTech services.

PU is a key factor driving FinTech service usage behavior. The greater the perceived benefits of using FinTech, the higher the individual's intention to use it, which then leads to increased usage behavior (Igamo *et al*., 2024; Daragmeh *et al*., 2021; Setiawan *et al*., 2024). The benefits of FinTech in increasing transaction efficiency, ease of access, and time savings also strengthen users' intention to utilize these services and ultimately drive actual usage behavior (Almashhadani *et al*., 2023; Jena, 2025; Wu and Peng, 2024). Furthermore, according to the TAM, perceived usefulness significantly influences behavioral intention, which in turn influences actual use of a technology (Shahzad *et al*., 2022). Thus, perceived usefulness indirectly influences usage behavior by increasing an individual's intention to use FinTech services (Patnaik *et al*., 2023). H5: PU positively influences UB through the mediation of BI in the use of FinTech services.

SI is a crucial factor driving individuals to use FinTech services. Collaboration with FinTech companies and attention to ESG factors can increase user awareness and intention to utilize digital services, ultimately influencing usage behavior (Galeone *et al*., 2024). Furthermore, opinions and recommendations from friends, family, and the surrounding community consistently drive individuals' intention to use digital financial services (Ghose *et al*., 2025). SI also occurs through media and influential figures, increasing user interest in adopting FinTech services (Hassan *et al*., 2025). Cultural norms and social group opinions also reinforce these intentions, significantly impacting FinTech usage behavior (Sharma *et al*., 2024). Thus, social influence plays an indirect role in FinTech usage behavior by increasing individual intentions to use them (Almashhadani *et al*., 2023; Hassan *et al*., 2022; Hassan *et al*., 2023; Hassan *et al*., 2024). H6: SI positively influences UB through the mediation of BI in the use of FinTech services.

The availability of resources and technical support not only directly affects ease of adoption but also shapes the intentions that drive actual usage behavior. When individuals perceive they have access to devices, a stable internet connection, and adequate technical support, they are more motivated to try and continue using FinTech services (Tariq *et al*., 2024; Hassan *et al*., 2022). Organizational support, collaboration with FinTech providers, and attention to environmental, social, and governance (ESG) factors also strengthen users' trust and intention to adopt digital services (Galeone *et al*., 2024; Ghose *et al*., 2025). This intention then develops into actual usage behavior when users perceive that the adoption process presents no technical barriers. Overall, FC plays an indirect role in usage behavior by increasing individual intentions. Strong infrastructure, consistent technical support, and ease of access are important factors linking intention to use FinTech services (Hassan *et al*., 2024). H7: FC has a positive effect on UB through the mediation of BI in using FinTech services.

The ease of use of FinTech services is a key factor influencing user intent and behavior. A user-friendly interface and accessibility across multiple devices have been shown to increase user intention to use the service, which in turn drives actual usage behavior (Igamo *et al*., 2024; Zhao *et al*., 2024). Furthermore, clear, understandable, and effortless usability also enhances user convenience, thereby strengthening the intention to continue using FinTech services (Almashhadani et al., 2023). Ease of access and intuitive design play a crucial role in driving FinTech service adoption, as perceived ease of use increases intention and indirectly impacts financial technology usage behavior (Patnaik *et al*., 2023; Tian and Chan, 2024). H8: PEOU positively influences UB through the mediation of behavioral intention (BI) in FinTech service use.

BI is a crucial element influencing how much individuals will utilize FinTech services. Most studies indicate that behavioral intention has a positive influence on UB, although some studies found insignificant results (Igamo et al., 2024). The stronger a person's intention to use FinTech services, the more likely they are to actually utilize them in their daily financial activities (Ashoer *et al*., 2024; Galeone *et al*., 2024). Therefore, individuals with strong intentions are more likely to realize these intentions in the form of actual usage behavior, indicating that behavioral intention plays a significant role in driving the actual adoption of FinTech services *(*Almashhadani *et al*., 2023; Tian and Chan, 2024). H9: BI has a positive influence on UB in the use of FinTech services.

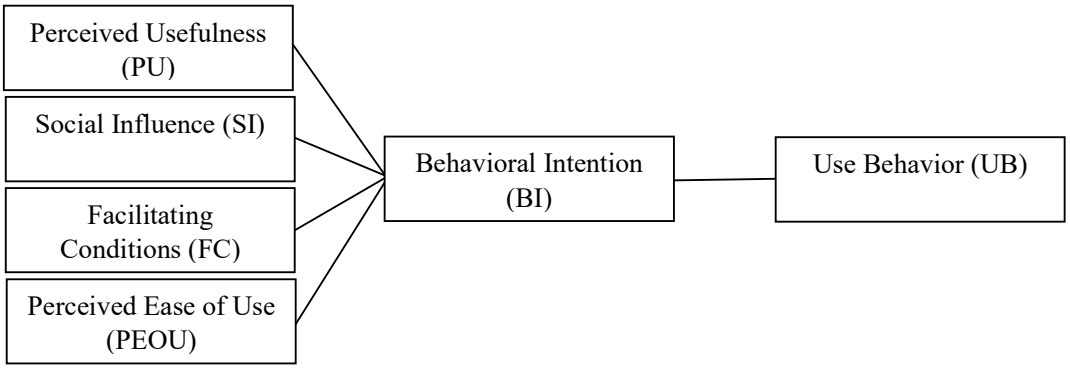

Fig. 1. Research Framework

This study employed a quantitative method with a causal-comparative approach, aiming to analyze the causal relationship between independent and dependent variables through an analysis of existing conditions (Pertiwi and Jailani, 2023). The study population comprised Generation Z individuals in Indonesia with experience using Financial Technology (FinTech) services. The sample was chosen through a purposive sampling method, which entails selecting participants based on particular criteria. The criteria for respondents in this research were Generation Z, particularly those born from 1997 to 2012, who have utilized FinTech services. Initially, 415 respondents were gathered; however, following the data screening process, 407 respondents were assessed to meet the research criteria and were incorporated into the analysis.

The research questionnaire contained questions covering one dependent variable, four independent variables, and one mediating variable. The dependent variable is the variable that is the focus of measurement and is influenced by other variables in the study (Ludianah *et al*., 2022). In this study, the dependent variable is UB, which describes the actual actions of users in using a technology or system after having an intention to use it. UB measures the extent to which users actually use FinTech services in their daily activities, including the frequency, intensity, and consistency of use, such as digital payments, fund transfers, purchases, and other financial services (Igamo *et al*., 2024). This variable plays a crucial role because it reflects the true level of technology acceptance not only at the stage of interest or intention, but also at the stage of implementation and actual use in daily life (Ashoer *et al*., 2024). UB is measured using three indicators, as described in Table 1.

Table 1. Operational Definition of Dependent Variable

No	Question
1.	I look forward to using FinTech services in the next few weeks.
2.	I have a very positive perception of using FinTech services.
3.	My attitude toward using FinTech services has always been positive.

(A. M. Igamo et al., 2024)

Meanwhile, independent variables are variables that can be controlled or regulated by researchers and act as factors influencing the dependent variable in a study (Ludianah *et al*., 2022). This study used four independent variables as predictors: PU, SI, FC, and PEOU. PU refers to the extent to which a person believes that using a system or technology can improve their performance or productivity. The more a user believes that a technology is useful, the greater their desire to use it (Igamo et al., 2024). This variable is crucial in determining the level of technology acceptance and use by users (Hornuf *et al*., 2025). In addition, SI signifies how much an individual perceives that important people in their life, like family, friends, colleagues, or their community, motivate or impact their decision to adopt a specific technology. As social influence increases, a person's tendency to use the technology increases (Hassan *et al*., 2025).

Furthermore, FC refers to an individual's perception of the availability of resources, facilities, and technical support that enable them to use the technology easily (Bajunaied *et al*., 2023). Conditions such as internet connectivity, device access, and technical assistance are factors that can increase user comfort and ease in utilizing technology (Tariq et al., 2024). PEOU is a user's belief that a technology or system can be used without requiring significant effort. If users can understand and operate the technology easily, they will have a more positive attitude toward its use (Daragmeh *et al*., 2021). The details of each independent variable are measured using three to four indicators, as described in Table 2.

Table 2. Operational Definition of Independent Variable

No	Question
	Perceived Usefulness
1.	Using FinTech can meet my financial service needs.
2.	FinTech services can save time.
3.	FinTech services can improve efficiency.
4.	Overall, FinTech services are beneficial for me.
	Social Influence
1.	People around me think that I should use FinTech.
2.	I am more likely to use FinTech if my friends and family use it.
3.	I use FinTech because my colleagues also use it.
	Facilitating Conditions
1.	I have good knowledge about how to use FinTech services.
2.	FinTech services are compatible with other systems that I use.
3.	If I encounter problems when using FinTech services, I can resolve them quickly.
	Perceived Ease of Use
1.	FinTech services are easy to use.
2.	I find the FinTech application interface friendly and easy to understand.
3.	It is easy for me to access the devices required to use FinTech services (e.g., applications, WiFi, etc).

(Igamo *et al*., 2024; Ghose *et al*., 2025)

Furthermore, the mediating variable acts as an intermediary between the independent and dependent variables, explaining the mechanism by which the independent variable influences the dependent variable indirectly, but rather through the mediating variable. In this study, the mediating variable used is BI, which indicates a user's intention or tendency to utilize FinTech services, which then drives the formation of actual behavior (Igamo et al., 2024). This mediating variable is measured using three indicators, as described in Table 3.

Table 3. Operational Definition of Mediation Variable

No	Question
1.	If I have access to FinTech, I intend to use it.
2.	If I have never used FinTech before, I intend to try it soon.
3.	I will recommend Fintech to my friends.

(Igamo *et al*., 2024)

Data were collected through an online questionnaire using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), using a closed-ended questionnaire, where respondents were required to choose the most appropriate answer (Romdona Siti, Junista Senja Silvia and Gunawan Ahmad, 2025). Data was gathered through Google Forms from September 25, 2025, until February 4, 2026. The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS version 3. PLS-SEM was chosen because this method can handle complex research models, including testing direct and indirect relationships (mediation) between variables (Hair Jr *et al*., 2021).

3. Results and Discussion

This study collected 415 respondents from distributed questionnaires. However, after data filtering, 407 valid responses were retained for analysis. The filtering was carried out based on the research sample criteria, namely, respondents who were included in the Generation Z category. A total of 8 respondents who were outside the Generation Z age category were excluded from the analysis. The details of the respondent data are arranged as follows in Table 4.

Table 4. Sample Characteristics

		Frequency	Percentage
Gender	Male	177	43.49%
	Female	230	56.51%
Year of Birth	1997-2000	14	3.44%
	2001-2004	116	28.50%
	2005-2008	252	61.92%
	2009-2012	25	6.14%
Education Level	Junior High School/Equivalent	5	1.23%
	Senior High School/Vocational High School/Equivalent	310	76.17%
	Diploma (D1/D2/D3)	7	1.72%
	Bachelor's Degree (S1)	83	20.39%
	Postgraduate (S2/S3)	2	0.49%
Employment Status	Entrepreneur	206	10.57%
	Private Sector Employee	4	50.61%
	Government Employee	154	0.98%
	Unemployed	225	37.84%
Average Monthly Income	< Rp5.000.000	225	55.28%
	Rp5.000.001-Rp10.000.000	158	38.82%
	Rp10.000.001-Rp15.000.000	13	3.19%
	Rp15.000.001-Rp20.000.000	4	0.98%

	>Rp20.000.001	7	1.72%
Use of FinTech Services	Digital Wallet (E-Wallet) such as OVO, GoPay, Dana	387	95.09%
	P2P Lending (Online Loans)	5	1.23%
	Digital Banks (Jago, Seabank, Blu BCA)	209	51.35%
	Digital Insurance (Insurtech)	12	2.95%
	Investment Platforms (Bibit, Ajaib, Bareksa)	87	21.38%
	Crowdfunding/Online Donations (Kitabisa)	27	6.63%
	Crypto/Blockchain (Indodax, Pintu)	68	16.71%
Frequency of FinTech Usage	Everyday	179	43.98%
	3-4 Times a Week	125	30.71%
	1-2 Times a Week	53	13.02%
	1-2 Times a Month	26	6.39%
	Rarely	24	5.90%

Primary data processed by researchers, 2026

According to the information in the table, there were 407 participants in this study who satisfied the criteria. In terms of gender, the majority of respondents were female, namely 230 people (56.51%), while male respondents numbered 177 people (43.49%). This shows that female participation in this study is more dominant than male. Furthermore, most respondents were born in the 2005-2008 period, as many as 252 people (61.92%). Furthermore, respondents born in the 2001-2004 period numbered 116 people (28.50%), the 2009-2012 period numbered 25 people (6.14%), and the 1997-2000 period numbered 14 people (3.44%). This information indicates that most respondents belong to the Generation Z demographic, particularly within the younger age bracket. Regarding education levels, most respondents possessed a high school/vocational high school/equivalent education, specifically 310 individuals (76.17%). Respondents with a bachelor's degree (S1) numbered 83 people (20.39%), Diploma (D1/D2/D3) as many as 7 people (1.72%), junior high school/equivalent 5 people (1.23%), and postgraduate (S2/S3) as many as 2 people (0.49%). This indicates that the majority of respondents were at the upper secondary education level.

In terms of employment status, the majority of respondents were private employees, amounting to 206 people (50.61%). Furthermore, 154 people (37.84%) were unemployed, 43 people (10.57%) were self-employed, and 4 people (0.98%) were civil servants. This data indicates that the majority of respondents were actively working, although quite a number were also unemployed. Based on average monthly income, the majority of respondents had an income of less than Rp5,000,000, numbered 225 people (55.28%). Respondents with incomes of Rp5,000,001-Rp10,000,000 numbered 158 people (38.82%), Rp10,000,001-Rp15,000,000 numbered 13 people (3.19%), Rp15,000,001-Rp20,000,000 numbered 4 people (0.98%), and above Rp20,000,001 numbered 7 people (1.72%). This shows that the majority of respondents are in the lower-middle income group.

In terms of FinTech service usage, the most widely used services are digital wallets (e-wallets) such as OVO, GoPay, and DANA, with 387 respondents (95.09%). Furthermore, digital banks such as Jago, SeaBank, and Blu BCA are used by 209 respondents (51.35%), investment platforms (Bibit, Ajaib, Bareksa) by 87 respondents (21.38%), crypto or blockchain services by 68 respondents (16.71%), crowdfunding/online donations by 27 respondents (6.63%), digital insurance by 12 respondents (2.95%), and P2P lending by 5 respondents (1.23%). This indicates that digital wallets are the most dominant FinTech service used by respondents. Finally, based on the intensity of FinTech service usage, 179 respondents (43.98%) use FinTech services daily. A total of 125 people (30.71%) use it 3-4 times a week, 53 people (13.02%) use it once or twice a week, 26 people (6.39%) use it once or twice a month, and 24 people (5.90%) use it very rarely. This data indicates that the majority of respondents use FinTech quite frequently in their daily lives.

In this study, testing began with a construct validity test. Validity was assessed using the Outer Loading and Average Variance Extracted (AVE) values. An indicator is deemed valid when its outer loading value exceeds 0.7, and its AVE value is above 0.5. This indicates that all variable items are valid and can be used for further analysis (Budiarti and Morita, 2024). The results of the construct validity test are presented in Table 5.

Table 5. Construct Validity Test Results

	Outer Loading	Average Variance Extracted	Result
PU1	0.864	0.765	Valid
PU2	0.880		
PU3	0.874		
PU4	0.881		
SI1	0.840	0.737	Valid
SI2	0.873		
SI3	0.862		
FC1	0.863	0.724	Valid
FC2	0.865		
FC3	0.823		
PEOU1	0.873	0.765	Valid
PEOU2	0.886		
PEOU3	0.861		
BI1	0.863	0.714	Valid
BI2	0.834		
BI3	0.837		
UB1	0.872	0.758	Valid
UB2	0.869		
UB3	0.872		

Primary data processed by researchers, 2026

The findings from the construct validity assessment of the measurement model (outer model) indicated that all indicators had Outer Loading values greater than 0.7, ranging from 0.823 to 0.886. These values suggest that every indicator is closely related to the construct being assessed. Thus, it can be inferred that every item in this research satisfies the standards for indicator validity, and no indicators require removal. Additionally, the assessment of convergent validity was conducted through the analysis of AVE values. The results from this examination revealed that each construct had AVE values exceeding 0.5, specifically PU of 0.765; SI of 0.737; FC of 0.724; PEOU of 0.765; BI of 0.714; and UB of 0.758. These AVE values signify that every construct accounts for over 50% of the variance within its indicators, thus fulfilling the requirements for convergent validity. Overall, the outcomes of this assessment imply that the measurement model used in this study meets the standards for construct validity. Consequently, every construct fulfills the validity requirements and is appropriate for construct reliability assessment. Reliability testing was performed by analyzing Cronbach's Alpha and Composite Reliability. A variable is declared reliable if the Cronbach's Alpha value is above 0.6 and the Composite Reliability value is above 0.7 (Setianingsih and Sari, 2025). The test results are presented in Table 6.

Table 6. Construct Reliability Test Results

	Cronbach's Alpha	Composite Reliability	Result
PU	0.898	0.899	Reliabel
SI	0.822	0.824	Reliabel
FC	0.809	0.811	Reliabel
PEOU	0.845	0.899	Reliabel
BI	0.800	0.805	Reliabel
UB	0.842	0.851	Reliabel

Primary data processed by researchers, 2026

According to the findings from the construct reliability assessment of the measurement model, all variables in this study met the reliability criteria. This is shown by the Cronbach's Alpha scores, which are above 0.6 for each construct, namely PU of 0.898; SI of 0.822; FC of 0.809; PEOU of 0.845; BI of 0.800; and UB of 0.842. These figures suggest that every construct demonstrates strong internal reliability in assessing its indicators. In addition, the composite

reliability scores for all constructs exceeded 0.7, with several approaching or exceeding 0.8. This suggests that the indicators for each variable reliably and consistently assess the construct.

The Fornell-Larcker Criterion test is used to assess the discriminant validity of a construct. According to this criterion, a variable is considered valid if the value indicating the variable's relationship with its own construct is higher than the correlation between different constructs (Hair Jr *et al*., 2021). The test results are presented in Table 7.

Table 7. Fornell-Larcker Criteria Test Results

	BI	FC	PEOU	PU	SI	UB
BI	**0.845**					
FC	0.625	**0.851**				
PEOU	0.618	0.628	**0.874**			
PU	0.658	0.559	0.679	**0.875**		
SI	0.592	0.468	0.479	0.471	**0.858**	
UB	0.708	0.660	0.692	0.693	0.514	**0.871**

Primary data processed by researchers, 2026

According to the findings from the discriminant validity assessment utilizing the Fornell-Larcker criteria, every construct in this research satisfied the defined criteria. This is evident from the square root of the AVE value for every variable being higher than the correlation coefficient among the other constructs. Thus, each variable, such as BI, FC, PEOU, PU, SI, and UB, demonstrates a strong ability to distinguish itself from other constructs in the model, thus fulfilling the requirements for discriminant validity.

Next, the Heterotrait-Monotrait Ratio (HTMT) test served as an additional approach to evaluate discriminant validity. If the HTMT value is below 0.9, this indicates that discriminant validity has been achieved optimally (Hair Jr *et al*., 2021). The results of this test are shown in Table 8 below.

Table 8. Heterotrait-Monotrait Ratio (HTMT) Test Results

	BI	FC	PEOU	PU	SI	UB
BI						
FC	**0.774**					
PEOU	0.748	**0.758**				
PU	0.771	0.652	**0.780**			
SI	0.722	0.571	0.573	**0.543**		
UB	0.852	0.800	0.820	0.790	**0.607**	

Primary data processed by researchers, 2026

According to Table 8, the assessment using the Heterotrait-Monotrait Ratio (HTMT) approach indicated that all values remained under the tolerance threshold of 0.90. The maximum HTMT value of 0.852 remains within the permissible range. These findings suggest that there is no overly strong correlation between the constructs. Therefore, one can conclude that each construct has satisfied the requirements for discriminant validity.

After testing the outer model, the researchers then tested the inner model (the research's structural model). The resulting structural model is shown in Figure 2 below:

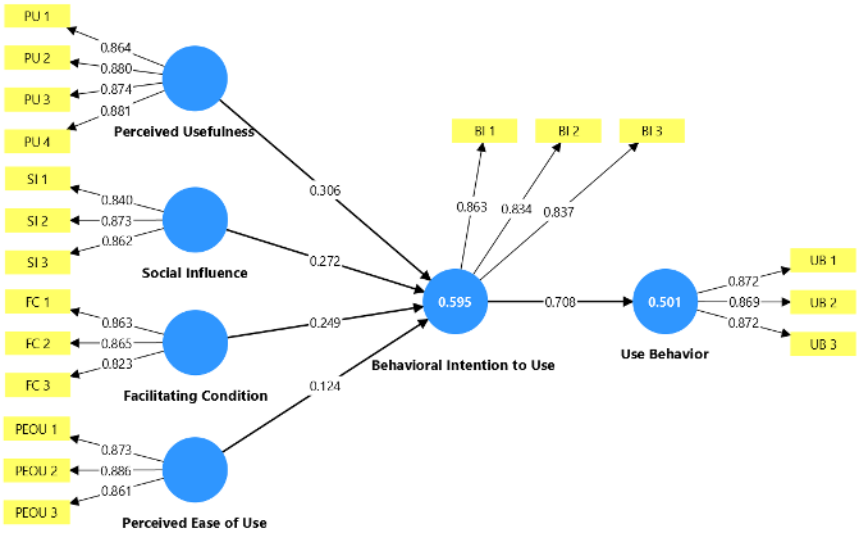

Fig. 2. Research Structural Model

In testing a structural model without mediating variables, direct effects analysis is used. This analysis aims to assess the magnitude of the direct influence of the independent variable on the dependent variable, as well as the influence between latent variables in the model (Affan and Widyastuti, 2022). The level of significance of the relationship between variables can be seen in the direct effects table (Hair Jr *et al*., 2021). A relationship is considered significant at the 5% (0.05) level if it meets the criteria of a t-statistic value > 1.96 or has a p-value < 0.05. The test results are shown in Table 9 below:

Table 9. Direct Effect Test Results

	Coefficients	T-Statistic	P-Value	Result	Hypothesis
PU → BI	0.306	5.282	0.000	Significant & Positive	H_1 Accepted
SI → BI	0.272	5.487	0.000	Significant & Positive	H_2 Accepted
FC → BI	0.249	4.743	0.000	Significant & Positive	H_3 Accepted
PEOU → BI	0.124	1.830	0.067	Not Significant	H_4 Rejected
BI → UB	0.708	19.299	0.000	Significant & Positive	H_9 Accepted

Primary data processed by researchers, 2026

The first hypothesis explores how PU influences BI regarding FinTech services. The results indicate that PU has a positive and significant effect on BI. These findings suggest that the higher the perceived benefits of FinTech services, the more intense the intention to use them. This finding aligns with previous research conducted by Igamo *et al*. (2024) and Almashhadani *et al.* (2023), which found that PU significantly influences BI in the context of digital financial service adoption. These results affirm that concrete advantages, including time savings, transaction simplicity, and enhanced productivity, are critical elements influencing a person's desire to keep utilizing FinTech services. Therefore, H1 is accepted.

The second hypothesis investigates how SI impacts BI. The study results show that SI positively and significantly impacts BI. This implies that the opinions and support from individuals in the user's close environment, including family, friends, and social networks, significantly influence the intent to utilize FinTech services. This finding is consistent with research by Bajunaied *et al*. (2023), Idrees and Ullah (2024), and Sharma *et al*. (2024), which showed that social support and cultural norms positively contribute to technology adoption intentions, especially in environments with high financial literacy and technology acceptance. Thus, H2 is accepted, confirming the importance of social factors in driving FinTech users' BI.

The third hypothesis examines the effect of FC on BI. The results of the test show that FC positively and significantly influences BI. This implies that having sufficient technical support, infrastructure, and resources enhances user trust in utilizing FinTech services. This finding is

consistent with research by Tariq *et al*. (2024) and Hassan *et al*. (2022), which emphasizes that enabling conditions such as internet access, devices, and technical training play a crucial role in strengthening an individual's intention to adopt digital services. Thus, H3 is accepted, emphasizing the important role of enabling conditions in enhancing BI.

The fourth hypothesis examines the effect of PEOU on BI. It suggests that the perceived ease of use of FinTech services does not directly influence users' intentions in this study. This result differs from previous research, such as Igamo *et al*. (2024) and Daragmeh *et al*. (2021), which found a positive effect of PEOU on adoption intention. In numerous studies on technology adoption, simplicity of use is frequently viewed as a crucial element affecting the intention to adopt, since a user-friendly system can lessen the effort needed for users to understand new technology. Nevertheless, demographic elements like age can affect the connection between PEOU and BI. Research on mobile banking adoption shows that younger users tend to adapt more easily to digital technology and have higher levels of digital literacy, while older users often face challenges and obstacles in adapting to new technologies (Kusairi *et al*., 2025). Within the scope of this research centered on Generation Z, the simplicity of use might no longer be a major factor affecting the intention to engage with FinTech services. This occurs because this generation is familiar with utilizing different digital applications in their everyday lives, making user-friendliness no longer a key factor in technology adoption choices. Therefore, H4 is rejected.

The ninth hypothesis examines the influence of BI on UB. The test results indicate that BI has a positive and significant effect on UB. This finding confirms that individual intention directly drives FinTech service usage behavior. These results align with research by Ashoer *et al*. (2024 and Galeone *et al*. (2024), which showed that the higher a person's intention, the greater the likelihood of actually using it in daily financial activities. Thus, H9 is accepted, confirming the important role of intention in realizing the use of FinTech services.

In structural equation modeling involving mediating variables, indirect effect analysis is performed to evaluate the size of the indirect effect of one latent variable on another latent variable through the role of the mediating variable. The significance level of this indirect effect can be examined using the indirect effects table, as explained by Hair Jr *et al*. (2021). A relationship is deemed noteworthy at the 5% significance threshold (0.05) if it meets the criteria of a t-statistic value > 1.96 or has a p-value < 0.05. The findings of this test are shown in Table 10.

Table 10. Indirect Effect Test Results

	Coefficients	T-Statistic	P-Value	Result	Hypothesis
PU → BI → UB	0.217	4.871	0.000	Mediating	H_5 Accepted
SI → BI → UB	0.192	5.502	0.000	Mediating	H_6 Accepted
FC → BI → UB	0.176	4.410	0.000	Mediating	H_7 Accepted
PEOU → BI → UB	0.087	1.816	0.069	Not Mediating	H_8 Rejected

Primary data processed by researchers, 2026

A test for indirect effects was performed to investigate the function of BI as a mediating variable between the independent variables and UB. The analysis showed that PU significantly influenced UB through BI, thus supporting hypothesis H5. This finding aligns with previous studies showing that PU increases user intention to adopt FinTech services, as users perceive tangible benefits such as efficiency and improved performance (Igamo *et al*., 2024; Daragmeh *et al*., 2021; Setiawan *et al*., 2024). Furthermore, other studies have confirmed that increased intention through PU subsequently drives actual usage behavior (Almashhadani *et al*., 2023; Jena, 2025; Wu and Peng, 2024; Shahzad *et al*., 2022; Patnaik *et al*., 2023).

Furthermore, SI also exerts a significant indirect influence on UB through BI, thus accepting hypothesis H6. These results indicate that social influence from friends, family, media, and public figures drives users' intention to adopt FinTech services. Previous research supports this, emphasizing the role of SI in shaping service usage intentions (Galeone *et al*., 2024; Ghose *et al*., 2025), while other studies confirm that these intentions impact actual usage behavior (Sharma *et al*., 2024; Almashhadani *et al*., 2023; Hassan *et al*., 2022; Hassan *et al*., 2023; Hassan *et al*., 2024).

Furthermore, FC were shown to have a significant indirect influence on UB through BI, thus accepting hypothesis H7. These results indicate that having sufficient resources, technical assistance, and infrastructure enhances users' willingness to engage with FinTech services. Previous studies are in line with these results, emphasizing the importance of system support, accessibility, and infrastructure in driving the adoption of digital services and strengthening the mediating relationship between intention and usage behavior (Tariq *et al*., 2024; Hassan *et al*., 2022; Galeone *et al*., 2024; Ghose *et al*., 2025).

In contrast, PEOU did not show a significant indirect effect on UB through BI, thus rejecting hypothesis H8. This indicates that ease of use of a service, although increasing user convenience, is not sufficient to drive usage behavior through intention in the context of this study sample. This finding is not entirely in line with several previous studies that stated that PEOU can increase usage intention and indirectly influence digital service usage behavior (Igamo *et al*., 2024; Zhao *et al*., 2024; Almashhadani *et al*., 2023; Patnaik *et al*., 2023; Tian and Chan, 2024). In various studies on technology adoption, ease of use is generally a key factor in increasing acceptance of technology, especially among user groups who are not yet familiar with digital technology. However, research shows that younger generations tend to adapt to digital technology more quickly than older generations due to their higher levels of digital literacy and broader technology experience (Kusairi *et al*., 2025). Therefore, within the framework of this study that centers around Generation Z, the simplicity of use is probably no longer a significant element affecting the utilization of FinTech services.

Model fit tests were conducted in this research to assess how effectively the developed model can depict the relationships among the variables. One indicator used was the Standardized Root Mean Square Residual (SRMR), which measures the degree of agreement between the observed correlation matrix and the correlation matrix predicted by the model (Hair Jr *et al*., 2021). A model is considered to be of good quality if the SRMR value is < 0.08 (Sathyanarayana and Mohanasundaram, 2024). Furthermore, model fit was evaluated using the Normed Fit Index (NFI), which compares the proposed research model with a baseline model. An NFI value approaching 1 indicates a better level of model fit, and a value above 0.80 is generally considered to indicate an adequate model (Chalise and Poudel, 2025).

The R^2 value serves to show the effectiveness of independent variables in explaining the dependent variable. A greater adjusted R^2 value reflects a better ability of the model to clarify the situation under investigation. According to Maulana and Astaginy (2024), the R-Square value can be classified into three levels of model strength: a value of 0.70 indicates a model with a strong level of explanation, a value of 0.50 indicates a moderate level, and a value of 0.25 indicates a weak level of explanation. The next testing step is F-Square (f^2), which is used to measure the magnitude of the influence or contribution of each exogenous variable to the endogenous variable in the research model. The f^2 value is categorized as a large effect if > 0.35, a medium effect if > 0.15, and a small effect if ≥ 0.02 (Yan *et al*., 2022). Table 11 displays the outcomes of the F^2 test conducted on this research model.

Table 11. Model Fit Test Results

		Saturated Model
Standardized Root Mean Square Residual (SRMR)		0.058
Normed Fit Index (NFI)		0.834
R Square (R^2)		
	Behavioral Intention	0.595
	Use Behavior	0.501
F Square (f^2)		
	Behavioral Intention → Use Behavior	1.004
	Facilitating Conditions → Behavioral Intention	0.084
	Perceived Ease of Use → Behavioral Intention	0.017
	Perceived Usefulness → Behavioral Intention	0.114
	Social Influence → Behavioral Intention	0.128

Primary data processed by researchers, 2026

The analysis findings in this study indicate that the SRMR value of 0.058, which is below the recommended threshold of 0.08, demonstrates a good model fit. Moreover, the NFI score of 0.834 indicates that the model demonstrates a fairly good alignment with the data. Consequently, the model applied in this research is deemed appropriate for implementation during the hypothesis testing stage.

The R^2 value indicates that BI has a value of 0.595, meaning that 59.5% of the variance can be explained by PU, SI, FC, and PEOU. Meanwhile, UB has an R^2 value of 0.501, indicating that 50.1% of the variance is explained by BI. Both values are in the moderate category, indicating that the model has fairly good explanatory power. Based on the f^2 value, the influence of BI on UB is relatively large, at 1.004. SI of 0.128 and PU of 0.114 are classified as small to moderate on BI, while FC of 0.084 and PEOU of 0.017 are classified as small to very small. Overall, BI is the most dominant variable in influencing UB.

4. Conclusion

This research intends to examine how BI serves as a mediating factor between technology acceptance elements and the UB of Financial Technology (FinTech) services among Generation Z. Findings suggest that PU, SI, and FC positively and significantly impact BI. On the other hand, PEOU was found not to significantly influence BI. Furthermore, BI was identified as positively influencing UB and can mediate the connections between PU, SI, and FC regarding actual FinTech usage behavior. The results suggest that perceived usefulness, social pressure, and technological assistance are essential elements propelling Generation Z's acceptance of FinTech services. As a result, FinTech providers must enhance service advantages and bolster infrastructure support, along with strategies based on social influence to promote broader adoption. This research has limitations as it exclusively centers on Generation Z participants and incorporates various variables from the TAM and UTAUT frameworks. Consequently, additional studies are advised to incorporate other factors like trust (T), perceived risk (PR), or financial literacy (FL), along with broadening the participant range to gain a deeper insight into FinTech usage behavior.

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