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SMARTPHONE ACTIVITIES IN PREDICTING TENDENCY TOWARDS ONLINE FINANCIAL SERVICES

Abstract

Purpose: Considering the rapid progress of information and communication technology (ICT) and its influence on daily life, it is inevitable that its impact will also be visible in the financial sector, especially through efforts to present digital financial services as widely as possible and bring them closer to potential users. Therefore, the aim of this study is to investigate university students' smartphone activities, their use and attitudes towards digital financial services, and to build a neural network model capable of distinguishing students according to their awareness of the benefits related to using online financial services.

Methodology: An online questionnaire was applied to collect data on students' smartphone activity and their tendency to use online financial services. Depending on the variable type, the Kruskal-Wallis H test and Kendall's tau-b were used to assess the association between variables, while multilayer perceptron and radial basis function neural networks were used for the creation of the optimal model.

Results: Participants in this study achieved an average score of 6.56 (SD = 1.27) for smartphone activity, and the results showed that the optimal neural network model obtained had an overall accuracy of 70.73%. However, smartphone activity did not have an excessive effect on the efficiency of this model.

Conclusion: The obtained neural network model and its sensitivity analysis managed to reveal some hidden patterns which could be beneficial to educators in terms of improvements of students' digital and financial literacy as well as to the financial sector in terms of increasing performance and interest of this population in digital financial services.

Keywords: Smartphone activities, online financial services, neural networks, online payments

1. Introduction

Life to which we were accustomed has changed rapidly as a result of the COVID-19 pandemic and subsequent regulations and recommendations issued to prevent its further spread. As daily life has changed, so have common customer behavior and payment options (Liébana-Cabanillas et al., 2020, Hashem, 2020, Mišić, 2021, Toh & Tran, 2020), with online (European Central Bank, 2022) and mobile payments (m-payments) showing growth globally and with an even greater increase expected in 2024 (De Best & Calio, 2022). Nevertheless, the technology, infrastructure, and thus the security and complexity of using each payment method remained unchanged, and users of digital payments are still exposed to adverse effects, which remain one of the main concerns of users (Al-Qudah et al., 2020) and a reason for hesitation in their adoption.

Following a literature review and the identified research gap in the analysis of behavioral tendencies of the younger population in transition countries, the authors investigated the relationship between students' smartphone activities and their tendency to use digital financial services. In addition, a neural network model will try to recognise participants based on their awareness of the benefits of digital financial services based on their demographic characteristics (input variables).

The theoretical background for this research design includes several key concepts and theories. Firstly, the research design is based on the premise that smartphones have become ubiquitous in people's daily lives and have had a significant impact on various aspects of life, including financial activities. This is supported by research that has shown the increasing use of smartphones for financial transactions and services, particularly among younger and more educated populations (Fan et al., 2018; Khan et al., 2019; Lee & Lee, 2000; Rugimbana, 2007; Sun et al., 2017). Secondly, the research design relies on an expanded version of the Technology Acceptance Model (TAM) (Davis, 1989), with integrated security variables as suggested in recent research (Liébana-Cabanillas et al., 2018a; Fan et al., 2018). Thirdly, the research design utilizes the neural network model as an unconventional method for exploring the relationship between smartphone use and the use of digital financial services. This approach is based on the concept of machine learning, which involves training algorithms to learn from data and make predictions or decisions based on that learning. The use of neural networks in this research design allows the exploration of complex patterns and relationships that may not be readily apparent through traditional statistical analysis.

In customer behavior research, data mining, decision trees, and artificial neural networks are increasingly used due to large amounts of data that need to be processed to draw valid and useful conclusions. For example, Khan et al. (2010) used decision trees, logistic regression, and neural networks to identify the customers who are at high risk of churn. Mak et al. (2011) developed a financial data mining model to extract information about customer buying behavior and the impact on financial industry marketing. Neural networks are used to evaluate the influence of selected predictors on m-payment behavior. Rabaa'i et al. (2022) used neural networks to identify the most important factors influencing user adoption of m-payments, and identified attractiveness, trust, perceived ease of use, and security as most influential. Neural network models were used in predicting financial industry customer behavioral patterns, where the authors trained the model to detect abnormal customer transaction activities (Ogwueleka et al., 2012).

There are other studies examining the impact of demographic characteristics on mobile payment adoption. For instance, Yen and Wu (2016) developed a model to test gender differences and investigate how gender moderates the relationships between variables in the proposed model. They extended the Technology Acceptance Model (TAM) by adding new variables to predict the adoption of the use of mobile financial services. Their findings suggest that users of mobile financial services should not be treated as a homogeneous group, and that new surveys should adopt a more dynamic cross-environment perspective. Kanungo (2022) studied digital financial awareness among different age groups in Indian rural areas and found differences in terms of demographic characteristics such as age and living conditions. Sultana and Bousrih (2020) examined the relationship between student use of digital banking, penetration, and awareness with demographic variables among the student population. They found a relationship between digital banking penetration and benefit awareness, as well as an association between demographic variables such as age, gender, and education, and digital banking penetration. Sulaiman et al. (2007) employed Rogers' diffusion of innovation model to analyze consumer behavior and motivation for mobile banking. The study revealed that demographic and personal characteristics of mobile banking users are critical factors that affect their adoption decisions. The theoretical foundation for this study can also be found in behavior theory and Fogg's (1997) persuasive technologies theory.

Among the few recently developed scales to determine smartphone use (Harris et al., 2020), the smartphone usage subscale from the Media and Technology Usage and Attitudes Scale (Rosen et al., 2013) was used to determine the activity level of smartphone use. The Media and Technology Usage and Attitudes Scale (MTUAS) consists of 11 usage subscales in which a person self-assesses his or her frequency of use on a 10-point frequency scale, and four attitude-based subscales (15 items) in which the person indicates his or her agreement with the statement on a 5-point scale (ranging from strongly agree to strongly disagree). The authors suggested its use as a whole set of items (a 60-item scale) or as one or more subscale items (Rosen et al., 2013). The authors reported Cronbach's α as a measure of internal consistency, ranging from 0.60 to 0.97 for all MTUAS subscales. This scale, i.e., the smartphone use subscale, was selected because of the large number of participants (942 participants) who participated in the research to develop the MTUAS, its strong reported reliability, and the numerous studies that have used this scale to determine technology use.

Since this study examines the younger population's openness to the use of digital financial services, the general demographic questions used to profile respondents and the MTUAS smartphone subscale were expanded to include a series of questions about online financial services (financial services respondents have previously used or conducted online and statements about using online financial services). The questions related to digital financial services were based on previous research conducted by e.g. Shin et al. (2014), Statista (2019), Institutul Român pentru Evaluare și Strategie (2020), and Eurostat (2021). Prior surveys have investigated factors such as perceived usability, ease of use, and security risks, which are all important elements of the expanded version of the TAM model (according to Patil et al., 2019; Liébana-Cabanillas et al., 2018a; Fan et al., 2018).

Overall, the convergence of information and communication technology and finance serves as the theoretical foundation for this research design, with an emphasis on understanding the factors that influence young, educated people's adoption and use of digital financial services. The results of the survey and their analysis will fill the gap of an insufficient number of geographically distributed studies, especially in transition and developing countries, as well as for the financial industry in designing their promotion and sales activities in this market.

The paper consists of 5 sections. The next section presents a literature review of the Technology Acceptance Model (TAM) and the Unified Theories of Acceptance and Use of Technology (UTAUT and UTAUT2), which are most commonly used in empirical studies of consumer behavior in choosing mobile and other digital payment methods. The third section describes the materials and methods. It is followed by the section that presents the research results, while the last section provides a discussion and final conclusions.

2. Literature review

The Technology Acceptance Model (TAM) and the Unified Theories of Acceptance and Use of Technology (UTAUT and UTAUT2) are most commonly used in empirical studies of consumer behaviour in choosing mobile and other digital payment methods (Al-Okaily et al., 2020; Chopdar et al., 2018; Fan et al., 2018; Liébana-Cabanillas et al., 2018a; Patil et al., 2019; Tounekti et al., 2020; Ziwei et al., 2019). Using the UTAUT method, Venkatesh at al. (2003) present factors that influence information technology (IT) intention and usage, as follows: performance and effort expectancy, facilitating conditions, and social influence, whereas hedonic motivation, value for money, and habit were introduced later by UTAUT2 (Chang, 2012; Huang & Kao, 2015). The TAM, on the other hand, introduces the variables of perceived usefulness and perceived ease of use, which Davis (1989) considers as fundamental factors for user acceptance.

Patil et al. (2019) stated that the classical methods (UTAUT, UTAUT2, and TAM) have shortcomings in researching user behavior in choosing digital payment methods because these models were created to analyze the acceptance of novel technologies and do not consider security issues as important factors in the research area of acceptance of digital payment methods. The security issues are emphasized by Shin et al. (2014) as an important factor influencing the frequency of smartphone payments. To address this issue, some authors (Liébana-Cabanillas et al., 2018a; Fan et al., 2018) integrated trust and perceived risk into traditional models, making the classical methods more suitable for this research area.

In recent years, other methods have been used to research the acceptance of digital payment methods. In studying users' intention to use digital payment models, Loh et al. (2020) used the push-pull-mooring factors model. The model introduces monetary value/price (a push factor), alternative attractiveness (a pull factor), and trust and perceived security and privacy (mooring factors). The authors found that all factors are positively related to the intention to use m-payment, while traditional payment habits and inertia have a negative relationship (Loh et al., 2020).

By using status quo bias theory and coping theory, Gong et al. (2020) found that inertia is an obstacle to the wider use of m-payment services. Fan et al. (2021) used push-pull factors to investigate customers to transfer from the Internet to m-payment in China. They found that "push factors (perceived switching costs and personal innovativeness) and pull factors (relative advantages of substituting information technology and critical mass) are affecting customer switching intention" (Fan et al., 2021, p. 155). If m-payment offers significant benefits to users and is highly innovative, users tend to accept and use it, but if this transfer to new technologies involves high switching costs, customers are reluctant to choose this option. Therefore, additional financial benefits in the initial phase may help to attract new users (Fan et al., 2021). These results are somewhat similar to those of Patil et al. (2019), who analyzed the influence of attitude, cost, mobility, affordability, and innovativeness on using m-payments, and found that all of them, except cost, were significant, with user attitude and innovativeness having the strongest positive influence (Patil et al., 2019).

Liébana-Cabanillas et al. (2018b) claim that perceived usefulness and security (as subjective norms) influence predicting factors of m-payment adoption. The results confirm the findings of Tounekti et al. (2020) and agree to some extent with the findings of Sun et al. (2017), who presented perceived security and perceived ease of use as the most important factors for most respondents. Comparable conclusions were also drawn by Al-Qudah et al. (2022), who studied the acceptance of m-payments during the COVID-19 pandemic in the UAE.

The categories related to the psychological dimension, as a social image, and the perceived usefulness influence the intention to use m-payments, while the categories related to perceived risk (including uncertainty and risk related to digital payment instruments and even online purchases) are negatively related (Liébana-Cabanillas et al., 2018a). Fear of COVID-19 virus transmission through currency exchange and physical contact has contributed to greater acceptance of digital payment methods, with perceived value, possibly including the convenience of 24/7 use, and perceptions of benefit and risk being the variables that most strongly influence intentions to use different forms of digital payments. Risk was found to have a strong negative impact, as even a small amount of risk significantly reduces the likelihood of using a digital payment. The higher the risk, the lower the probability that new digital payment instruments will be adopted (Liébana-Cabanillas et al., 2020).

Some studies point to the influence of cultural differences among users (Chopdar et al., 2018; Fan et al., 2018; Liébana-Cabanillas et al., 2020; Singla & Sardana, 2020/2021). Chopdar et al. (2018) found that the expressions of perceived risk were significant only for the countries with the highest Computer-Based Media Support Index (CMSI) value (India) compared to the countries with the lowest CMSI value (U.S.), suggesting that culture has a strong influence on the acceptance of m-shopping (Chopdar et al., 2018) and consequently m-payments.

When analyzing geographic distribution, only few countries are mainly represented, led by China and the U.S. Studies looking at other countries, particularly developing and emerging economies, are significantly less represented (Liébana-Cabanillas et al., 2020). China is dominant in m-payments as 25% of the population used a smartphone for at least one transaction (De Best, 2022), with trust, risk, perceived ease of use and perceived usefulness being important factors affecting m-payments adoption (Chin et al., 2020). There are also differences between China and the U.S., e.g., the effects of m-payment and perceived security on trust were significantly higher in China than in the U.S. (Fan et al., 2018; Wiese & Humbani, 2019). In a study conducted in the eastern province of China using structural equation modeling and the artificial neural networks approach, Khan et al. (2019) found that the Big 5 personality traits have an impact on m-payment acceptance, with conscientiousness and agreeableness being the most important factors for m-payment acceptance, while neuroticism is a negative but insignificant factor (Khan et al., 2019).

Statista's (2019) study surveyed 1,012 individuals in the U.S. who use the Internet to examine their satisfaction with traditional and direct banking institutions, familiarity with FinTech and InsurTech services, and preferences and inclinations towards mobile payment. Eurostat's (2021) survey examines ICT usage in households and individuals aged 16 to 74 years old in the EU, focusing on perceived obstacles to making internet purchases and consumers' attitudes towards online shopping. The survey found that in Croatia, only 3.10% of respondents mentioned lacking skills as a reason for not purchasing online, while 5.82% had privacy concerns. Institutul Român pentru Evaluare și Strategie's (2020) research investigated the relationship between customers and banks in Romania during the COVID-19 pandemic, with 78% of respondents stating that they did not typically use mobile financial services and did not plan to do so in the future. The main reasons for not using mobile banking services were insufficient knowledge, age, and not needing or wanting to use the services. Singla and Sardana (2020/2021) found that convenience and perceived ease of use are the main motivations for using m-payments in India. Moorthy et al. (2019) found that neither social influence nor effort expectancy was important for working adults' intention to use m-payments in Malaysia, but effort expectancy, facilitating conditions, hedonistic motivation, and perceived security were positively and significantly related (ibid., 2019). In the acceptance of a new m-payment system in Jordan by public sector employees, social influence had the strongest influence, followed by performance expectancy, affordability, security, and privacy (Al-Okaily et al., 2020). In the survey conducted in 52 countries, Tounekti et al. (2020) found that perceived security and perceived ease of use were most important for the users. At the same time, the 18-45 age group is most concerned about the security of their digital payments.

To conclude, perceived ease of use and perceived usefulness are commonly studied categories related to the adoption of digital payment methods, followed by security and trust, and social influence (Al-Okaily et al., 2020; Fan et al., 2018; Khan et al., 2017; Liébana-Cabanillas et al., 2018a; Loh et al., 2020; Moorthy et al. 2019; Singla & Sardana, 2020/2021; Sun et al., 2017; Tounekti et al., 2020; Ziwei et al., 2019). The relationship between demographic characteristics and intensity of digital payments use was also explored, concluding that young and better educated consumers are more open to digital technologies and payment methods (Fan et al., 2018; Khan et al., 2019; Lee & Lee, 2000; Rugimbana, 2007; Sun et al., 2017). Despite the abundance of research on consumer behavior in relation to the adoption of digital payments, the geographic distribution of such studies remains limited. This is an important limitation given the notable variation in mobile payment usage rates across regions and countries (Bestvina Bukvić, 2021; Shin et al., 2014). While there are a few studies that focus on large economies (Patil et al., 2019; Fan et al., 2018; Khan et al., 2017), there is a lack of research on the adoption of digital payments in other regions. Therefore, further research was found to be needed to provide a more comprehensive understanding of the factors that influence digital payment adoption in different geographic locations. In addition, most studies just focus on user adoption of different payment methods (Humbani & Wiese, 2019; Patil et al., 2019), but few, relatively geographically narrowed, focus on awareness of the benefits of digital financial services, user attitudes towards digital financial services and demographic influence in relation to users' smartphone activities.

Based on previous research and existing gaps in the field, the authors aimed to investigate the relationship between smartphone activities and other variables, and develop a neural network model capable of distinguishing students according to their awareness of the benefits of using online financial services. The results are presented in the following sections.

3. Methodology

Responses were collected via an online questionnaire from 409 students at the Faculty of Education and the Faculty of Economics, University of Osijek, about their smartphone activity and tendency to use online financial services, along with demographic data (see Table 1). The data were collected in the academic year 2021/2022. Data analysis and neural network modeling were performed using Statistica software. Regarding the profile of the participants, most of them were female (86.31%), between the ages 18 and 21 (47.67%), more than a third (37.41%) of them were enrolled in the second year of study, 59.66% attended the Faculty of Economics, and less than a fifth of them lived in their own apartment or house (19.80%).

Table 1 Structure of used data collection

Subgroup	Variables
General	Demographic variables (5 variables)
Smartphone activity	Smartphone usage subscale
Online financial services	Financial services provided online (10 variables), Statements about use of online financial services (7 variables)

Source: Authors

To determine the activity level of smartphone use, the smartphone usage subscale from the Media and Technology Usage and Attitudes Scale (Rosen et al., 2013) was used. This subscale consists of 9 statements in which participants indicate their smartphone activity on a scale from 1 (never) to 10 (all the time). Corresponding points are assigned to each participant's response to each statement, and the sum of the points corresponds to each participant's smartphone activity. The reported reliability for this subscale was 0.93.

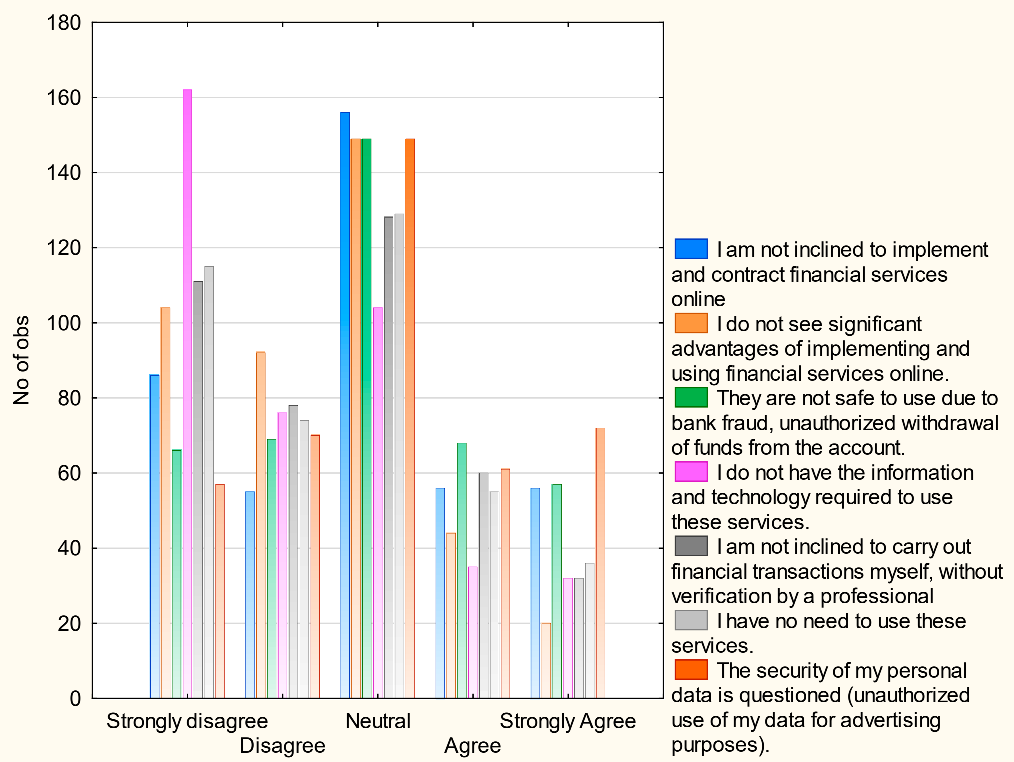
The authors created 10 variables to ask participants about their use or access to online financial services available on the market and 7 variables to gather information about participants' attitudes towards the use of online financial services. The variables were developed based on previous research by Shin et al. (2014), Statista (2019), Institutul Român pentru Evaluare și Strategie (2020), and Eurostat (2021).

4. Results

The results show that the mean smartphone activity of the entire group of participants is 6.56 (SD = 1.27), which is slightly higher than the mean reported by Rosen et al. (2013). At the 5% level of significance, the Kruskal-Wallis H test did not show a statistically significant difference in smartphone usage and demographic variables: gender ($\chi^2(1)$ = 1.48, p = .22), faculty $\chi^2(1)$ = .85, p = .36), age ($\chi^2(3)$ = 4.45, p = .22), study year ($\chi^2(4)$ = 2.74, p = .60), and accommodation ($\chi^2(4)$ = 3.48, p = .48).

Regarding the online financial services statements, more than three eighths (38.14%) of participants neither agree nor disagree with the statement *I am not inclined to implement and contract financial services online.*, 36.43% remain neutral about the statement concerning the benefits of adopting and using online financial services, and the same percentage of participants neither agree nor disagree that it is unsafe to use them, 39.61% strongly disagree with the statement *I do not have the information and technology required to use these services.*, less than a third of them (31.30%) neither agree nor disagree that they are not inclined to carry out financial transactions and contract financial services on their own, 31.54% neither agree nor disagree that they do not have the need to use these services, and more than one third (36.43%) neither agree nor disagree that the security of their personal data is called into question (see Figure 1).

Figure 1 Agreement with the online financial services statements



Source: Authors

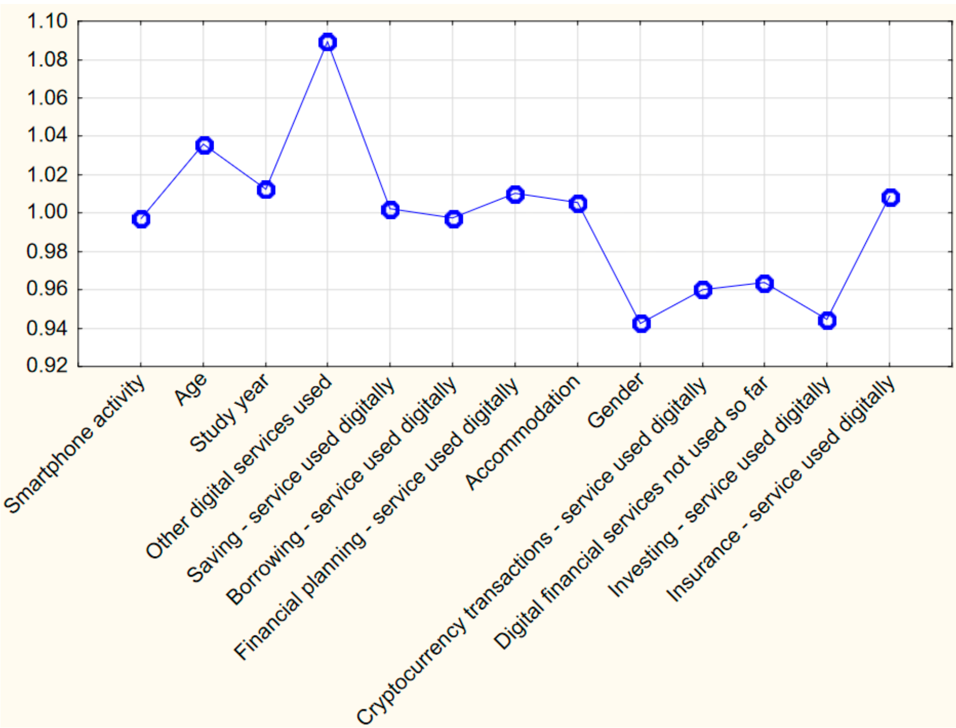
At a significance level of 0.05, Kendall's tau-b was used to assess the association between smartphone activity and statements regarding the use of online financial services, and it revealed that there are no statistically significant associations (*I am not inclined to implement and contract financial services online.* (τ_b = -.06, p > .05), *I do not see significant advantages of implementing and using financial services online.* (τ_b = -.02, p >.05), *They are not safe to use due to bank fraud, unauthorized withdrawal of funds from the account.* (τ_b = -.06, p >.05), *I do not have the information and technology required to use these services.* (τ_b = -.01, p >.05), *I am not inclined to carry out financial transactions myself, without verification by a professional.* (τ_b = -.01, p >.05), *I have no need to use these services.* (τ_b = -.01, p >.05), and *The security of my personal data is questioned (unauthorized use of my data for advertising purposes).* (τ_b = -.07, p >.05)).

To create an optimal neural network model, participants were divided into two categories depending on their opinion on the statement *I do not see significant advantages of implementing and using financial services online.* The category of students who are aware of the benefits of online financial services, which was labeled 0, consisted of students who strongly disagree or disagree with this statement (47.92%), and the rest of the participants were categorized as those who are not aware of the benefits of online financial services (52.08%). This variable was chosen as the output variable for neural networks and the total sample was divided into a training (70%), testing (20%), and validation (10%) sample.

The generalization ability of neural networks models was checked on the validation sample. Before the beginning of the process of neural network modeling, variables suited for the modeling process were selected, and the χ^2 test was used for the purpose of establishing if there is a relationship between the output variable and other collected variables. The χ^2 test revealed that at the level of significance of

5% there is a statistically significant association between the output variable and the following variables: the faculty that the respondents attend ($\chi^2(1) = 4.13$, p = .042), money transfer and online bill payments as services they have used so far ($\chi^2(1) = 9.32$, p = .002), and online shopping as a service they have used so far ($\chi^2(1) = 4.42$, p =.035), and statements: *I am not inclined to implement and contract financial services online.*, ($\chi^2(4) = 52.98$, p = .000), *They are not safe to use due to bank fraud, unauthorized withdrawal of funds from the account.*, ($\chi^2(4) = 75.74$, p = .000), *I do not have the information and technology required to use these services.*, ($\chi^2(4) = 69.68$, p = .000), *I am not inclined to carry out financial transactions myself, without verification by a professional.*, ($\chi^2(4) = 62.55$, p = .000), *I have no need to use these services.*, ($\chi^2(4) = 82.90$, p = .000), and *The security of my personal data is questioned (unauthorized use of my data for advertising purposes).*, ($\chi^2(4) = 45.02$, p = .000), so these variables were excluded from neural network design. A total of 13 input variables were used for modeling. To create a suitable neural network model, 600 neural network models with modified architecture were trained, tested and validated. A change in neural network architecture included changing the neural network type (multilayer perceptron (MLP) or radial basis function (RBF)), the number of hidden units, the training algorithm, the error function, the activation function for MLP neural networks, and the weight decay in the output and hidden layers. The best model was the MLP neural network with 13 input variables, 12 neurons in the hidden layer, 2 outputs, the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm as the training algorithm, entropy as the error function, the hyperbolic tangent function as the hidden activation, and Softmax as the output activation. This model had an overall classification of 70.73% and was able to detect 76.19% of participants who were not aware and 65% of participants who were aware of advantages of online financial services. As can be seen in Figure 2, the input variable *Other digital services used* had the greatest impact on model performance, while the variable *Gender* had the least impact.

Figure 2 Sensitivity analysis of input variables used by the best MLP model



Source: Authors

5. Discussion and conclusion

In today's digital world, a smartphone is a device most commonly used for online communication and socialization because it is so convenient and functional. As it permeates all areas of life, it was inevitable that it would also affect the financial activities of individuals that became even more evident during the COVID-19 pandemic (Al-Qudah et al., 2022; Liébana-Cabanillas et al., 2020; Hashem, 2020). Moreover, previous research has shown that the educated and younger population is more open to the use of new digital financial technologies (Lee & Lee, 2000; Khan et al., 2019; Fan et al., 2018; Sun et al., 2017; Garrett, 2014; Rosen et al., 2013; Rugimbana, 2007), which emphasizes the importance of researching the factors influencing their adoption of various digital financing services. Therefore, the study on smartphone activities of university students, their tendency to use digital financial services and their attitude towards them was conducted on the student population at the University of Osijek. Given the impact that the smartphone has on people's daily lives, this study investigated whether its use has an impact on the use of digital financial services and whether some interesting patterns could be found using neural networks. In line with Yen and Wu's (2016) recommendation that new studies in this area should adopt a more dynamic, cross-environmental perspective, a neural network model was used as an unconventional method to obtain information linking the variables used.

The research found that the majority of participants believe that they are sufficiently informed and possess the technology necessary for the implementation of mobile payments that are found to be important aspects of mobile payments adoption (Wisniewski et al., 2021; KPMG, 2020). The participants in this study had average smartphone activity of 6.56 (SD = 1.27). Using Kruskal-Wallis and Kendal's tau-b, no linear causal relationships were found between smartphone use and demographic variables, which differs from the results of previous studies (Kanungo, 2022; Sultana & Bousrih, 2020; Sulaiman et al., 2007; Suoranta & Mattila, 2004). Additionally, the impact of smartphone usage on the effectiveness of the model was not significant, contrary to the expectations. This finding is not consistent with the results of Shaw et al. (2019), who reported the influence of smartphone addiction on the acceptance of mobile wallet payments. Furthermore, it is interesting to observe that a substantial portion of the participants (36.43%) were neutral towards the security of their personal data and to risk of bank fraud, unauthorized withdrawal of funds from the account, which is surprising as previous studies have found that perceived risk is one of the key factors in the adoption of mobile payments (Yan et al., 2022; Liébana-Cabanillas et al., 2020; Tounekti et al., 2020; Loh et al., 2020; Chin et al., 2020; Liébana-Cabanillas et al., 2018a; Sun et al., 2017). The remaining respondents were almost equally divided between those who agreed and disagreed with the statement that there is a security risk associated with personal data misuse or the potential for fraud in mobile payments.

On the other hand, the developed neural network model successfully uncovered some hidden regularities with an overall classification accuracy of 70.73%. Sensitivity analysis showed that age, accommodation, the use of some other digital services, the use of savings, financial planning and insurance services by digital means have an impact on the accuracy of the model. There are numerous digital financial services that fall within the scope of the variable *Other digital services*, which showed the greatest impact on model accuracy. These can include financial services such as personal investment advice and services, e-money accounts and transactions, digital wallets, peer-to-peer lending, credit card operations, cryptocurrency withdrawals, and so on. Like previous research that used neural network models to predict customer behavior in the financial industry (Rabaa'i et al., 2022; Khan et al., 2010; Ogwueleka et al., 2012), this new information could be valuable for the financial sector, which wants to ensure that its online services are used by this population, but also for educators as a good starting point for their efforts to improve their students' digital and financial literacy.

The limitations of this study mostly relate to the sample used, i.e., some other students from other faculties or countries may use their smartphones more intensively and use more online financial services in general, so the results are limited to this sample. Since some researchers (e.g., Harris et al., 2020) believe that self-report scales are not objective and therefore cannot truly measure smartphone use, and all scales developed to date to determine smartphone use are self-report (Harris et al., 2020), other methods of obtaining more objective data (e.g., smartphone application usage data) could be used to address this issue. The study may not be generalizable to other contexts or countries, as the factors influencing the adoption of digital financial services may vary depending on cultural and socio-economic factors (Chopdar et al., 2018; Fan et al., 2018; Liébana-Cabanillas et al., 2020; Singla & Sardana, 2020/2021). Future research could also apply some other theoretical models, discuss, and include other variables on which the intensity of smartphone use might depend, consider the role of some other online services in the use of online financial services, and include other data mining methods. For example, future studies could analyze the barriers to the adoption and usage of digital financial services for online payments among smartphone users, such as lack of trust in digital payment platforms, concerns about data privacy and security, and poor user experience. Furthermore, it could be interesting to explore the potential of mobile wallets and other innovative payment methods that are enabled by smartphones, and examine how they are used and accepted by consumers and merchants. Future research could examine the relationship between smartphone usage patterns (e.g., frequency, duration, purpose) and digital financial service usage for online payments, to determine whether heavy smartphone users are more likely to adopt and use digital financial services than infrequent users (expanding foundations set by Shaw and Kesharwani (2019)).

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