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Unveiling the Future of FinTech: Exploring the Behavioral Intentions Behind FinTech Adoption

Attila Kurucz [1], Tamás Vinkóczi [1,*], Borbála Tamás [2] and Ewelina Idziak [3,4,5]

1 Department of Corporate Leadership and Marketing, Kautz Gyula Faculty of Business and Economics, Széchenyi István University, 9026 Győr, Hungary; kurucz.attila@sze.hu
2 Department of Applied Psychology, Babeș-Bolyai University, 400347 Cluj-Napoca, Romania; borbala.tamas@ubbcluj.ro
3 Department of Law and Economics, Uniwersytet Kazimierza Wielkiego, 85-064 Bydgoszcz, Poland; ewelina.idziak@ukw.edu.pl
4 Women Research Council, Azerbaijan State University of Economics, AZ1001 Baku, Azerbaijan
5 Faculty of Economics, Department of Banking, Vilniaus Kolegija, HEI, 08106 Vilnius, Lithuania
* Correspondence: vinkoczi.tamas@sze.hu

Abstract

In addition to the technological aspects of FinTech solutions, it is important to consider user willingness, particularly among the digitally savvy Generation Z. We conducted a survey in Hungary and Poland to gather information on young people's use of FinTech applications and their attitudes towards FinTech services. In our research, we built on the already known technology adoption model (UTAUT) and combined it with an attitudinal study. To determine the factors that influence the propensity to use these services, we developed a hypothetical model and tested it with the results of the first round of the survey (n = 117). CB-SEM was used to investigate the relationship between attitudes, social influence, and intention to use behavior. The paper presents the significant relationship characteristics, model structure, and potential business applications of the results.

Keywords: FinTech; digital attitudes; generation Z; CB-SEM modeling

JEL Classification: C38; G21; G23; G41; O33

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1. Introduction

Financial technology has become a pervasive subject in both business and consumer discourse, as well as in academic publications (Gallego-Losada et al., 2023). The advent of digital technologies has been a seminal moment in the financial sector, with profound implications for the industry. Financial institutions with substantial financial resources have demonstrated a capacity for rapid innovation. However, not all actors possess the capacity to maintain pace with technological advancements in a uniform manner. This phenomenon is particularly salient in the context of small and medium-sized enterprises, which often exhibit a delayed adoption of digital technologies. Additionally, older generations of the population may not have become regular users of digital products, underscoring the need for consideration of these diverse user groups in digital transformation initiatives. The international research team has directed its attention toward Generation Z, the generation that has been termed "digital natives." This focus stems from the ambiguity surrounding their relationship with technological innovations, given their status as both customers and users of the future.

The Definition of FinTech

The intertwining of finance and technology is widely accepted in the modern age, and it is noteworthy that the term and its definition were first introduced in the 1970s in the work of Bettinger (1972). To date, a multitude of definitions for FinTech have been proposed by academics and practitioners. The present approach was grounded in a comprehensive interpretation of the term, encompassing both applications and software utilized in the domain of digital finance (Mention, 2019; Giglio, 2021). The focal point of our research endeavors did not lie in the domain of crypto markets or cryptocurrencies; rather, it centered on the digital underpinning of banking and financial transactions, along with their software solutions. A number of studies have examined digital-only banking from regulatory, inclusion, and business perspectives (see Boskov, 2019; Shifa Fathima, 2020; Lau & Leimer, 2019; Tosun, 2020). However, research focusing on customer experiences—particularly among Generation Z—remains scarce. Digital-only banks represent a revolutionary development within the FinTech sector, characterized by their complete reliance on digital technologies and their deviation from traditional banking practices. These institutions are notable for their complete absence of physical branches and the use of digital signatures, thereby eliminating the need for paper-based transactions. Therefore, it has been demonstrated that the aforementioned phenomenon engenders a transformation in the financial ecosystem landscape and the modus operandi of businesses. This, in turn, has the effect of enhancing operational efficiency. However, it must be noted that this transformation is not without its drawbacks, as it also presents businesses with a series of challenges related to security and privacy (Dharamshi, 2019). However, despite its extensive adoption, there is a paucity of empirical studies published in peer-reviewed journals regarding digital-only banking from the perspective of the customer and customer experiences, particularly with regard to Gen Z customers. In view of these characteristics, it is imperative to undertake a more profound examination of FinTech's utilization and significance.

Our research indicates that users are increasingly adopting FinTech tools from a variety of sources and with divergent motivations. Therefore, an investigation was conducted into Gen Z's attitudes toward digital financial applications and solutions, with the investigation encompassing two elements: the first component is utilization, and the second is attitude.

A considerable body of research has been dedicated to the study of innovation adoption and the development of digital competencies. In accordance with our scientific approach, we constructed a theoretical model to investigate the related research on FinTech adoption and attitudes toward FinTech. This was performed to ascertain how these factors influence future willingness to use it. For the purposes of our research, we adapted extant attitudinal survey questions regarding FinTech and concurrently collected usage patterns. The study commenced with the administration of interviews to young individuals in three countries within the North–South axis of the Central-Eastern European region: Poland, Hungary, and Romania. A substantial body of research has already been conducted in each country on these issues (Solarz & Adamek, 2022; Krupa & Buszko, 2023). For instance, a comparison of Polish-Romanian FinTech markets was conducted by Shala and Perri (2022), and similar comparisons can be found between Hungary and Romania (Pintér et al., 2021). Moreover, research on FinTech in EU countries employs a financial institutional approach and incorporates gender-based analyses (Grigorescu et al., 2023; Apostu et al., 2023). In the initial phase of this research, we were able to gather sufficient data for the testing phase from Poland and Hungary. This allowed us to test our new hypothetical model using the CB-SEM method as a survey with a clear Polish-Hungarian focus.

The structure of this study is as follows: The first part of the study is devoted to the theoretical literature research on the use of digital tools and FinTech tools, as well as related attitude models. The second part is concerned with the hypothetical model structure and methodological background. The third part presents the results of the first survey and tests the model. The fourth part includes the main findings of the research, including the discussion, limitations, and future research directions, as well as conclusions.

2. The Theoretical Background of the Relationship Between Digitalization and Generation Z

This paper makes a significant contribution to the extant literature on Gen Z attitudes toward FinTech usage. Specifically, it addresses the lacuna in research regarding behavioral intention to use FinTech services by incorporating latent variables. Therefore, the present study contributes to the important component of academic finance by extending the theory of finance.

The advent of the latest technological revolution has been accompanied by the pervasive integration of digital technologies, including big data, cloud computing, and artificial intelligence, into the financial sector. This integration has catalyzed the robust development of the FinTech industry. Additionally, it is inextricably linked with the banking industry, as evidenced by its correlation with bank risk-taking (Zhao et al., 2023). This issue is of particular concern for two primary reasons. Firstly, the stability of the FinTech industry is of paramount importance in the context of the recent and significant decline of prominent financial institutions, such as Silicon Valley Bank. Secondly, from the perspective of Generation Z, who are highly susceptible to utilizing FinTech services and possess limited financial experience, yet are of considerable numerical significance as they are just entering the labor market and beginning to establish financial independence.

2.1. Research on Fintech and Gen Z

In the context of the ongoing global pandemic, the accelerated digital transformation of the economy has become a matter of pressing concern, underscoring the imperative for the populace to possess proficient digital literacy skills. Lucendo-Monedero et al. (2019) have analyzed the impact of socioeconomic and geographical variables on the level of advanced digital skills of the Spanish population. The authors have confirmed that there is less regional than provincial dispersion in the probability of converging in digital skills. This study makes a significant contribution to the ongoing evolution of the model of digital skills acquisition by incorporating socioeconomic and geographical variables. It identifies intra-regional differences and determines whether there is spatial dependence between regional and local levels (Lucendo-Monedero et al., 2019). This objective aligns with the primary aim of the present research endeavor. In this regard, it is imperative to acknowledge the European Commission's proposal that every individual should have the opportunity to thrive, to exercise autonomy in their choices, and to engage securely within the information society (European Commission, 2016). In accordance with its commitment to sustainability and a digital future, the European Union (EU) passed its "Digital Compass 2030," which aims to achieve a digital society in which 80% of adults possess at least basic digital skills by 2030. Furthermore, Lucendo-Mondero concluded that the level of digital development of European regions is based on households and individuals' daily use of e-commerce, e-banking, and e-government services (Lucendo-Monedero et al., 2019).

For Generation Z, living in the digital age has engendered a unique understanding of the concept of "digitalization." This generation is distinctive in that they are the first to have grown up in a world with the possibility of endless information and infinite connectivity of the digital age (Katz et al., 2021). In a similar vein, Windasari et al. (2022) presented conclusions from empirical insights of digital-only banking usage from young customers. Their qualitative study identified eight variables that influence the digital banking behaviors of Generation Y and Generation Z customers: economic value, perceived ease of use, social influence, firm reputation, sales promotions, product features, curiosity, and rewards. However, the promotion of curiosity, the utilization of promotions as a gimmick, and the employment of short-term strategies that endorse impulsive behavior do not invariably result in usage intention and commitments, particularly for highly utilitarian products such as financial services (Windasari et al., 2022). This study was conducted in Indonesia, where the monthly user growth of digital banking has increased twofold over the past three years. Furthermore, 55% of non-digital customers intend to use a digital bank in the next six months, indicating the appeal of this financial instrument (McKinsey & Company, 2019). Nevertheless, research on digital banking and customer behavior regarding these services remains scarce.

The extant research on digital-only banking has largely focused on regulatory, financial inclusion, and business-related perspectives (Boskov, 2019; Shifa Fathima, 2020; Lau & Leimer, 2019; Tosun, 2020). Digital-only banks represent a revolutionary development within the FinTech sector, characterized by their complete departure from conventional banking norms. These entities operate entirely in a digital realm, eschewing physical documents and signatures and operating without physical branches. Therefore, it has been demonstrated that the aforementioned phenomenon engenders a fundamental shift in the financial ecosystem landscape and the modus operandi of businesses. This, in turn, has the effect of enhancing operational efficiency. However, it must be noted that this process is not without its drawbacks, as it also faces significant challenges related to security and privacy (Dharamshi, 2019). However, despite its extensive adoption, there is a paucity of empirical studies published in peer-reviewed journals regarding digital-only banking from the perspective of the customer and customer experiences, particularly with regard to Gen Z customers. In view of these characteristics, it is imperative to undertake a more profound examination of FinTech's utilization and significance.

2.2. FinTech's Usage and Importance

The demographic composition of the mobile self-service app user base is such that, at present, the largest proportion comprises Generation Z. The proliferation of these applications has been meteoric, and the sheer volume of daily consumer interactions with these applications highlights the need for guidance on how to better facilitate Gen Z consumers to co-create value-in-use and motivate their engagement with the services in various contexts. However, as Zou et al. (2023) emphasize, there is a paucity of empirical research available to gain deeper insights into the mobile service.

It is evident that the efficacy of FinTech solutions is of significant importance and pertinence to Generation Z. In their research, Kim et al. (2022) substantiated that the characteristics of Millennials and Generation Z exert a substantial influence on their predilection for contactless services, with the exception of their pursuit of security. Furthermore, Generation Z and millennial respondents exhibited a higher propensity to prioritize interests in new technology and safety measures. The influence of technology self-efficacy on the preference for contactless service is moderated by social conformity (Kim et al., 2022).

One of the services frequently utilized by Generation Z is electronic wallets. Rosli et al. have emphasized that in constructing a model of e-wallet acceptance among Generation Z, they have found that cashless transactions are on the verge of becoming the norm, with the potential to render physical transactions with fiat currency obsolete (Rosli et al., 2023). Furthermore, the advent of FinTech (F. Chen & Jiang, 2022) and the ongoing pandemic (Riska et al., 2022) have contributed to the proliferation of cashless transactions.

The advent of the coronavirus (COVID-19) has further accelerated the proliferation of cashless transactions. This phenomenon is attributable to several factors, including the propulsion of national digitalization (Tan & Xue, 2021), a substantial escalation in cashless transactions (Uesugi et al., 2021), an enhancement in consumer receptivity to electronic banking (Feruś, 2022), and the enforcement of health-related regulations associated with the virus (Khan et al., 2023). In the post-pandemic era, the digital transaction ecology has evolved to become more sophisticated and competitive (Srouji & Torre, 2022). Research conducted in the United States, Great Britain, Japan, Canada, and Australia during the outbreak period revealed a significant increase in the digitalization of transactions (Shaikh et al., 2022). In the future, cashless transactions will predominate as the prevailing method of payment. This is particularly salient in order to understand the behaviors of young generations, which have been identified as the primary agents of change. The following text is intended to provide a comprehensive overview of the subject matter.

E-wallets are considered a primary means through which the innovative developments of FinTech are disseminated, due to their security, mobility, and accessibility. An e-wallet is defined as a method of digitalized payment in which the available funds are held on a server as opposed to a chip (Aji et al., 2020).

Nevertheless, extant literature has hitherto scarcely contemplated the nature of the relationship between FinTech and Generation Z. As noted by numerous researchers cited in the text, significant gaps persist in our understanding of Generation Z's engagement with FinTech services. They emphasize that existing research in this domain is currently limited in scope.

2.3. Technology Adoption Models for Generation Z's Attitudes Toward FinTech Usage

The impact of attitudes on behavior has been a topic of study in the literature for many decades. According to extant literature, attitudes are defined as evaluations of objects or beliefs ranging from highly unfavorable to highly favorable (Fishbein & Ajzen, 2005; Sherman & Klein, 2021). Therefore, behavioral intention toward financial technology usage is influenced by attitudes. Two significant theoretical frameworks, namely the Technology Acceptance Model (TAM) (Davis, 1993) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), offer theoretical contexts for assessing beliefs and attitudes to forecast forthcoming behaviors (Lee & Song, 2013). To achieve a more comprehensive understanding of financial technology usage from a sociological, psychological, and technological perspective, the UTAUT has emerged as the predominant theoretical approach (Alkhwaldi et al., 2022).

A plethora of endeavors have been initiated to explore the intricate web of determinants that exert influence on the adoption and utilization of FinTech services (Daragmeh et al., 2021; van Deursen et al., 2019; Xie et al., 2021). The behavioral intention of the user is a factor that influences the adaptation of FinTech services (Daragmeh et al., 2021). According to Ajzen (2002), behavioral intention is conceptualized as the degree to which an individual is inclined to perform a certain behavior, the result of a multifaceted integration of personal beliefs, attitudes, perceived social norms, and perceptions of behavioral control. Furthermore, this phenomenon has been identified as a reliable predictor of technology adoption, as evidenced by Aditya and Wardhana (2016)'s seminal study. As posited by Perwitasari (2022), behavioral intention is frequently influenced by perceived usefulness or perceived ease of use.

Despite assertions that behavioral intention is influenced by the aforementioned factors, the extant literature offers equivocal results. A previous study's findings suggest that perceived usefulness and perceived ease of use do not influence mobile banking behavior in the United Arab Emirates (Lule et al., 2012). Nevertheless, a recent study by Perwitasari (2022) reported that both the perceived usefulness and perceived ease of use variables collectively influenced individuals' behavioral intentions to utilize financial technology services. The perceived usefulness of these services exerts a partial influence on the inclination to use them, and the perceived ease of use also exerts an impact on the intention to engage with financial technology services.

The integration of novel technologies frequently encounters obstacles. Research findings indicate that favorable attitudes are imperative for the adoption of new technologies (Hu et al., 2019; van Deursen et al., 2019). Consequently, perceived risk and trust have a significant impact on behavioral intention (Lee & Song, 2013). A recent study posits that perceived usefulness, ease of usage, and user innovativeness influence the adoption of FinTech. Nevertheless, trust mediates the perceived risk associated with FinTech usage. However, perceived risk does not affect technology adoption (Samarasekara et al., 2023). The adoption of FinTech is influenced by behavioral aspects that impact technology acceptance. A study revealed that perceived risk was not a significant predictor of behavioral intention (Mascarenhas et al., 2020). The findings of this study are consistent with the results of the study conducted by Tang et al. (2020). That study indicated that consumers' perceptions regarding e-payment and perceived security are not significantly related.

According to the UTAUT model, factors that influence technology acceptance and forecast future behavior are performance expectancy, effort expectancy, social influence, facilitating conditions, and personal innovativeness (Alkhwaldi et al., 2022). Social influence, therefore, can be defined as the perception of individuals regarding the importance of embracing a technology as part of their process of acceptance and utilization. As indicated in the extant literature, social influence exerts a positive influence on the behavioral outcomes of individuals within the UTAUT model (Venkatesh et al., 2003). Consequently, social influence plays a pivotal role in shaping the individual's attitude toward technology acceptance. In their recent paper, Xie et al. (2021) revealed that social influence and perceived value affected adoption intention positively, while perceived risk negatively impacted adoption intention.

The UTAUT model comprises four moderator factors in addition to the four primary constructs. The findings suggest that the aforementioned factors, including educational attainment, age, and adoption intention and behavior, play a significant role in the study's outcomes (van Deursen et al., 2019; Xie et al., 2021). As demonstrated in the works of Wei et al. (2021), the role of the moderator is played by the constructs of UTAUT, including performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003, 2012). A systematic literature review revealed that additional factors, such as trust, financial literacy, and safety, have a significant impact on FinTech adoption (Firmansyah et al., 2022).

In summary, the novelty value of the model developed herein is as follows: While the Technology Acceptance Model (TAM) and Unified Theory of Acceptance of Technology (UTAUT) are considered to be quite robust frameworks for analyzing technology adaptation, they do not fully capture the nuanced interplay of social influence, attitudes, and behavioral intention in the FinTech context. In this study, we build upon extant models yet adapt them to the specificities of FinTech adoption among Generation Z. We implement select constructs from UTAUT yet adjust the operationalization of variables to reflect FinTech-specific usage patterns. The integration of latent variables derived from empirical data serves to expand the theoretical framework of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance of Technology (UTAUT). This incorporation facilitates a more precise examination of the tangible impacts on attitudes and behavioral intentions concerning the utilization of FinTech. This approach provides a multifaceted contribution to the field. Firstly, it offers a novel framework for understanding adaptation dynamics in younger, digitally native cohorts. Secondly, it contextualizes established models within the FinTech domain.

A review of the extant literature reveals that, while social influence undeniably exerts a substantial influence on individuals' decisions regarding financial technology, other research findings underscore the equally critical influence of education and income levels in this regard. Education and income have been identified as significant factors in determining individuals' propensity and capacity to adopt FinTech solutions (Alshari & Lokhande, 2022). A recent study by Jaiswal et al. (2023) investigated the segmentation and profiling of FinTech service users. The findings of the study indicated that sociodemographic variables, including gender, age, income, and education, are significant determinants of FinTech adoption. Additionally, the level of income and education has been found to play a substantial role in technology usage segmentation. Furthermore, lower monthly income and less education are associated with a lower frequency of FinTech usage.

3. Materials and Methods

In this study, primary research was used based on a questionnaire, as this is the method that is commonly employed to measure public opinion. In addition to demographic questions (main demographic data: Table 1), the questionnaire included 5-point Likert scaling questions (3–5 per factor), which allowed for the scaling of essentially 8 factors (perceived risk, social influence, facilitating conditions intention, motivation, performance expectancy, FinTech usage, attitude, and behavioral intention) by partially adapting the model of Alkhwaldi et al. (2022). A five-point Likert scale was chosen because, based on the literature (e.g., X. Chen et al., 2015), it is considered the most appropriate for processing information. The present study focused on testing statistically how the hypothetical model (Figure 1) could be applied in the Eastern European context. Following the approach of Diamantopoulos and Siguaw (2000), the independent variables are considered exogenous and the dependent variables endogenous. The planned model was to be constructed on the basis of the statistical results, preserving the relevant paths between the factors.

Table 1. Main demographic data based on the questionnaire.

Hungary (n = 86)		
Gender	Male	24 (28%)
	Female	62 (72%)
Date of birth	1965–1979	7 (8%)
	1980–1994	12 (14%)
	1995–2009	67 (78%)
Poland (n = 31)		
Gender	Male	13 (41%)
	Female	18 (58%)
Date of birth	1980–1994	3 (10%)
	1995–2009	28 (90%)

Source: Own elaboration based on questionnaire data.

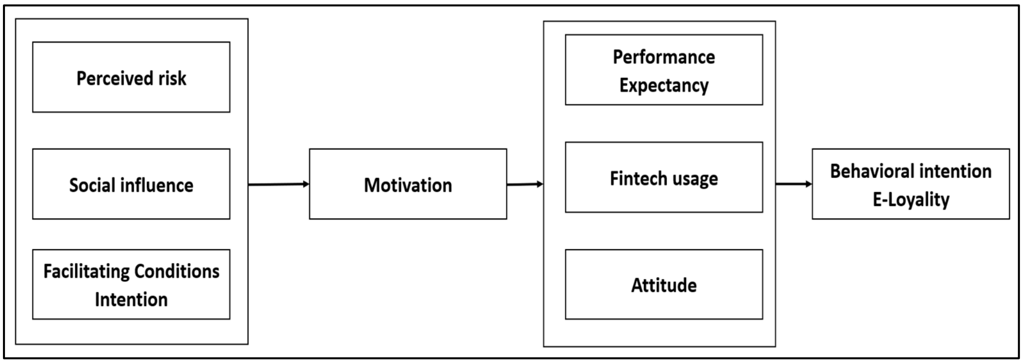

Figure 1. Hypothetical model (8 factors). Source: Own elaboration partially based on Alkhwaldi et al. (2022).

The online questionnaire survey was conducted in two countries, Hungary and Poland, where the questionnaire was shared with potential respondents through the authors' social media platform (Facebook) using snowball sampling. The questionnaire was open to potential respondents from 1 June 2023 to 21 July 2023. The questionnaire was available in both Hungarian and Polish in order to reduce any language barrier. The items analyzed in the study were published in English in the underlying studies. The translations were conducted by native-speaking experts from the countries under study. These experts were familiar with the terminology of the field and took into account both semantic equivalence and cultural adaptation in their translations. The coding of it prior to analysis took into account the nationality of the respondents, and care was taken to ensure that the databases from the two questionnaires were correctly combined.

The present study was aimed at conducting exploratory (EFA) and confirmatory (CFA) factor analysis to identify the factors that promote the use of FinTech services. Therefore, the following research question needed to be answered: Is it possible to explain the behavioral intention to use FinTech services by means of EFA and CFA?

The current sample size (n = 117, n_{hun} = 86, n_{pl} = 31) was quite small, so the questionnaire will be expanded in the current countries to construct the structural model, and there are plans to include other countries. In accordance with the recommendation made by Kline (2005), the present sample size may be considered adequate for structural equation modeling, as it falls within the medium range (100–200) specified by the author.

The first steps before creating a Structural Equation Model (SEM) are exploratory (EFA) and confirmatory (CFA) factor analysis. The former method is typically used to explore the aggregate measures (factors) in advance, as knowledge of the latent variables and their underlying manifest variables is essential to the construction of the model. Sample size can be a critical issue in SEM modeling, as it can directly affect fit analyses (Peng & Lai, 2012; Kaufmann & Gaeckler, 2015). Thus, a sample size of at least 100, but preferably 150, is recommended for model construction (Anderson & Gerbing, 1991). Furthermore, the minimum required sample size was determined by conducting a G*Power (version 3.1.9.7) test, as recommended by the literature (Schumacker & Komax, 2010; Kang, 2021), and the results (configuration: effect size: 0.15; p = 0.05; power: 0.80; number of predictors: 2) indicated that a sample size of 68 was necessary to achieve the desired level of statistical power. The statistical power and convergence of the model can thus be considered adequate despite the small sample size. For this reason, based on the current sample size (n = 117), a partial sample is presented as it meets the sample size criterion. The latent and manifest variables of the best factor construct, based on the tests presented in this paper, are shown in Table 2.

Table 2. Latent variables and associated manifest variables based on test results.

Latent Variable		Manifest Variable		Literature
Name	Code	5-point Likert-scale question	Code	Source
Social influence	SI	My peers and close friends support the idea of me using FinTech services.	SI_1	Venkatesh et al. (2003)
		Most people I admire and I 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	
Attitude	A	I believe using E-Payments or other FinTech services by mobile services is a good idea.	A_1	Yee-Loong Chong et 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 FinTech applications and services.	A_3	
Behavioral intention	BI	I intend to use FinTech applications and services when I purchase items.	BI_2	Tian et al. (2023)
		I plan to use FinTech applications and services frequently in my daily life.	BI_3	
		The likelihood that I will recommend FinTech applications and services to a friend is very high.	BI_4	Nathan et al. (2022)

Source: Own elaboration based on questionnaire data.

Furthermore, it was also necessary to have a description of the codes for the variables, as they will be used systematically throughout the paper for ease of reference. In the course of model development, the degree of model fit was systematically evaluated, leading to the exclusion of specific latent (e.g., perceived risk) and manifest (e.g., BI_1) variables. The necessary statistical analyses were carried out using the IBM SPSS Statistics 25 and IBM SPSS Amos 24 software packages.

4. Results

Preliminary tests (Kaiser–Meyer–Olkin; Cronbach's alpha; composite reliability [CR]; average variance extracted [AVE]) (Miskolczi et al., 2022) were conducted to construct the latent variables to be included in the future modeling and corresponding indicator groups following the design of the analytical sample ($n = 117$). The results showed that the sampling adequacy (KMO = 0.855) was acceptable (KMO > 0.6) (Reddy & Kulshrestha, 2019). For factor-based statistical tests, it is also important to have a substantial number of correlations between variables above 0.3 (Habing, 2003). High correlation values (correlation > 0.9) are an indication of multicollinearity and should therefore be avoided (Dohoo et al., 1997), which was also taken into account in the correlation tests (Table 3). As these are ordinal variables, Spearman's correlation coefficient (Spearman's rho) is an appropriate measure of relationships (Ritter, 2012).

Table 3. Spearman's correlation coefficient between the included variables.

Variables	SI_1	SI_2	SI_3	A_1	A_2	A_3	B_2	B_3	B_4
SI_1	1.000	0.666 **	0.561 **	0.332 **	0.304 **	0.311 **	0.475 **	0.404 **	0.425 **
SI_2	-	1.000	0.672 **	0.365 **	0.322 **	0.401 **	0.449 **	0.457 **	0.506 **
SI_3	-	-	1.000	0.245 **	0.229 *	0.324 **	0.348 **	0.313 **	0.321 **
A_1	-	-	-	1.000	0.614 **	0.619 **	0.560 **	0.487 **	0.512 **
A_2	-	-	-	-	1.000	0.555 **	0.433 **	0.403 **	0.423 **
A_3	-	-	-	-	-	1.000	0.533 **	0.491 **	0.489 **
B_2	-	-	-	-	-	-	1.000	0.823 **	0.780 **
B_3	-	-	-	-	-	-	-	1.000	0.831 **
B_4	-	-	-	-	-	-	-	-	1.000

* $p < 0.05$, ** $p < 0.01$; Source: Own elaboration based on questionnaire data.

Research on the methodology of factor analysis has placed emphasis on testing normality (Fornell & Larcker, 1981), but in the case of the Likert scales used in this analysis, it is important to note that these are not continuous interval scales and therefore typically do not meet the criteria of traditional tests of normality (e.g., Kolmogorov–Smirnov test, Shapiro–Wilk test, skewness, and kurtosis). Instead of normality, it has been suggested to test for the degree of normality violation (Rózsa et al., 2019), which can be performed by considering skewness and kurtosis values. In their book on methods of statistical analysis, George and Mallery (2010) suggested a cut-off value between +2 and −2 for questionnaire studies that use ordinal variables for psychometric purposes (e.g., attitudes, exploration of personal characteristics) that are suitable for testing. Multicollinearity analysis is also an important part of factor analysis, which is considered acceptable if the variance inflation factor (VIF) value is below the threshold of 5 (Olusegun et al., 2015). Regarding normality and multicollinearity, the variables included meet the tests described (Table 4).

Table 4. Skewness, kurtosis (normality), and VIF values of variables included in the model.

Manifest Variable Code	Skewness	Kurtosis	VIF
SI_1	−0.015	−0.324	1.977
SI_2	−0.155	−0.749	2.496
SI_3	0.038	−0.823	2.045
A_1	−0.433	0.809	2.101
A_2	−0.395	0.155	1.854
A_3	−0.242	0.080	1.850
BI_2	−0.488	−0.126	3.614
BI_3	−0.143	−0.313	4.772
BI_4	−0.247	−0.446	3.456

Source: own elaboration based on questionnaire data.

Based on Table 5, the additional test results (Cronbach's alpha, composite reliability, average variance extracted) for the latent variables exceeded the acceptable cut-offs reported in the literature (Nunnally, 1978; Hair et al., 2014; Ateş & Altuner Çoban, 2022); therefore our preliminary results can be considered valid.

Table 5. Summary of exploratory factor analysis.

Latent Variable	Statistical Test	Test Value	Threshold	Source
Social influence	Cronbach's alpha	0.852	>0.600	Hair et al. (2014); Nunnally (1978); Ateş and Altuner Çoban (2022)
	Composite reliability (CR)	0.869	>0.600	
	Average Variance Extracted (AVE)	0.771	>0.500	
Attitude	Cronbach's alpha	0.831	>0.600	
	Composite reliability (CR)	0.841	>0.600	
	Average Variance Extracted (AVE)	0.747	>0.500	
Behavioral intention	Cronbach's alpha	0.930	>0.600	
	Composite reliability (CR)	0.930	>0.600	
	Average Variance Extracted (AVE)	0.877	>0.500	

Source: Own elaboration based on questionnaire data.

After the exploratory factor analysis, the absolute, incremental, and parsimony fit tests (Gubik et al., 2018) of the model were tested by means of confirmatory factor analysis (CFA). However, only the test results of the best-fitting model are presented in this paper (Table 6). The tests were carried out using the cutoffs accepted in the literature (Wheaton et al., 1977; Mulaik et al., 1989; Schreiber et al., 2006; Tabachnick & Fidell, 2007).

Table 6. Measures of model fit.

Fitting Type	Statistical Indexes	Test Value	Threshold	Acceptance
Absolute fit	GFI (goodness-of-fit index)	0.935	>0.800	Yes
	RMSR (root mean square residual)	0.078	<0.080	Yes
	RMSEA (root mean square error of approximation)	0.064	<0.100	Yes
Incremental fit	TLI (Tucker–Lewis index	0.974	>0.900	Yes
	IFI (incremental fit index)	0.982	>0.900	Yes
	CFI (comparative fit index)	0.982	>0.900	Yes
Parsimony fit	PGFI (parsimony-adjusted goodness of fit index)	0.520	>0.500	Yes
	PCFI (parsimony-adjusted comparative fit index)	0.682	>0.500	Yes
	PNFI (parsimony-adjusted normed fit index)	0.657	>0.500	Yes

Source: Own elaboration based on questionnaire data.

With regard to discriminant validity (Table 7), the model is deemed valid, since no values exceed 0.85 based on the Heterotrait–Monotrait Ratio of Correlations (HTMT) test.

Table 7. HTMT test results.

	SI	A	BI
SI	-	-	-
A	0.503	-	-
BI	0.378	0.751	-

Source: Own elaboration based on questionnaire data.

It is also a condition that the coefficient of determination (R^2) of the endogenous variables is greater than 0.1 (Falk & Miller, 1992). This criterion was also met in the analyses (Figure 2), so the best-fitting model, constructed with three latent variables and nine indicators (Table 2), is accepted by the statistical tests.

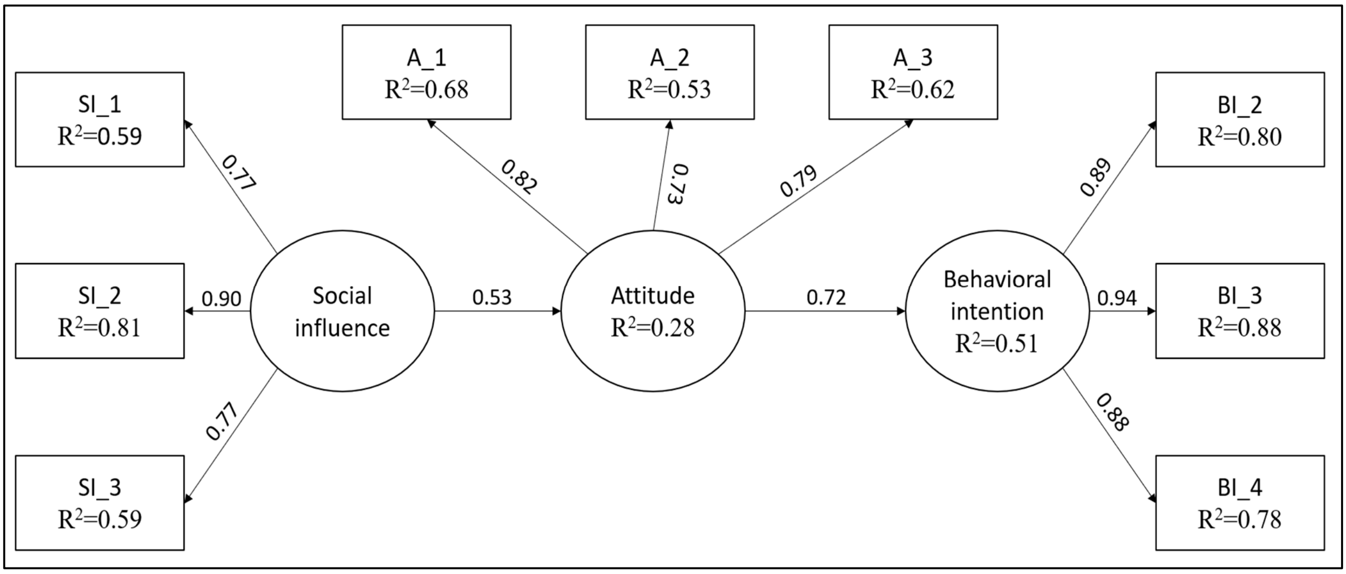

Figure 2. Path diagram with determinations and standardized factor loadings. Source: Own elaboration based on questionnaire data. In comparison with the hypothetical model, the final model incorporated three latent variables instead of eight, a decision that was made on the basis that this construction formed the best-fitting model.

The bias-corrected intervals (n = 500, p = 0.05) are included in Table 8 in order to exclude model biases. It is evident from the results that no interval contains zero (Hair et al., 2014), thereby validating the significance of the identified paths.

Table 8. Bootstrapped (bias-corrected) path intervals (standardized values).

Path	Estimate	Lower	Upper	p
A←SI	0.528	0.301	0.737	0.003
BI←A	0.716	0.517	0.839	0.005
BI←A←SI	0.192	0.192	0.604	0.002
SI_1←SI	0.770	0.614	0.895	0.003
SI_2←SI	0.898	0.811	0.963	0.007
SI_3←SI	0.768	0.640	0.866	0.005
A_1←A	0.822	0.701	0.908	0.007
A_2←A	0.731	0.56	0.837	0.011
A_3←A	0.786	0.608	0.894	0.004
BI_2←BI	0.893	0.808	0.953	0.004
BI_3←BI	0.937	0.886	0.971	0.007
BI_4←BI	0.882	0.791	0.932	0.008

Source: Own elaboration based on questionnaire data.

On the basis of the results of the fit tests and bias test, the latent variables identified in the confirmatory factor analysis can be interpreted well in the model, and thus, with the help of the manifest variables (indicators) described, they are suitable for the analysis of the presented research question and drawing conclusions.

5. Discussion

Our study confirms that FinTech adoption in banking services is growing dynamically. As apps and digital solutions come to the fore, more and more people are using them (Galeone et al., 2024). Moreover, the focus of our research was on Generation Z, which is stronger in digital skills. Therefore, the hypothetical model works in that two factors determine the propensity to use (behavioral intention).

An influential relationship can be detected for social influence and attitude. The former only leads to an indirect influence through attitude, but it adequately illustrates that social influence can affect the perception of FinTech services by individuals, although other factors—not measured by us—also influence this ($R^2 = 0.28$). Generation Z relies heavily on the opinion of people in their age group. This process, which is assessed as a social influence, is amplified and can encourage or even discourage the use of FinTech solutions.

When we look at the relationship outlined in the model in a positive business–market development or customer-centric perspective, it deserves special attention in the context of social influence. In this context, we can also underline the importance of experience transfer, as the results show that the impact (experience transfer) of those who are already using FinTech services is the most significant in this respect. Attitudes may therefore change, and Generation Z members may be persuaded of the positive value of FinTech services by their social environment.

Attitudes have been a significant factor in our research and have been included as a separate variable in the model, based on the work of Yee-Loong Chong et al. (2010). The most important factor related to attitudes is the perception of usability (is it a good idea to use?). This is preceded by a social networking phase (interviewing, research, reflection). This phase also aims to reduce information noise and minimize risk. From the perspective of business actors, it provides a good platform to share information on FinTech services with appropriate frequency. On the other hand, it suggests that a testable version should be made available to potential young buyers as soon as possible. This can have an impact on both attitudes and social influence.

Our model shows that the combined effect of these two factors on behavioral intention is very significant ($R^2 = 0.51$), so they significantly determine the intention to use these services for the generation under study. Therefore, decisions and actions to do so become strategic for FinTech service providers.

5.1. Practical Implications

It is possible to draw practical implications from the model, which are based primarily on the key effects of peers and attitudes. It is recommended that FinTech providers consider the development of "peer ambassador" programs for university students and young professionals. These programs could be supplemented by experiential workshops or pilot funds, with the objective of shaping initial attitudes towards services by means of the influence of peers. Moreover, the provision of concise introductory tasks and immediate, personalized feedback in FinTech applications has been demonstrated to be efficacious in reinforcing the perceived simplicity and usability of the services. This, in turn, has been shown to engender a positive attitude shift among novice users. In the realm of mobile gaming applications, the integration of gamification elements within FinTech contexts holds potential for enhancing user engagement and incentivization. This integration could be facilitated through the implementation of point-scoring challenges and the awarding of badges or levels, thereby fostering a competitive environment among users and facilitating social interaction. Participation in games is incentivized through the allocation of virtual money or credits, which are accumulated through the completion of modest financial tasks. These tasks may include the attainment of savings objectives or the monitoring of expenditure patterns. Subsequently, these virtual assets can be exchanged for tangible discounts. This gamified approach has the potential to increase peer influence, strengthen commitment, and support the development of positive attitudes toward simplicity and usefulness.

5.2. Limitation

This research is a Hungarian–Polish case study that examines the intention to use FinTech services and explores the applicability of a possible model for Eastern Europe. The analysis is based on a questionnaire survey using relevant variables supported by literature.

The participants were recruited through Facebook, a platform that has been found to be effective in engaging populations that are typically difficult to reach. However, it is important to note that Facebook is also susceptible to self-selection and non-response bias, which can introduce selection and information biases into the data. The distribution of the sample by age is asymmetrical, and the gender ratio is skewed towards female respondents. Consequently, the sample is likely to overrepresent individuals who are more active on social media, who demonstrate a heightened interest in the research topic, and who belong to the female population. This overrepresentation has the potential to distort the results, typically in the direction of overestimating the intensity of the phenomenon under study. It is imperative that these limitations are given due consideration during the review process, as they impede the generalizability of the findings. In order to ascertain the robustness of the model, a multigroup analysis (MGA) was also performed in order to test the model structure between genders (Table 9).

Table 9. Bootstrapped (bias-corrected) path intervals (standardized values) of the MGA.

Path	Estimate		Lower		Upper		*p*	
	Female	Male	Female	Male	Female	Male	Female	Male
A←SI	0.453	0.612	−0.014	0.358	0.805	0.763	0.069	0.001
BI←A	0.733	0.694	0.267	0.468	0.950	0.863	0.011	0.003
BI←A←SI	0.332	0.425	0.014	0.175	0.801	0.631	0.028	0.002
SI_1←SI	0.886	0.720	0.675	0.495	1.266	0.852	0.003	0.011
SI_2←SI	0.910	0.887	0.488	0.774	1.035	0.974	0.004	0.008
SI_3←SI	0.740	0.766	0.332	0.591	0.912	0.883	0.004	0.004
A_1←A	0.907	0.750	0.647	0.574	1.048	0.865	0.003	0.010
A_2←A	0.777	0.685	0.438	0.488	0.919	0.849	0.004	0.008
A_3←A	0.771	0.802	0.428	0.549	0.934	0.947	0.002	0.007
BI_2←BI	0.837	0.921	0.618	0.845	0.959	0.967	0.005	0.005
BI_3←BI	0.920	0.968	0.810	0.908	0.972	1.000	0.004	0.013
BI_4←BI	0.944	0.855	0.852	0.756	1.005	0.921	0.004	0.008

Source: own elaboration based on questionnaire data.

The findings indicate that the impact of social influence on attitude is not significant in the female group, with a 95% confidence interval. However, the indirect effect between social influence and behavioral intention can be interpreted as an unbiased effect in both groups, as evidenced by the bootstrap test. The MGA has expressed its support for the robustness of the proposed model. In the context of future research endeavors, the conduction of sensitivity analyses, such as weighting by key demographic variables, is imperative. This approach will be instrumental in enhancing the robustness of the findings, particularly as the availability of a larger sample size becomes a reality.

Finally, the research method has obvious limitations due to the questionnaire, as it is a non-representative, cross-sectional analysis. Consequently, the research is an examination of data from a population in a sample at a given point in time. However, it provides a good starting point for future research in the social sciences.

5.3. Future Directions

Increasing the sample size and the number of Eastern European countries included would be beneficial for future research. However, based on the results of exploratory and confirmatory factor analysis, the most important future direction is to develop a structural model to identify and measure the factors that influence the use of FinTech services in the region.

6. Conclusions

Overall, the research question (Is it possible to explain the behavioral intention to use FinTech services by means of EFA and CFA?) has been answered, as the test results show that the behavioral intention to use FinTech services can be adequately explained by the inclusion of three latent variables. The future aim is to increase the sample in the countries currently participating in the research and to extend the research to other Eastern European countries, as described in the methodology. Some statistical methodological analyses (Peng & Lai, 2012; Kaufmann & Gaeckler, 2015) have shown that the sample size directly affects model fit, parameter estimates, and statistical power. Based on the analysis of Sari (2021), this is particularly true for PGFI and RMSEA. Therefore, with the development of the final model (covariance-based structural equation modeling: CB-SEM), further improvements in the fit indicators, which are currently considered adequate, are expected. Nevertheless, CFA showed that the current total explained variance ($R^2 = 0.51$) exceeds the expected value in social science ($R^2 > 0.50$) (Ozili, 2023). It is proposed to study FinTech services in this direction, which could yield important and exciting results for social science, in light of the favorable test results.

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