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Article

Tech titans: Generation Z's role in the FinTech evolution

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Abstract: The accessibility of FinTech services is increasing, and their convenience is making them more popular than traditional banks, particularly among Generation Z. The objective of this research is to identify and compare the factors influencing the conscious use of FinTech services among Generation Z members, who are the most active participants in this field of financial technology. The questionnaire based purposive sample consisted of Generation Z students who demonstrated adequate financial literacy and utilized FinTech, and who were learning in a university environment in Hungary and Romania. A sample of 600 respondents was selected for analysis after cleaning the data online. The methodological approach entailed the utilization of covariance-based structural equation modeling (CB-SEM). The results indicate that social influence (β = 0.18), consumer attitude (β = 0.53) and facilitating conditions intention (β = 0.11) all have a significant effect on the behavior intention, explaining 49% of the variance. In the context of performance expectation, the effect of facilitating conditions intention is not significant (p = 0.491). The motivation of Generation Z towards fintech solutions is evident in their preference for speed and ease of use. However, in order to reinforce consumer expectations and transfer the necessary experience and attitudes, it may be beneficial for service providers to adopt a partially different strategy in different countries. Generation Z can thus serve as a crucial reference point for the even more discerning expectations of subsequent generations. The findings may inform the formulation of strategies for fintech service providers to better understand customer behavior.

Keywords: attitudes; CB-SEM; financial digitalization; fintech; generation Z

1. Introduction

In the context of globalization and digitalization, the analysis of the use and adoption of online banking and fintech services, which are of considerable importance to the public, represents a major topic of interest within the field of social science research. The growing accessibility of financial services due to technological advances makes it both more convenient and riskier for users to conduct financial transactions (Kálmán and Grotte, 2023; Saksonova and Kuzmina-Merlino, 2017). A number of studies on financial digitalization have been published, including comparisons of the level of financial digitalization in the European Union (Kovács and Vinkóczi, 2020; Kovács and Vinkóczi, 2022) and assessments of the differences between digital banking and fintech services (Varga, 2017). The literature on this topic includes studies on the uptake of and customer satisfaction with these services (Nathan et al., 2022; Venkatesh et al., 2003; Venkatesh et al., 2012). Other studies have focused on the determinants of digital banking adoption (Jihane and Aziz, 2022), while still others have examined the impact of digital banking on financial inclusion (Saksonova and Kuzmina-Merlino, 2017).

Therefore, analyses in the fintech field are highly diverse, yet the majority of studies (Pagel et al., 2019) examine customer perceptions of fintech usage and adoption in a single country, thereby avoiding an analysis of cross-country variation. Some studies analyze cross-country differences in the context of fintech company formation and operations (Kowalewski and Pisany, 2020), location theories (Kézai and Skala, 2024), economic development (Kireyeva et al., 2022), crisis resilience (Kézai and Kurucz, 2023) and financial stability (Koranteng and You, 2024; Mahmud et al., 2023). Other researchers have explored the financial security and attitudes of university students, particularly during periods of economic crisis or in the context of financial literacy (Poyda-Nosyk et al., 2022). In light of these findings, it can be argued that similar analyses of customer behavior represent a research gap in the field of fintech research. This paper aims to fill this gap by including the Hungarian-Romanian context in the research on financial digitalization. The relevance of the consumer behavior research is enhanced by the fact that the digital development of the two countries does not differ considerably, according to Dragan et al. (2024). However, economically,

Romania's development is currently more notable than that of Hungary (Nándori and Zsido, 2024). The present study is thus designed to investigate the customer acceptance of fintech use, with a view to answering the following research questions: What factors influence the use of fintech services between Hungarian and Romanian users? Are there significant differences in consumer fintech acceptance between the two countries? In order to answer research questions involving psychological aspects, the existing literature (Haenlein and Kaplan, 2004) suggests the use of structural models as a means of analyzing complex relationships. Therefore, the objective of the present study is to examine consumer behavior and potential cross-country variations through the implementation of this methodology.

The term "fintech," or financial technology, is most accurately defined as the application of digital innovations to enhance and streamline financial services. This research is concerned with three principal areas of fintech: digital payment, digital banking, and e-wallet applications. It considers these in the context of their relevance to the younger generation. These services employ digital platforms and technologies to facilitate financial transactions, banking operations, and the storage of funds. The objective is to enhance the customer experience through increased efficiency, transparency, and reduced costs (Valavan, 2023; Zihan et al., 2023).

Fintech companies that specialize in digital payments, digital banking, and e-wallets operate in a highly competitive landscape that includes traditional banks and other financial institutions. A significant number of these companies have undergone a process of evolution, becoming what are known as "neo-banks" or comprehensive digital platforms that offer a comprehensive range of financial services. This enables users, particularly those who are technologically adept, to manage their finances in a seamless manner across different channels (Campino et al., 2020). Despite their potential, these fintech solutions encounter obstacles, including data security concerns, regulatory compliance issues, and operational inefficiencies when compared to established banks. These challenges may impede their growth and scalability (Romānova and Kudinska, 2016).

The ongoing digital transformation in the financial sector demonstrates that while fintech in digital payment, digital banking, and e-wallets is reshaping the market, these services still require further development to achieve the operational maturity of traditional financial institutions. Moreover, the integration of advanced technologies, including blockchain, artificial intelligence, and biometric authentication, into these fintech solutions is expected to address some of the aforementioned challenges and stimulate further innovation (Gopal et al., 2023).

Consequently, the field of fintech, encompassing digital payment, digital banking, and e-wallet applications, represents a dynamic nexus of technology and finance. It is particularly focused on the delivery of innovative solutions to meet the evolving needs of the younger generation, particularly in an increasingly digital and cashless economy. In this study, this focus is particularly pertinent when compared to other fintech topics, such as blockchain, peer-to-peer lending, or crowdfunding, and is especially relevant for the Z generation.

Hypothesis development and literature review

The purpose of the hypotheses was to gain insight into the factors that influence the utilization of fintech services by Generation Z through two countries. A review of the literature reveals that research on the facilitating conditions intention for fintech services is a relatively new research area. The Scopus database indicates that only 26 scientific documents were published and noted by Scopus during the period between 2020 and 2023. The initial document pertaining to facilitating conditions intention for fintech service was published in 2020. However, a notable surge in interest was observed in subsequent years, with 2 documents published in 2021, 7 in 2022, and 16 in 2023. It is worthwhile to cite the conclusions of several of the most recent studies. The determinants of fintech adoption are becoming increasingly significant from both a scientific and a practical standpoint. A number of studies have sought to identify the factors that influence the behavioral intention to use fintech services. These factors include performance expectancy, effort expectancy, social influence, and facilitating conditions (Alkhwaldi, et al., 2022; Bee and Yoong, 2023; Elsaman, et al., 2024; Fare, et al., 2023; Hoque, et al., 2024; Koloseni and Mandari, 2024). In order to gain insight into the specific outcomes along the hypotheses, the factors and their items identified from previous international research (Chong at al., 2010; Venkatesh et al., 2003) were adapted and applied to Hungary and Romania. The following hypotheses are employed in the analysis.

H1. Facilitating conditions intention has a significant impact on the behavior intention of fintech users.

H2. Facilitating conditions intention has a significant impact on the performance expectancy to use fintech users.

The first two hypotheses relate to the effects of facilitating conditions, which may be relevant to behavioral intentions because effective use of technology requires adequate resources, infrastructure, and support (Ammas et al, 2023; Bajunaied et al., 2023; Venkatesh et al., 2012). The availability of the necessary slots, mobile devices and skills, and technological knowledge to access fintech services is essential for their use (Alalwan et al., 2016; Ammas et al., 2023; Asif et al., 2023). Ammas et al. (2023) find that this factor has a positive impact on the adoption and intention to use fintech services. These findings are the contribution of the present study, which is thus related to the diffusion of innovation theory (Shirowzhan et al., 2020), which focuses on predicting the behavior of technology adopters and implementing system sustainability.

Performance expectancy is defined as the extent to which users believe that the implementation of a system will enhance their job performance. It is regarded as a robust predictor of consumers' intention to adopt novel technologies, including e-banking services (Sultana et al., 2023). Additionally, it pertains to the degree to which the utilization of a technology will provide advantages or benefits to consumers in the execution of particular activities (Zarco, et al., 2024). In a study employing structural model, Frare et al. (2023) demonstrates a positive effect of performance expectancy, effort expectancy, and security on the behavioral intention to use fintech services. A study of students in the business field revealed that performance expectancy, effort expectancy, and security positively influence the behavioral intention to use fintech services (Fare et al., 2023). Additionally, Hoque et al. (2024) conducted research involving 237 participants. The findings indicate that image, compatibility, and prior experience with FinTech services are key determinants of user intention to adopt FinTech, while perceived social norms have a limited influence on this decision. A significant interaction was observed between user compatibility and the experience of use in relation to Fintech. It is noteworthy that perceived behavioral control exerted a negative influence on female participants' propensity to adopt Fintech. The research findings indicated that image, compatibility, and experiences of fintech use are significant predictors of fintech user intention, with perceived behavioral control negatively influencing females to adopt fintech (Hoque, et al., 2024). Furthermore, the influence of technological attributes, trust, and perceived risk on the adoption of financial technology (fintech) was investigated. The findings suggest that facilitating conditions play a mediating role in the relationship between technological attributes and fintech adoption, with education level acting as a moderating factor in certain relationships (Koloseni and Mandari, 2024). In their proposed research model, Bee and Yoong draw on the extended Technology Acceptance Model (TAM) to posit that customer innovativeness, hedonic motivation, perceived usefulness, perceived ease of use, system quality, and technology self-efficacy have a positive effect on customer satisfaction and subsequently on continuance intention to adopt Fintech. The findings suggest that fintech service providers should develop effective strategic frameworks to enhance consumer satisfaction and encourage their continued intention to adopt fintech (Bee and Yoong, 2023).

The majority of research (Antwi-Boampong, 2022; Frare et al., 2023) only assesses the direct effect of effort expectancy on behavioral intention, typically without accounting for a separate endogenous variable effect. This finding is partially related to the second hypothesis, which posits that effort expectancy has a significant positive effect on performance expectancy for the perception of healthcare applications by users (Utomo et al., 2021). The second hypothesis is related to the lack of research in fintech services and the assumption that the performance expectancy may affect performance expectancy. This is based on the idea that users' perceptions of how they feel using the service contributes to performance gains in their purchases (Chang et al., 2017) as the increasingly divergent existence of preconditions can taint this kind of motivation. In this context, the present study aims to explore the potential significant relationship between facilitating conditions and performance expectancy.

H3. Attitude has a significant impact on facilitating conditions intention.

Research has been conducted on the relationship between facilitating condition and attitude in relation to digitalization. However, the results of this research do not support the third hypothesis, which states that attitude affects facilitating condition. Instead, the results indicate that facilitating condition does not have a significant effect on attitude (Siswanto et al., 2018). This suggests that there may be a still reverse effect in relation to fintech services. The Unified Theory of Acceptance and Use of Technology (UTAUT) models usually have a well-defined role for the attitude factor, while facilitating conditions are usually optional extensions of the model construct (Shuhaiber, 2016). Therefore, in the present research, it seemed important to consider both factors, as the attitudes of Generation Z youth users may be significantly influenced by today's digital environment (Tunna et al., 2020), which may guide their orientation towards using fintech services through a psychological presupposition, even influencing their prior perceptions.

H4. Social influence has a significant impact on attitude.

The impact of social influence on attitudes is partly related to the explanation of the relevance of the third hypothesis, as evidenced by the literature (Wood et al., 1994). This literature demonstrates that the value judgments, opinions, and approval of many people often exert a significant influence, whereas the opinions of a minority exert a comparatively lower impact (Wood et al., 1994). Furthermore, the impact of social influence on attitudes extends to beliefs, opinions, and behavior, as the perceptions of others influence people's behavior (Hewstone and Martin, 2008). Additionally, Allport (1924) observed that the presence of others can lead to performance improvements as part of the phenomenon of social facilitation.

The study published by Kini et al. (2024) underscores the pivotal role of communal focus, encompassing a sense of belonging and positive brand engagement, in shaping the formation of self-brand connections. These connections, which are reinforced by customer interactions and social media engagement, are of paramount importance in maintaining brand loyalty among users of financial technology (FinTech). The term "social influence in fintech adoption" is used to describe the impact of peer recommendations, social interactions, and cultural norms on individuals' decisions regarding the adoption of financial technology. As evidenced by research presented in multiple articles (Nguyen et al., 2022; Wang et al., 2020), social influence has been identified as a key factor influencing customer attitudes and intentions regarding the adoption of financial payment systems. The study highlights the significant influence of interpersonal relationships and societal expectations on individuals' adoption behaviors in the fintech sector (Sharma et al., 2024). In several studies, social impact has been identified as a significant factor influencing customers' readiness to adopt mobile payment services (Wang et al., 2020). Similarly, in a study involving 337 Malaysian farmers, social influence was identified as the most influential factor shaping their intentions to adopt technology (Omar et al., 2022). These studies illustrate the crucial role of social influence in shaping adoption behaviors across diverse contexts, emphasizing its significance in technology acceptance among heterogeneous populations.

H5. Attitude has a significant impact on the performance expectancy to use FinTech users.

H6. Attitude has a significant impact on the behavior intention of fintech users.

In regard to the fifth and sixth hypotheses, it is also essential to consider the role of loyalty, as this element represents the strength of the relationship between attitude and behavior (Dick and Basu, 1994). Since attitude can be defined as a human trait, typically a framework for evaluating human habits complemented by life experiences (Athiyaman, 2002), it is a factor that can substantially influence the adoption of technology (Rizkalla et al., 2024) as users experience when they perform an action or activity (Athiyaman, 2002).

The results of previous studies indicate that attitudes are the most important factor in explaining the intentions of fintech users with regard to their future behavior. Prior research (Akinwale and Kyari, 2022; Nathan et al., 2022) has demonstrated a robust correlation between attitude and Fintech adoption. However, recent research (Chen et al., 2023) indicates that while attitude is closely associated with fintech adoption, other factors contribute minimally to the overall gap (Igamo et al., 2024). In the study conducted by Kini et al. (2024), the authors posit that attitudes are a crucial factor in fostering brand loyalty in the context of financial technology (fintech) services. The research demonstrates that self-concept exerts an indirect influence on brand loyalty through the intermediary mechanisms of self-brand connection and customer engagement behavior. Positive interactions with the brand serve to reinforce these connections, thereby enhancing loyalty. This suggests that consumers' self-perception and their engagement with the brand are of considerable importance with regard to their loyalty to fintech services (Kini et al., 2024). Other study results indicate that attitudes toward digital entrepreneurship significantly mediate the relationship between Fintech literacy and entrepreneurial intentions. Positive attitudes enhance the impact of fintech literacy on one's intention to engage in digital entrepreneurship, indicating that the promotion of positive attitudes is essential for encouraging digital entrepreneurial activity (Nguyen, et al., 2024). These insights demonstrate that attitudinal effects can influence the value judgments of both potential new consumers and existing ones.

H7. Social influence has a significant impact on the performance expectancy to use fintech users.

H8. Social influence has a significant impact on the behavior intention of fintech users.

The impact of social influence on non-attitudes has been previously investigated (Hutabarat et al., 2022), as spatial social factors influence individuals' behavior and decisions (Wang, 2014). Nevertheless, consumers often depend on others (friends, peers, family members) to make their decisions, indicating the significant role of social influence beyond attitudes to concrete decisions.

H9. Performance expectancy has a significant impact on behavior intention to use fintech.

The ninth hypothesis is corroborated by the findings of Venkatesh et al. (2003), which indicate that users will continue to engage in activities and in circumstances that are beneficial and useful for them in the long term. In this context, performance expectation can be regarded as a quality that may be perceived as divisive among consumers due to the diverse range of service and user experience offerings from different providers.

H10. There is no significant difference in the Romanian-Hungarian pathways to fintech behavioral intention.

A comparison of countries in similar technology situations may yield intriguing insights regarding the tenth hypothesis. However, it is important to note that these two countries are lagging behind the European average in terms of digital progress and digital transformation (Dragan et al., 2024). In addition to the nearly identical relationship with digitalism, the partly similar historical context may also inform the relevance of the hypothesis.

The ten hypotheses permitted a comprehensive examination of the interrelationships between latent variables, thereby elucidating the insights of Generation Z with regard to fintech services.

2. Materials and methods

The present study focuses on Generation Z, as previous studies (Nugroho and Novitasari, 2023) have confirmed that this age group will be the most frequent users of financial technology. This can be monitored and achieved by continuous analysis of user intentions by researchers and service providers. Nevertheless, in 2019, Romania exhibited a notable lag in the digitalization of financial services relative to other European countries, while Hungary demonstrated a substantially higher level of potential in this domain (Pakhnenko et al., 2021). The social links between the two countries (e.g., similar historical past, presence of nationalities) make the analysis of fintech perceptions in both areas an exciting issue. Furthermore, fintech service providers can also provide services as companies established outside national borders in some countries, which suggests that the current level of digital development in the country may not necessarily act as a barrier to these services.

The methodology of structural equation modelling (SEM) was selected for this study as it allows for the investigation of psychological and attitudinal phenomena (Saris and Stronkhorst, 1984). The context of this study, covariance-based structural equation modelling (CB-SEM) is the most appropriate, as it allows for the testing of a specific, practice-specific model by adapting theoretical and previously studied models, as recommended in the literature (Münnich and Hidekuti, 2012). The selected model structure is conducive to the exploration of latent variables, with the potential to uncover significant relationships (pathways) (Diamantopoulos and Siguaw, 2000). The CB-SEM models can only use reflective measurement models, which is recommended in the literature for the study of human personality characteristics and attitudes (Haenlein and Kaplan, 2004). The analyses were conducted utilizing IBM SPSS Statistics 25 and IBM SPSS Amos 24 software.

First, a description of the sampling and data collection characteristics underlying the analysis is presented in **Table 1**. The sampling method was purposive, as the level of financial literacy among university business students is higher than the general level. Therefore, the data collection was carried out in universities in Hungary and Romania between 01/10/2023 and 21/12/2023. However, a pilot test was conducted prior to the finalization of the questionnaire, as the adopted English-validated questions used had to be formulated in both Hungarian and Romanian. In order to ensure linguistic correctness and item comprehensibility, local experts from both countries were consulted and a 15-item pre-questionnaire was implemented. The feedback obtained was used to finalize the questionnaire.

Table 1. Details of the sample and data collection.

Property	Value
Sample size	1461
Context	Hungary, Romania
Valid responses	600
Sampling method	purposive
Confidence level	95%
Validity rate	41.06%
Data collection format	online questionnaire
Data collection implementation	Voter
Data collection period	01/10/2023–21/12/2023
Main scale types	nominal, ordinal
Ordinal scale type	5-point Likert scale

In the data processing stage, respondents were asked to provide their perceptions of the utilization of fintech services. It was a prerequisite for completion that they actively use the services in question. This was conducted by university students on a 5-point Likert scale (strongly disagree—strongly agree), which is the optimal solution for information transfer as recommended in the literature (Chen et al., 2015). The data cleaning process excluded those respondents who exhibited a high degree of similarity in their responses (standard deviation < 0.25) and those who provided incomplete responses. The most common reason for the exclusion of respondents from the data analysis was a flaw in the online survey interface, Voter, which could have resulted in the registration of a number of partially completed questionnaires. This permitted the inclusion of 600 valid responses in the data analysis phase, with a validity rate of 41.06%.

In consideration of the sample size, it is pertinent to note that, in accordance with the recommendation of Hair et al. (2017), the 10-times rule was applied. This rule stipulates that the sample element number should be greater than 10 times the number of indicators of the latent variable that can be described by the majority of manifest variables. Consequently, a maximum of 6 manifest variables per latent variable were employed in the model construction process. In accordance with the methodology proposed by Pirani (2024), the A-priori Sample Size Calculator was employed to ascertain the requisite minimum sample size for conducting SEM analyses. The following parameters were utilized: anticipated effect size (0.3), desired statistical power level (0.8), number of latent variables (5), number of observed variables (13), probability level (0.05). The calculation indicated that a minimum sample size of 268 was required, a threshold that was met by the sample obtained from the valid respondents. This confirmed the reliability of the results.

Secondly, the exploratory factor analysis (EFA) was conducted prior to the application of CB-SEM, and the indicators measuring the model fit of CB-SEM itself were identified and summarized in **Table 2**. The variance inflation factor (VIF), composite reliability (CR), average variance extracted (AVE) and Cronbach's alpha associated with EFA can be used to determine the construct's validity, reliability and appropriateness (Zhang et al., 2015). In consideration of the use of ordinal scales (Likert scale), the application of Spearman's correlation coefficient (Spearman rho) is advised Further analyses can be conducted when there is a substantial number of correlations between variables exceeding 0.3 (Ritter, 2012). In such contexts, the variance inflation factor (VIF) can be employed to rule out multicollinearity by considering the degree of correlation between variables (Akinwande et al., 2015). The use of Likert scales precludes the expectation of a normal distribution for the data. Instead, the kurtosis and skewness values of the data should be examined in this respect (Dash and Paul, 2021; Muthén and Kaplan, 1985).

Table 2. Indicators to be tested in EFA, CB-SEM and bias test and their threshold values.

Stage	Test	Threshold	Source
EFA	Variance inflation factor (VIF)	<5.00	Akinwande et al. (2015)
	Composite reliability (CR)	>0.60	Nunnally, (1978); Hair et al. (2014b); Ates, (2022)
	Average variance extracted (AVE)	>0.50	
	Cronbach's alpha	>0.60	
	Correlation	<0.30	Habing, 2003
	Kurtosis and skewness	between −2 and +2	George and Mallery, 2010
	Kaiser-Meyer-Olkin (KMO)	>0.60	Reddy and Kulshrestha, 2019
CB-SEM	Absolute model fit	GFI>0.80	Mulaik et al. (1989); Wheaton et al. (1977); Schreiber et al. (2006); Tabachnick and Fidell, (2007); Gubik et al. (2018)
		RMSR<0.08	
		RMSEA<0.10	
	Incremental model fit	TLI>0.90	
		IFI>0.90	
		CFI>0.90	
	Parsimony model fit	PGFI>0.50	
		PCFI>0.50	
		PNFI>0.50	
Bias test	Common method bias	explained variance< 50%	Harman, 1960

The Kaiser-Meyer-Olkin (KMO) value indicates the adequacy of the EFA construct. In a similar manner, but indicating the adequacy of the CB-SEM developed, are the absolute, incremental and parsimony model fits. The absolute fit statistic can be employed to assess the degree of fit between the sample data and the prior model, thereby enabling the identification of the optimal fitting model. The incremental fit statistic provides a means of measuring the comparative, relative or incremental fit of a model in relation to the null model (Dash and Paul, 2021; McDonald and Ho, 2002). The parsimony test enables the comparison of competing models by assessing the fit of a model relative to its complexity (Marsh and Hau, 1996; Nebojsa, 2014). The CB-SEM approach offers the advantage of enabling moderator effect analysis to be conducted, which can be achieved by including a moderator variable. This approach can be used to determine whether a moderator variable exerts a significant moderating effect on the relationship between two latent variables (factors) under investigation (Hair et al., 2010). This approach is frequently employed in cross-cultural (cross-country) studies to identify moderating effects (Hair et al., 2014b), rendering it an appropriate methodology for the present study. In evaluating hypotheses, it is advisable to consider the potential for common method bias. This can be effectively addressed through the Harman single-factor test, which is suitable for testing and excluding the possibility of model bias. In this analysis, all manifest variables that comprise the construct are treated as a single factor in a principal component analysis without rotation. (Harman, 1960) The analysis is therefore based on a comprehensive and rigorous statistical testing and analysis.

3. Results and discussion

Following data validation, the total sample size was 600. The sample size from the university populations of the two countries was almost identical, which is considered favorable for analysis and comparison. In accordance with the objective of the analysis, the purpose was to examine the psychological factors and their interrelationships that influence fintech adoption and utilization. This does not necessitate the inclusion of demographic characteristics beyond nationality. Consequently, a certain degree of distortion in the demographic data is not a criterion for excluding this research. Although the data for the sample shown in **Table 3** are comparable in terms of gender and educational level to those for students in university business faculties.

Table 3. Descriptive statistics of the sample.

Country	Variables and the coding of response options		N	%
Hungary (1) *n* = 302	Gender	Male (1)	123	40.7
		Female (2)	179	59.3
	Study level	Higher vocational education (1)	83	27.5
		Bachelor (2)	203	67.2
		Master (3)	16	5.3
Romania (2) *n* = 298	Gender	Male (1)	68	22.8
		Female (2)	230	77.2
	Study level	Higher vocational education (1)	76	25.5
		Bachelor (2)	210	70.5
		Master (3)	12	4.0

The results indicate that, while there is a slight discrepancy in the gender distribution of the sample between the two countries, the proportions of individuals with different educational levels are almost identical. In the context of the analysis, this latter similarity is preferable, as it ensures that any potential differences in educational attainment do not influence the interpretation of the hypothesis comparing the countries. With regard to EFA and CB-SEM, it should be noted that only the best-fitting model fit indicators are presented, in accordance with the established criteria for evaluation.

In terms of the EFA, all of the fit criteria are met by the construct developed (**Table 4**). The exploratory analysis construct comprised 5 latent variables and 13 manifest variables. Following preliminary testing of the manifest variables, the correlation values were found to align with those reported in the literature. Additionally, the skewness (values between −0.826 and 0.26) and kurtosis (values between −0.601 and 0.839) were acceptable in terms of normality. Furthermore, the values of the VIF (values between 1.284 and 2.168) indicate that there is no problem of multicollinearity between the variables in this form for the construct. In addition, the KMO value (0.846), which indicates the adequacy of the design, was also acceptable.

Table 4. Latent and manifest variables identified by EFA.

Latent variable	Manifest variable	Code	Source
Attitude	I believe using E-Payments or other fintech services by mobile services is a good idea.	A_1	Chong at al. (2010)
	Using E-Payments or other fintech services by mobile is a pleasant experience.	A_2	
	In my opinion, it would be desirable to use the fintech applications and services.	A_3	
Facilitating Conditions Intention	I have the knowledge and capability to use fintech services.	FCI_1	Venkatesh et al. (2003)
	fintech product is compatible with all of my computing devices, mobile and gadgets.	FCI_2	
	I have sufficient experience to comfortably use fintech.	FCI_4	
Social Influence	My peers and close friends support the idea of me using fintech services	SI_1	
	Most people I admire and am influenced by are using fintech services	SI_2	
	People who are important to me could assist me in the use of fintech services	SI_3	
Performance Expectancy	Using fintech services increases my overall productivity	PE_3	
	Using fintech services improves my performance in many of my daily activities	PE_4	
Behavior Intention	I intend to continue using fintech services in the future.	BI_1	Venkatesh et al. (2012)
	The likelihood that I will recommend the fintech applications and services to a friend is very high.	BI_4	Nathan et al. (2022)

The validity, reliability and appropriateness of the developed construct were also found to be acceptable based on **Table 5**.

Table 5. Summary of EFA validity, reliability and appropriateness.

Latent variable	Statistical test	Test value
Attitude	Cronbach-alpha	0.843
	Composite reliability (CR)	0.905
	Average Explained Variance (AVE)	0.761
Behavioral Intention	Cronbach-alpha	0.809
	Composite reliability (CR)	0.913
	Average Explained Variance (AVE)	0.839
Facilitating Conditions Intention	Cronbach-alpha	0.752
	Composite reliability (CR)	0.859
	Average Explained Variance (AVE)	0.627
Performance Expectancy	Cronbach-alpha	0.847
	Composite reliability (CR)	0.929
	Average Explained Variance (AVE)	0.867
Social Influence	Cronbach-alpha	0.765
	Composite reliability (CR)	0.865
	Average Explained Variance (AVE)	0.681

The results therefore indicated that the best-fit model construction developed during the EFA was acceptable for all compliance indicators. The EFA results were then used in CB-SEM to test the adequacy of the model fits. The results (**Table 6**) showed that all tests for all three sets of priority model fit indicators were satisfied by the CB-SEM construct developed, indicating the requirement for additional analysis. It was consequently feasible to make decisions regarding the hypotheses, which entailed the examination of the significant pathways of the construct as revealed by the CB-SEM construction.

Table 6. Measures of CB-SEM model fit indicators.

Type of Fit	Statistical index	Test value	Acceptance
Absolute fit	GFI (goodness of fit index)	0.969	Yes
	RMSR (root mean square residual)	0.036	Yes
	RMSEA (root mean square error of approximation)	0.044	Yes
Incremental fit	TLI (Tucker-Lewis-index	0.973	Yes
	IFI (incremental fit index)	0.981	Yes
	CFI (comparative fit index)	0.980	Yes
Parsimony fit	PGFI (parsimony-adjusted goodness of fit index)	0.596	Yes
	PCFI (parsimony-adjusted comparative fit index)	0.704	Yes
	PNFI (parsimony-adjusted normed fit index)	0.692	Yes

The results were employed to identify the significant and non-significant paths in the latent-latent and latent-manifest variable relations, which facilitated the most appropriate hypothesis testing decisions. The application of significance levels (*P*-

values) has revealed that only two paths are not significant (**Table 7**), namely those identified in the Facilitating Conditions Intention—Performance Expectancy and Behavior Intention—Performance Expectancy relations.

Table 7. CB–SEM model unstandardized regression weights.

Manifest variable	**Latent variable**	**Predicted *β***	**SE**	**CR**	**P**
Attitude	Social Influence	0.421	0.046	9.082	***
Facilitating Conditions Int.	Attitude	0.664	0.056	11.880	***
Performance Expectancy	Facilitating Conditions Int.	0.041	0.064	0.648	0.517
Performance Expectancy	Attitude	0.673	0.086	7.845	***
Performance Expectancy	Social Influence	0.201	0.060	3.336	***
Behavioral Intention	Facilitating Conditions Int.	0.107	0.054	1.988	0.047
Behavioral Intention	Attitude	0.621	0.085	7.310	***
Behavioral Intention	Social influence	0.186	0.052	3.580	***
Behavioral Intention	Performance Expectancy	−0.016	0.046	−0.347	0.729
BI_1	Behavioral Intention	1	-	-	-
BI_4	Behavioral Intention	1.142	0.070	16.410	***
A_1	Attitude	1	-	-	-
A_2	Attitude	0.982	0.048	20.339	***
A_3	Attitude	1.028	0.052	19.954	***
SI_1	Social Influence	1	-	-	-
SI_2	Social Influence	1.033	0.071	14.578	***
SI_3	Social Influence	0.861	0.064	13.469	***
PE_3	Performance Expectancy	1	-	-	-
PE_4	Performance Expectancy	0.959	0.058	16.669	***
FCI_1	Facilitating Conditions Int.	1	-	-	-
FCI_2	Facilitating Conditions Int.	0.703	0.057	12.302	***
FCI_4	Facilitating Conditions Int.	0.913	0.056	16.223	***

* *** $p < 0{,}001$.

In the application of CB-SEM, three possible approaches to the analysis of moderator effects have been proposed (**Table 8**): the constrained approach, the unconstrained approach, and the orthogonalized approach (Algina and Moulder, 2001; Cheah et al., 2020; Little et al., 2006; Marsh et al., 2006). A multigroup analysis is recommended for analysis with categorical variables to avoid loss of information (Cheah et al., 2020).

Table 8. Moderator effect test for differences between countries.

Measurement level of deviation	**DF**	**CMIN**	**P**
Overall model deviation	17	13.815	0.680
Attitude ← Social influence	1	0.055	0.814
Facilitating Conditions Int. ← Attitude	1	0.119	0.731
Performance Expectancy ← Facilitating Conditions Int.	1	3.614	0.057
Performance Expectancy ← Attitude	1	3.597	0.058

Table 8. (*Continued*).

Measurement level of deviation	DF	CMIN	P
Performance Expectancy ← Social Influence	1	0.085	0.771
Behavioral Intention ← Facilitating Conditions Int.	1	0.546	0.460
Behavioral Intention ← Attitude	1	0.008	0.929
Behavioral Intention ← Social influence	1	0.676	0.411
Behavioral Intention ← Performance Expectancy	1	0.146	0.702

In this study, an unconstrained approach was applied to the analysis of between-group model variance and moderator effects across paths, following the recommendation of Marsh et al. (2007). The results show that the overall model divergence between the Hungarian and Romanian subsamples is not statistically significant. Moreover, the examination of the relationships between specific latent variables did not reveal any significant differences in the pathways. Although in two cases the test results are close to the 0.05 significance level, the confidence level (95%) used in this study does not permit their acceptance.

It would be prudent to note before the hypotheses testing that the explanatory power of the model should also be acknowledged, which is considered to be exceptionally high at 49% (R^2 = 0.49). Furthermore the 50% explained variance threshold set by Harman (1960) was not exceeded by the CB-SEM construct (explained variance: 39.94%), indicating that no evidence of bias was detected in the model based on Harman's single factor test.

3.1. Hypotheses testing

The evaluation of the hypotheses is systematically summarized in the light of the EFA and CB-SEM test results (**Table 9**). The Beta coefficients are presented in a standardized form for ease of interpretation. The majority of the hypotheses (8) were accepted when the statistical analyses were taken into account, leaving only 2 hypotheses that were rejected. It is important to note that the accepted confidence level for the results was 95%, which may be perceived as a relatively strict threshold for some hypotheses.

Table 9. Results of hypothesis testing based on CB-SEM results.

Path	Reason Standardized Coefficient Value (SCV), SE., CR, P	Result
H1: FC→BI	SCV: 0.110 S.E.: 0.054 C.R.: 1.988 P < 0.050	Supported
H2: FC → PE	SCV: 0.040 S.E.: 0.064 C.R.: 0.648 P = 0.517	Not supported
H3: A → FC	SCV: 0.660 S.E.: 0.056 C.R.: 11.880 P < 0.001	Supported
H4: SI → A	SCV: 0.420 S.E.: 0.046 C.R.: 9.082 P < 0.001	Supported
H5: A → PE	SCV: 0.510 S.E.: 0.086 C.R.: 7.845 P < 0.001	Supported
H6: A → BI	SCV: 0.530 S.E.: 0.085 C.R.: 7.310 P < 0.001	Supported
H7: SI → PE	SCV: 0.170 S.E.: 0.060 C.R.: 3.336 P < 0.001	Supported
H8: SI → BI	SCV: 0.052 S.E.: 3.580 C.R.: 8.279 P < 0.001	Supported
H9: PE → BI	SCV: −0.020 S.E.: 0.046 C.R.: −0.347 P = 0.729	Not supported
H10: HUN ←→ RO	Overall model deviation: P > 0.05; paths: P > 0.05	Supported

Source: Own elaboration based on questionnaire data.

It may therefore be beneficial to discuss the latent variables involved in terms of potential differences between countries.

4. Discussion

In addition to the overview of the results, it is of particular importance to review the properties of the construct represented by the CB-SEM model. These details may contribute to a more complex understanding of the relationships in the sample and may prompt discourse among researchers. In order to facilitate this idea, the latent and manifest variables and their relationships are presented in **Figure 1** as a comprehensive picture of the results. It is crucial to note that the country of the respondent has not been included in **Figure 1** as this would render the transparency of the data.

The manifest variable that best describes the facilitating conditions intention is the possession of knowledge and skills necessary for utility. In contrast, compatibility is the least descriptive of this latent variable (Shtembari and Elgün, 2023). Furthermore, an important characteristic of Generation Z is that they are technology dependent and socialize with technology practices mostly through social media and the Internet (Lopez and Abadiano, 2023). Although these personality traits are associated with globalization and digitalization, this type of learning pattern can be disadvantageous when making financial decisions, particularly in the context of readily available opportunities provided by fintech services (e.g., stock market, crypto). The low importance of multi-device usability for fintech is understandable for Generation Z. However, it is important for banks and fintech providers to offer services on both smaller (e.g., smartphone) and larger (e.g., laptop) devices, as both have advantages (smaller: convenience, performance durability; larger: larger screen, easy data entry) for users (Assensoh-Kodua, 2023). However, it is evident that the mobile phone is one of the most prevalent devices among Generation Z, with members using it on a constant basis in both their online and physical lives. This includes activities such as social media use and payments. The potential for dependency on this device is a consideration (Rushda and Nawarathna, 2021), yet it is clear that the choice between devices is not a question for members of this generation when it comes to their fintech service activities.

Regarding attitudes, the manifest variables describe the factor in a similar manner, yet the pleasant experience emerges as a notable exception. This may be attributed to the fact that, in the context of digital banking, Generation Z members are content if they are able to complete transactions in the simplest possible ways, utilizing an attractive and simple interface, in order to create a positive experience (Windasaria et al., 2022). In light of the observed similarities in attitudes, it can be argued that the primary factor is the finding by Howe and Strauss (2000) that generational differences can be more accurately determined by a few factors than age, with attitudes playing a prominent role. This suggests that by including more generations in the study, it is likely that greater differences in attitudes would be observed.

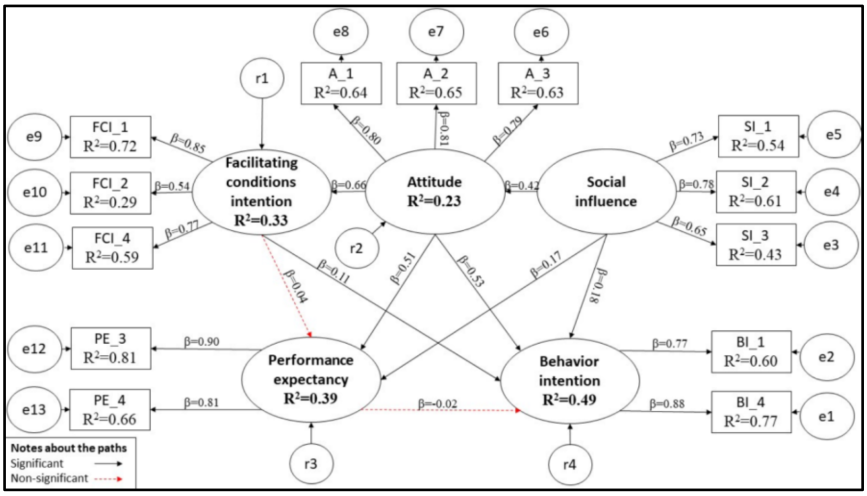

Figure 1. CB–SEM model with standardized regression weights.

According to the findings, the most relevant variable in terms of social influence was admiration and influence. This may be attributed to the fact that Generation Z is not accustomed to being taught by their parents and peers, opting instead to utilize the opportunities offered by media and information technology (Djamaly, 2023). This perception may also be linked to the sense of experience associated with digitalization, as self-learning can also have a positive impact on people (Gelencsér et al., 2024; Ton et al., 2022) although sometimes it can be risky (e.g., cryptocurrency trading). The impact of social influence on attitudes is not surprising in the context of today's world of social media access. Social media provides a platform for the dissemination of information and ideas, which can influence not only attitudes but also beliefs, opinions, values and even human behavior (Hewstone and Martin, 2008).

The manifest variable that best describes performance expectancy is related to overall productivity growth, which can be understood as part of efficiency. A study analyzing the use of fintech services by Generation Z in Romania found that online brokerage functions, money exchange facilities, and international transfers are part of this factor (Dospinescu et al., 2021). These conditions are related to the features that are expected from fintech service providers. They may be similar to the performance expectations of telecommunications services as perceived by consumers of electronic payment systems (Aseng, 2020), even in other countries.

The manifest variable of recommendations can be considered the best descriptor of the latent variable of behavioral intention. This is due to the fact that changes brought about by digitalization make it easier and more acceptable to both give and receive recommendations. The important role of recommendations is emerging in previously impossible venues (e.g., metaverse) and studies are being conducted on its importance and role in the online world (Lingwen et al., 2023). Consequently, it can be posited that this attitude towards recommendations is almost a given for a generation that has had easy access to the internet and technology from birth, both in terms of social life and employment (Olçum and Gülova, 2023).

In the case of the non-significant pathways, the results obtained in this paper differ from those of other studies, which found that enabling conditions had a positive and significant effect on behavioral intentions among multi-generational individuals (aged between approximately 18 and 50 years) (Rahi et al., 2017). This suggests that the existence of technological opportunities can alter one's perception of usage. The existing research has already demonstrated outcomes with regard to the generation of this pathway (Wibowo and Sobari, 2023), which is consistent with the findings of the present study, although it was conducted for the Millennium generation. The findings of this paper indicate that prior experience and skills are indicative of fintech usage. This suggests that there is no significant effect on behavioral intention, given that digital technology usage is almost universal among Generation Z. There is no consensus among researchers on the relationship between facilitating conditions and performance expectancy. However, the divergence in research findings can be explained. Yang and Forney (2013) identified a positive significant relationship between facilitating conditions and performance expectancy. However, this research focused on the product aspect of digitalization, namely mobile purchase intention. In both analyses, facilitating conditions are defined as elements that provide consumers with convenience in choosing and using a product or service (Triandis, 1980; Yang and Forney, 2013). This latent variable, as defined by Venkatesh et al. (2003), is essentially a factor that facilitates user difficulty avoidance. Yang and Forney (2013) applied it to the removal of technological barriers with other typological prepositions. The results of the present analysis corroborate the perspective put forth by Venkatesh et al. (2003), indicating that the increasing digitalization trends do not present a challenging obstacle to the utilization of these services for Generation Z and, by extension, for younger generations.

The comparison of Hungarian and Romanian consumer opinions revealed no significant differences. However, it should be noted that for two paths, the relationship was found to be almost significant at the 95% confidence level. Furthermore, the relationship between facilitating conditions and performance expectancy was not significant in the baseline model, rendering an explanation unnecessary. A marginally significant difference was found for attitude and performance expectancy. It is also important to note the close relationship between the levels of digital development and economic development in countries (Jesus et al., 2017). Hungary and Romania are ranked almost equally in terms of digital development in the 2017 research, but Romania is classified as a developing country compared to Hungary (developed) (Jesus et al., 2017). In the present study, the attitude effect—although not significant—was more pronounced in this context for the Hungarian subsample (β = 0.82) than for the Romanian one (β = 0.47). This discrepancy may be partially attributable to differing perceptions of development.

5. Conclusion

The perception of the use of fintech services has been researched on numerous occasions, yet the present study aimed to contribute to the field of research by comparing Generation Z users in Hungary and Romania. The results indicate that Generation Z will have a considerable impact on the future of fintech services. This age group is projected to become the largest user base of these services in the future (Nugroho and Novitasari, 2023), which will facilitate adaptation by service providers to the more specific needs of younger generations who will subsequently utilize the services. In light of the ongoing process of globalization, it becomes evident that corporate strategies pertaining to the sharing of service experiences and the fostering of positive attitudes may be necessitate a country-specific approach.

The constructed CB-SEM construct offered a number of analytical directions, some of which were not used in the present research. Consequently, the analysis of mediator effects between latent variables represents an additional research direction. Nevertheless, a larger, more representative sample of countries or even cross-border populations in relation to fintech services could provide interesting new insights. The research is limited by its reliance on a questionnaire-based database, which introduces cross-sectional constraints, thereby complicating the process of generalizing the conclusions. However, the results could contribute to a more effective strategy for influencing and persuading potential or existing Generation Z users to use fintech services. Moreover, it would be beneficial to assess these findings in the context of commercial banking practices, which could serve as a new research avenue for future studies. Overall, the partial and full identity and complementarity of the results with other studies confirm this research direction, and it is recommended to analyze other populations within the research area.

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