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Can online banking replace personal banking? A survey of Hungarian banking habits

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ABSTRACT

One of the important issues of banking today is the role bank branches and online banking solutions play in serving consumers. With the help of a representative Survey of 1,000 adults in Hungary conducted in 2022, we examine how well online and mobile banking solutions can provide a suitable alternative to bank branches. Based on our results, online banking solutions cannot fully replace personal banking in Hungary due to the customers' attitudes, as we can see that their use does not significantly affect the frequency of visits to the bank branch, and their usage rate does not increase with the distance from the bank branch. We also point out that for the Hungarian population the trend of bank branch closures may entail the risk of being left out of the formal financial system mostly for the older, digitally less receptive social strata living in small settlements and in a relatively worse financial situation.

KEYWORDS

bank branch, online banking, financial behavior, questionnaire survey, Hungary

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1. INTRODUCTION

The role of bank branches has undergone a significant transformation in recent decades. Branches, which once functioned as the main determining factor of market shares, are increasingly replaced by online banking. Thus, banks everywhere increasingly focus on the development of internet banking and mobile banking services. The motivations to reduce costs and increase efficiency after the financial crisis of 2008–2009 were connected with the rise of digital solutions. These have driven the trend of closing bank branches, which has become strongly dominant both in Hungary and in Europe in the last ten years (ECB 2022).[1] In relation to this, Pham et al. (2022) showed on the example of the USA that the cost reduction provided by branch closures leads to an increase in profits, and the resulting market loss can be partially compensated for by banks that simultaneously strengthen their digital services. In addition to the banking cost and marketing aspects, the demand side is also a particularly important aspect when it comes to the decrease in the accessibility of branches, i.e., what preferences the population has. The question arises as to whether the average consumer is able to adapt and keep up with these significant changes, or whether due to the change the relationship with the regulated financial system will cease or at least its strength will decrease for some consumers, which raises serious social and consumer protection issues.

In light of the above, this study examines whether online banking can replace personal contact in bank branches. In our research, we explored the issue of how distance from a bank branch affects the use and utilisation of personal and online (and mobile banking) administration methods. In addition, we examined whether the use of online banking solutions alone can influence the frequency of visits to the bank branch and, if so, to what extent, as well as the maximum amount of resources (money and time) consumers are willing to sacrifice in order to visit the branch. According to our initial hypothesis, online banking solutions in Hungary cannot yet fully replace the personal administration services available in bank branches due to the attitude of the clientele. We also believe that there is a social stratum in Hungary for which branch closures carry the risk of financial exclusion, the falling out of the formal financial system.

2. LITERATURE REVIEW

Several studies have dealt with the potential financial exclusion consequences of the location and closure of bank branches. Okeahalam (2009) and Qi et al. (2018) drew attention to the clustering of the location of bank branches, while Tranfaglia (2018) draws attention to the clustering of bank branch closures,[2] which in itself can cause a relatively low level of branch availability in some areas. In addition, based on the results of Okeahalam (2009), the location of the branches is influenced by the aggregate income level of the given settlement level. This can also be found

[1]Almost half of the bank branches in Hungary and more than one third of the bank branches in the European Union were closed down between 2008 and 2020 (ECB 2022).

[2]The clustering of closures means that branch closures are territorially autocorrelated and are grouped in specific areas.

in the study of Tranfaglia (2018) on the example of Chicago, where, in addition to income, population size can be highlighted as a determining factor of closures. In other words, the most vulnerable groups do not have access to adequate financial services. In their study of Spain, Alamá and Tortosa-Ausina (2012) confirmed the importance of the size of the population in branch opening decisions and also draw attention to the fact that these branch opening decisions have financial exclusion consequences for certain social strata. Morrison and O'Brien (2001) highlighted the vulnerable segment in terms of the distribution of the branch network, pointing out that residents who live at least 10 km away from the nearest branch are typically in a less favourable income and employment situation.

As for regional analyses, in his article analysing Austria, Burgstaller (2017) pointed out that financial desertification is most noticeable in less developed and functionally distant settlements because of the dynamics of the placement and closing of branches, due to which the possibility of choosing a bank also narrows around areas inhabited by an aging social stratum. As a result of these processes, in proportion to the population, 5% of Austrian settlements became branchless, and 5% of the population had to travel at least 5 km to the nearest bank branch (Stix 2020). Boďa and Čunderlíková (2020) used data from 2016 to examine the determining factors of the location of bank branches in Slovakia. In their research, they find that the number of bank branches in a given area is mostly determined by, in order of importance, the proportion of university graduates, the size of the population, the average nominal earnings, the concentration of bank branches and the average age.

In the case of Hungary, the eastern part of the country was considered more heavily banked than the western region, thanks to the economic development policy and strong industrialisation of the pre-1990s system (Gál 2005), which eased by the end of 2020, but was still present (El-Meouch – Alpek 2021). In his study of 2014 data, Kovács (2017) points out that, as a result of branch closures, the concentration in financial centres increased. Based on a study by El-Meouch et al. (2021), branch closures between 2008 and 2020 increased the number of people living in small settlements (mainly villages) not covered by branches from 950,000 to 2 million, as well as the average travel distance from the nearest bank branch for people living in these settlements (from 5.7 to 8.3 km).

Bank branch closures in Hungary took place in two waves: during the first wave, the large commercial banks reduced significantly the number of their branches between 2012 and 2015, while between 2017 and 2019 closures were mainly tied to the integration in the savings cooperative system, which served more isolated social strata (at the end of which the savings cooperatives merged into one big bank). Accordingly, in the case of the bank branch network, which has almost halved since the economic crisis of 2008–2009, the number of settlements not covered by branches increased significantly in the second wave (El-Meouch et al. 2021). As a consequence of this, in February 2022, at the time of conducting our Survey, the existing 1,820 bank branches were found in 715 settlements. This means that 2,458 settlements (mostly villages), 77% of the settlements, did not have a bank branch. Areas with small villages found mainly in Transdanubia and in the border region of Northern Hungary can be considered the most underbanked (Figure 1).

Not surprisingly, all the above-cited studies show that the location of the branches and their closings are not balanced territorially and are driven by various socio-demographic characteristics. Hence, the likelihood of using cash increases (with all its individual and social costs), and

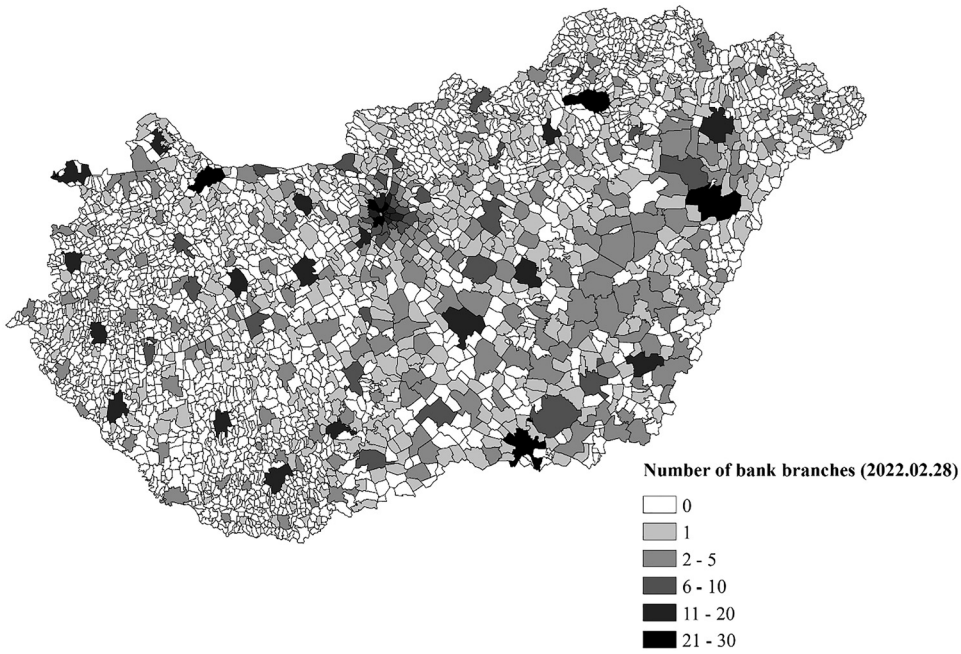

Fig. 1. Territorial distribution of the Hungarian bank branch network, February 2022
Source: Authors' presentation based on National Bank of Hungary (MNB) data.

the disprivileged groups become vulnerable to unregulated financial actors operating usury lending in the shadow banking sphere.

In addition to the availability of services, the role of bank branches also appears in financial awareness and financial education, as it provides space for a deeper understanding and knowledge of bank products and the development of conscious financial behaviour. The Hungarian population is ranked in the middle of the European field in terms of basic financial skills, based on the Standard and Poor's (S&P) Global Finlit Survey (GFLS) 2014, with 54% of the population having basic financial skills. If, on the other hand, we examine the level of financial skills on the labour market, in the 2019 survey of the Institute for Management Development (IMD) World Competitiveness Yearbook (WCY), Hungary is in a less favourable position in a European Union comparison, ranked in 22nd place out of 28 member countries (IMD 2019). The Banking System Competitiveness Index of the National Bank of Hungary (BVI – MNB), which uses these variables among others, also reveals that Hungarian financial awareness belongs to the European middle ground (the median is just not reached) (Asztalos et al. 2017) and no significant progress was measured in this regard after the 2020 update of the index (Bálint et al. 2020). All of this is supported by the results of the OECD/INFE financial education survey published in 2020, according to which, out of the 23 participating countries, Hungary came in slightly below the average, in 14th place, in which, of the three aspects surveyed (knowledge, behaviour, attitude), the country achieved a particularly

low score in the behaviour sub-index (OECD 2020). The MNB's survey measuring financial awareness in connection with interest rates and interest rate risk also showed low awareness of the population, with the majority of respondents failing to recognise the fixed interest rate product among the given product variations (Dancsik et al. 2019). Finally, this is supported by Pellandini-Simányi and Banai (2021), who show that the financial attitude and actual decisions of the Hungarian population are not in line with each other, and the difference is significantly greater than in the United States. All in all, it is therefore an important aspect that the informational and financial educational effects may be weakened by the termination of branches, since as a result it becomes more difficult to access the typically preferred personal administration options.[3]

In the literature related to bank branches, there is significant literature focusing the demand side, i.e., the customer side. Factors determining the use of online banking solutions became one of the main areas of investigation with the advancement of digitalisation. Based on 2020 data, 58% of the adult population of the European Union used internet banking in the three months prior to the survey, with significant differences between the individual age groups: the rate was 75% in the 25–34 age group, but only 34% in the 65–74 age group (Eurostat 2021). Among other things, the results of Flavián et al. (2006) also show that belonging to an older age group significantly reduces the chance of adopting the online solutions of a given bank. In their study, Devlin and Yeung (2003) examine the switch from traditional to online banking, confirming that younger consumers are more likely to switch and also pointing out that the quality of service available in the bank branch is a decisive factor in the switch. Conrad et al. (2019) show that in non-densely populated rural areas with a high average age and an average low level of education, the risk of information divide (heterogeneity with respect to digital access or internet usage) that negatively affects the demand for digital banking solutions can be higher. This may hinder this community's access to basic financial services during the ongoing digitalization. Dandapani et al. (2018) also find a similar nexus, pointing out that in the case of credit unions in the USA, the probability that a given institution provides transaction internet banking service is positively correlated with the share of the young population of the county where it operates.

Looking at the latest studies regarding the impact of bank digitalization on customers and their habits, Simmers et al. (2022) compare the USA and China and find that in terms of customer satisfaction, bank tellers are more important than mobile banking services, even for those consumers who, according to their own declaration, prefer self-service. Ahmeti and Prenaj (2022) applied the Technology Acceptance Model (TAM) model on the example of Kosovo to show that although consumers perceive the advantages of online banking, they still do not use it fully, which could be improved by a bank campaign promoting the ease and security of online banking. Using the same model (TAM), Albort-Morant et al. (2022) find that, although all direct (perceived ease of use (PEOU), perceived usefulness (PU)) and most

[3]In our Survey, when we asked whether the participants currently use advisory services in person or online, 61 per cent of respondents preferred personal arrangements, while in the case of a variation of the same question for the future (i.e., how you would like to use it in the future), personal arrangement was the preferred method for investment advice for 71 per cent of respondents. Both values were among the highest in terms of this kind of preferential distribution of various services (e.g., credit management, savings management, etc.).

indirect effects (perceived security (PB) used as mediator of the effects) significantly affect the level of use of online banking, there are minimal differences in Spanish cities and towns in terms of individual direct effects. Lee and Kim (2020) show that the number of provided services and trust have a positive effect, while security risks have a negative effect on the use of Internet-only banks' services, while in the case of pre-adoption, reaching the critical mass is a decisive factor in increasing the number of users. Dehnert and Schumann (2022) show based on the segmentation of bank clients in Germany that for the largest segment, traditional financial services that provide physical contact are still important, but they also show a visible need for better digitalized services. In addition, a younger, FinTech-oriented consumer segment that does not require physical contact at all emerges in their research. Becker et al. (2022) also examine German consumers and find that the stratum that have adopted mobile banking use internet banking solutions to a greater extent, while their activity related to ATMs, call centres and branches decreases. Digitalisation can also affect the financing of small and medium-sized enterprises (SMEs), in this regard, Lu et al. (2022) find that, based on Chinese data from 2007 to 2017, financing constraints of SMEs are negatively related to the proportion of local bank branches and degree of digital financial inclusiveness, which effect is particularly valid for small, transparent companies that operate in areas less dependent on bank loans. They also show that digital financial inclusion and local bank branches substitute each other in terms of financing constraints for SMEs.

Regarding the relationship between the distance from the branch and personal and online banking, Khan (2004) examined the relevance of distance with regard to the use of internet banking, based on data from the USA around the turn of the millennium. He came to the conclusion that the distance from the nearest bank did not affect the degree of use of online banking solutions, and so it could be interpreted more as a supplement to the traditional banking channel and not a substitute. Calisir and Gumussoy (2008) also reached a similar conclusion: based on their results, in the eyes of young people, net banking can complement the services provided by branches in shopping centres, it can be considered a replacement only for ATM and mobile banking. In his work, De Blasio (2009) also examined whether internet banking can replace administration at a bank branch for consumers whose personal administration options are limited due to the lack of urban infrastructure and thus the distance from the branch. Based on data from Italian households, he finds that the online banking habits of more isolated consumers are not more intensive than those of less isolated ones, the size of the city is not related to the use of Internet banking, and that less urban consumers attach more importance to personal relationships. Overall, based on literature investigating the relationship between branches and online banking from the residential customers' side, the results so far show that they complement rather than replace each other.

In our study, based on a new questionnaire database, we therefore investigate how the trend of branch closures in recent years has had an impact on residential consumers, and how the administration methods relate to each other as a result. The entire Central and Eastern European region have been characterised by a significant downsizing of branches since the beginning of the 2008–2009 economic crisis, which was justified by bank profitability aspects, but it is also important to see whether this has caused damage on a social level and whether an intervention may be necessary in the future.

3. DATA AND METHODOLOGY

The basis of this study is a Survey of 1,000 people in Hungary polled in February 2022, which contained questions about the branch visiting and online banking habits of the Hungarian adult population. The questionnaire was administered in a CATI (Computer Assisted Telephone Interview) format, which lasted 20 minutes and was structured in *five large blocks*. At the beginning of the Survey, in the screening questions, we asked about the respondent's basic characteristics used for representativeness dimensions (gender, age, type of settlement, county, education), followed by the longest block of the questionnaire which covers the population's bank branch visiting habits. We asked, among other things, what products and services the respondents use and how they use them, as well as their habits of visiting bank branches, how often, how, where and why they go there. The third block included banking digitalisation questions, in which we assessed the availability of digital devices and internet access, the use of banking (and other financial) online solutions, and digital affinity among the respondents. In the fourth block, we asked about the consequences of the possible closing of the bank branch frequently visited by the respondent in recent years, as well as the consequences of the restrictions imposed due to the outbreak of the coronavirus epidemic on the use of financial services. Finally, the last block included questions about financial knowledge, marital status, labour market status and income.

The Survey is representative[4] of the Hungarian adult population according to gender, age, type of settlement, educational level and county, so its results can be considered valid when extended to this population. In addition, since the aim in our research was to obtain the most valid sample in terms of the habits of visiting bank branches and use of online banking solutions, we ensured joint representativeness in the case of certain dimensions: the distribution of the age categories in the sample is proportional to the entire adult population both by type of settlement and by educational level.[5]

We used a wide range of variables for the analysis, which were classified into three groups: 1) outcome variables, for which we model the factors influencing them, 2) explanatory variables, from the coefficient values of which we expect the answers to our research questions, i.e. our results, and 3) control variables, the role of which is to ensure that the estimation and values of the coefficients of our essential explanatory variables are free from other distorting effects and biases. The *number of people living in the respondent's household* discrete variable was used as a control variable, while among the continuous variables, the *time and distance to get to the bank branch expressed in minutes and kilometres* were used as explanatory variables, and the *maximum willingness to access the branch in terms of time, distance and cost* were used as outcome variables in the analysis. The variables measuring representativeness (*gender*, *age group*, *type of settlement*, *educational level, county*) were included in the analysis as categorical control variables. For some questions, we created dummy variables, of which the *frequency of visits to the bank branch dummy* and the *use of online banking and mobile banking solutions (online banking (dummy), mobile banking(dummy))* were outcome variables, while the *subjective well-being dummy* and the *financial training dummy* were included in our models as control variables.

[4]The representativeness of the Survey and the randomness of the sample was ensured by the commissioned market research company.

[5]The detailed representativeness tables can be found in Appendix A.

We created indices to aggregate questions of similar nature in the questionnaire. The *bank product index* (control variable) shows how extensive of a bank product portfolio the respondent has, and the *service index* (control variable) shows how many banking services the respondent uses. One of the *online and mobile banking indexes* (outcome variables) describes the use of a wide range of digital banking solutions, while the other index also takes into account the frequency of use. With the help of the *digital affinity index* (explanatory variable), we assessed how receptive the respondents are to online banking solutions, how fast and convenient they consider them to be, how capable and willing they are to use them, and how much they trust them. The *willingness index* (outcome variable) was compiled from the answers to how much the respondent would be willing to do in terms of time and distance to get to the bank branch, as well as the maximum amount they would be willing to sacrifice for this.[6]

We used three types of regression models: Ordinary Least Square (OLS) linear, logistic and multinomial logistic models. In our two main regression model groups (visiting a bank branch; use of online and mobile banking solutions), we estimated our main results with logistic models, and accordingly we used binary outcome variables, while in the case of our models explaining the maximum willingness factors, we estimated our results with an OLS model.

As a robustness test, we used a multi-category variable as the outcome variable for the visit to the bank branch model group, so multinomial logistic models were estimated, while OLS estimates were used for the robustness test of the use of online solutions.[7] The estimated model equations of our main results:

Bank branch visiting:

$$\log\frac{P(Y_1=1)}{(1-P(Y_1=1))}=\alpha+\beta_1x_1+\beta_2x_2+\beta_3x_3+\beta_4x_1x_2+\beta_5x_1x_3+\overline{\beta}\overline{z}, \tag{1}$$

$$\text{Online banking}:\log\frac{P(Y_2=1)}{(1-P(Y_2=1))}=\alpha+\beta_1x_1+\beta_2x_2+\overline{\beta}\overline{z}, \tag{2}$$

$$\text{Mobile banking}:\log\frac{P(Y_3=1)}{(1-P(Y_3=1))}=\alpha+\beta_1x_1+\beta_2x_2+\overline{\beta}\overline{z}, \tag{3}$$

$$\text{Time willingness}:\widehat{y_4}=\alpha+\beta_1x_1+\beta_2x_2+\beta_3x_3+\overline{\beta}\overline{z}+u, \tag{4}$$

$$\text{Distance willingness}:\widehat{y_5}=\alpha+\beta_1x_1+\beta_2x_2+\beta_3x_3+\overline{\beta}\overline{z}+u, \tag{5}$$

$$\text{Cost willingness}:\widehat{y_6}=\alpha+\beta_1x_1+\beta_2x_2+\beta_3x_3+\overline{\beta}\overline{z}+u, \tag{6}$$

$$\text{Willingness index}:\widehat{y_7}=\alpha+\beta_1x_1+\beta_2x_2+\beta_3x_3+\overline{\beta}\overline{z}+u, \tag{7}$$

for which, in logistic regressions, $Y_1=1$ denotes frequent visits to bank branches, $Y_2=1$ the use of online banking solutions, $Y_3=1$ the use of mobile banking solutions, $\widehat{y_4}$ the time, $\widehat{y_5}$ the distance, $\widehat{y_6}$ the cost willingness, and $\widehat{y_7}$ denotes the willingness index. Among our explanatory variables, x_1 is the distance from the bank branch, x_2 is the digital affinity index, x_3 is the online

[6]A detailed presentation of the variables and indexes can be found in Appendix B.

[7]The model equations for the robustness tests are included in Appendix C.

banking index, $\overline{z}$ is the vector of control variables, and u is the error term. In terms of our research questions, the important coefficients are β_1 for the distance to the bank branch, β_2 for the digital affinity index, β_3 for the online banking index, and β_4 and β_5 for the interaction terms of the distance to the bank branch with the digital affinity index and with the online banking index, while $\overline{\beta}$ is the coefficient vector for the control variables $\overline{z}$. These coefficients show the given variable's effect on the result variable. In the case of the model explaining bank branch visiting (Equation 1), we estimated 6 different models, which differ in terms of which prominent explanatory variables (and their interaction terms) are included in each model version.

4. RESULTS

4.1. Bank branch visiting

The main question of our study is to what extent digital solutions can replace going to a bank branch. Our results support the expectation that the frequency of going to the bank branch is significantly determined by the distance from the branch, the chance of belonging to the category of frequently visiting the branch is significantly reduced by the distance from the branch. The question is whether, due to the increasing distance, online solutions become more preferred and replace going to the branch to some extent. Based on our results, the use of online solutions does not significantly affect the frequency of visits to the bank branch, regardless of whether the digital affinity index is included in the given model version (Table 1).[8] In addition, in the case of the distance from the branch and the online banking index interaction term, we can see that the effect of the use of online banking solutions on going to the branch does not significantly increase as the distance from the branch increases, and so this factor does not become more and more significant for those who live further from the branches. These results show that the use of online banking solutions alone cannot replace going to a bank branch (or even make it less frequent), i.e., there is no visible substitution effect. However, a significant effect can be detected in terms of digital affinity: it significantly reduces the probability of belonging to the category of frequently visiting a branch, and thus a high degree of digital aptitude reduces the need to visit a bank branch. On the other hand, the interaction term formed by the digital affinity index and the distance from the branch does not have a significant effect on going to a bank branch, so the importance of digital affinity does not increase in places that are further and further away from bank branches. Overall, digital receptivity is, unsurprisingly, more of a generational issue, and through that the declining frequency of going to the branch actually appears to be so as well. This is supported by the fact that in the model versions that do not include the digital affinity index, belonging to the older (40+) age group categories significantly increases the frequency of going to the bank branch, but this effect is reduced by including digital affinity in the model and is considered less significant (Table 1).[9]

[8]One of the important results of our study is that, contrary to intuition, the attitude towards digital solutions, i.e., digital affinity in our research, does not perfectly proxy the use of online banking solutions.

[9]Other significant effects: the number of services used and (compared to the reference group of primary school or lower education) the existence of a vocational training or vocational school education (without a high school diploma) increase the frequency of visits to the branch.

Table 1. Results of models explaining the frequency of visits to the bank branch (Eq. (1))[10]

Variable	Outcome variable: Frequency of visiting the bank branch dummy					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Distance from the branch (minutes)	−0.026***	−0.026***	−0.026***	−0.064***	−0.038***	−0.064***
Digital affinity index	−0.353***	–	−0.41***	−0.58***	–	−0.631***
Online banking index (frequency)	–	−0.006	0.053	–	−0.066	0.051
Digital aff. * Distance from the branch	–	–	–	0.014*	–	0.014
Online bank. * Distance from the branch	–	–	–	–	0.004	0.000
Age: 30–39 years old	−0.243	−0.155	−0.228	−0.271	−0.175	−0.257
Age: 40–49 years old	0.481*	0.58**	0.506*	0.463*	0.563**	0.487*
Age: 50–64 years old	0.455*	0.622**	0.488*	0.428	0.603**	0.46*
Age: 65+ years old	0.408	0.699**	0.47*	0.386	0.673**	0.445
Constant	−0.188	−1.174**	−0.218	0.402	−0.948*	0.365
Number of observations	844	856	844	844	856	844
Pseudo R-squared	0.091	0.082	0.092	0.093	0.084	0.094

Note: Visiting the branch more often than the *annual* category belongs to the *frequently* category of the outcome variable, while the *annual* category, the rarer categories, and the category of *doesn't go, does his/her business online* belong to the rarely category, which is the reference category in the models. In the case of the age groups, the *18-29 years old* group is the reference category. All models include all categories of gender, education, type of settlement, and county variables, the dummy variables of financial training and subjective well-being, as well as the number of people living in the household, bank product index and service index continuous variables. The results are robust: 1) if the online banking dummy or online banking index (number) variables are used instead of the online banking index (frequency), or 2) if the distance from the branch measured in time is replaced by the distance measured in km, or 3) if we use factors instead of indexes in the model. To create the factors, we used principal component analysis for the questions underlying the indexes. The factors formed in this way correlate at least 97% in absolute value with the specific indexes used in the main models, thanks to which the results are highly robust to the use of indexes or factors.

*$P < 0.1$; **$P < 0.05$; ***$P < 0.01$.

Source: Own estimations based on the questionnaire.

4.2. Online and mobile banking

In accordance with our preliminary assumptions, the digital affinity index significantly increases the use of online and mobile banking solutions. However, the increase in distance from the bank

[10]The longer version highlighting more variables is available from the authors upon request for each result table.

Table 2. Results of models explaining the use of online banking (Eq. (2)) and mobile banking solutions (Eq. (3))

Variable	Online banking (dummy)	Mobile banking (dummy)
Distance from branch (minutes)	−0.007	−0.023***
Digital affinity index	2.268***	1.379***
Age: 30–39 years old	−0.026	−0.381
Age: 40–49 years old	−1.232**	−1.176***
Age: 50–64 years old	−2.103***	−1.526***
Age: 65+ years old	−2.096***	−2.195***
Constant	−4.956***	−3.197***
Number of observations	844	844
Pseudo R-squared	0.53	0.349

Note: In the case of online banking, we included the use of both the net banking and mobile banking applications, so if the respondent uses even one of them, it already sets the value of the binary variable to 1. In the case of the age group, the *18-29 years old* group is the reference category. All models include all categories of gender, education, type of settlement, and county variables, the dummy variables of financial training and subjective well-being, as well as the number of people living in the household, bank product index and service index continuous variables. The results are robust: 1) if the distance measured in time from the branch is replaced by the distance measured in km, or 2) if we use factors instead of indexes in the model. To create the factors, we used principal component analysis for the questions underlying the indexes. The factors formed in this way correlate at least 97% in absolute value with the specific indexes used in the main models, thanks to which the results are highly robust to the use of indexes or factors.
*$P < 0.1$; **$P < 0.05$; ***$P < 0.01$.
Source: Own estimations based on the questionnaire.

branch does not increase the chance of using online solutions, which again confirms that the difficulty of getting to the bank branch does not clearly mean the transition to an online platform; it apparently does not substitute personal transactions (Table 2).[11] Our results concerning the frequency of bank branch visiting and online (and mobile) banking are therefore basically in line with those found in the literature (Khan 2004; Calisir – Gumussoy 2008; De Blasio 2009; Simmers et al. 2022; Ahmeti – Prenaj 2022; Dehnert – Schumann 2022), i.e., that for consumers, transactions in branches are still decisive, and cannot be completely replaced by online banking solutions.

[11]It is interesting that the distance even reduces the chance of using the mobile banking application, which may be related to the fact that in areas better equipped with bank branches there are typically people living among whom such solutions are more widespread, so they may be more proficient in mobile phone administration.

Among the significant influencing factors, the importance of age groups clearly stands out, as it was also highlighted in various articles (Devlin – Yeung 2003; Flavián et al. 2006; Dandapani et al. 2018; Conrad et al. 2019). Regarding the use of both online banking and mobile banking services, it can be observed that, compared to the youngest age group, belonging to the older age groups significantly reduces the use. It can be seen that not only the oldest, but also those over 40 years old use these solutions to a lesser extent than users under 40 years old, solely due to their age.[12] In other words, overall, we can see that it is the urban, young, better-off group for which the digital banking solutions are real alternatives and that these solutions do not appear as a substitute platform for older, rural communities that are increasingly cut off from branches.

Among the above results, it should be highlighted that belonging to an older age group has a negative effect on the use of digital banking solutions, despite the fact that digital affinity (also a negative effect in the case for the elderly) was controlled for in the model. In other words, the lower use cannot be traced back to ability alone, a kind of reluctance on the part of the older age groups can be observed in addition to that. Figure 2 shows that, on the one hand, the digital affinity index decreases significantly when considering the two oldest age groups, but the use of online banking solutions decreases in a relatively greater proportion in these two age groups compared to the other age groups. On the other hand, according to our results, belonging to these age groups only slightly increases the frequency of visits to the branch, which is more related to digital affinity.

4.3. Willingness to go to a branch

From the point of view of the choice between personal administration and the use of digital banking solutions (and from the frequency of branch visits aspect itself), the maximum amount of resources consumers are willing to sacrifice in order to be able to manage their finances in person at a bank branch is decisive. Related to this, we modelled the influencing factors of the maximum willingness for time, distance and cost, as well as the value of the index made up of the three indicators (Table 3). It is evident from the results that the willingness of individuals is significantly influenced by the actual distance to be travelled in all models. A basic explanation for this can be that the opportunities provided by the environment strongly influence the thinking about how much a given service is worth to the individual. Presumably, as soon as this changes negatively (that is, the individual moves further away from the bank branch), the willingness for a part of the people may also increase due to necessity, even if they experience this as an uncomfortable change.[13] Confirming the previous results, we also see here that online

[12]Other significant effects: 1) Online banking: the number of services used, subjective well-being, the number of people living in the household and higher education increase, living in a city with more than 8,000 people decrease the use (compared to the county seat); 2) Mobile banking: the number of services used, subjective well-being and the availability of financial training increase usage.

[13]Another explanation for the correlation could be that when choosing a place of residence, a part of the population already takes into account how much they are willing to do or sacrifice to access the infrastructure necessary for their daily life, so those with a higher willingness may live further away from bank branches. This correlation is valid only for those who are truly able to decide between alternatives when choosing a home, presumably less so for elderly people living in small settlements.

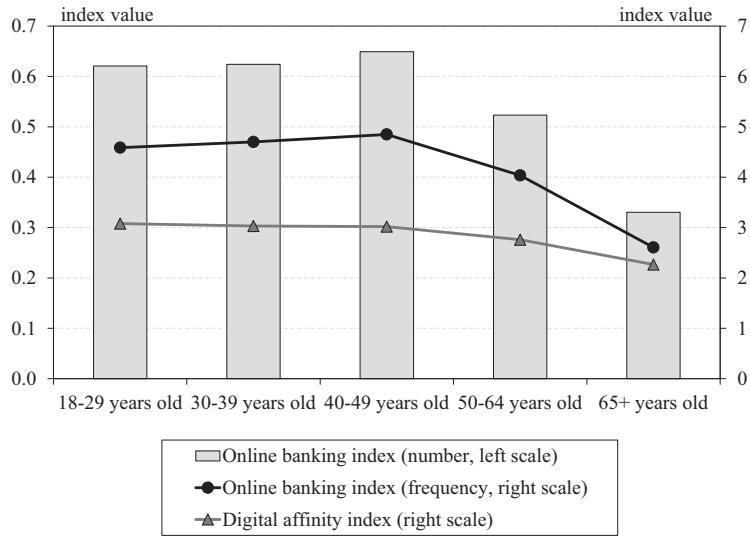

Fig. 2. Averages of digital affinity and online banking indexes by age groups
Source: Own editing based on the questionnaire.

solutions do not significantly change the willingness to visit the branch, and no significant effect can be seen in the case of the digital affinity index either.[14]

Another important result is that, belonging to the oldest age group (65+ years old) has a significant impact on the willingness to spend, while being in the 50–64 age group category also significantly reduces the willingness in terms of the maximum resources used to get to the bank branch in itself, which mostly stems from time and cost willingness. To further illustrate this, it can be observed in Figure 3 that the average willingness index of the younger age groups significantly exceeds that of the two oldest age groups.[15] In addition, the time and distance stretchedness[16] of the two oldest age groups has a much higher average value than the average values for the younger age groups. All of this shows that, in terms of the effort required to go to the bank branch, those belonging to the older age group are much closer to the level they would be willing to maximally do according to their response. As a result, these are the groups that

[14]Additional effects: The existence of a more complex product and service portfolio encourages customers who use it to be willing to sacrifice more resources for personal administration. Subjective well-being reduces the maximum amount of time spent on travel, the respondents are more permissive in terms of the distance to be travelled due to the educational qualification marked by the high school diploma, while those living in settlements with a population of less than 1,000 people are willing to sacrifice more financial resources, but all three effects disappear in the case of the regression run on the index.

[15]From Figure 3 can be guessed that if we had compared the older age groups to the 30–39 age group, we would have had an even stronger negative effect, which was also supported by alternative model runs.

[16]By time (distance) stretchedness, we mean the ratio of the actual time (distance) required to reach the branch and the time (distance) to be done according to the maximum willingness.

Table 3. Results of the models explaining the maximum willingness of time (Eq. (4)), distance (Eq. (5)) and cost (Eq. (6)) and the willingness index (Eq. (7))

Variable	Time willingness (minutes)	Distance willingness (km)	Cost willingness (HUF)	Willingness index
Distance from the branch (minutes or km)	0.703***	0.764***	24.52***	0.035***
Digital affinity index	0.526	0.272	−27.816	0.007
Online banking index (frequency)	−0.415	−0.366	30.948	−0.012
Age: 30–39 years old	2.747	0.994	48.501	0.085
Age: 40–49 years old	−0.808	−1.026	−204.067	−0.051
Age: 50–64 years old	−4.219**	−2.245	−365.3*	−0.202**
Age: 65+ years old	−1.731	−2.422	−541.443**	−0.161
Constant	14.104***	2.946	122.795	−0.466**
Number of observations	820	777	688	672
R-squared	0.279	0.359	0.162	0.289

Note: The willingness index is the arithmetic average of the standardised values of the time, distance and cost willingness variables. The distance from the branch variable covers the distance measured in minutes in the case of the time willingness model, while in the case of the other models it covers the distance measured in km. In the case of the age group, the *18–29 years old* group is the reference category. All models include all categories of gender, education, type of settlement, and county variables, the dummy variables of financial training and subjective well-being, as well as the number of people living in the household, bank product index and service index continuous variables. The results are robust: 1) to whether the online banking index (frequency) or the digital affinity index variables are included in the model together or separately, or 2) if we use factors instead of indexes in the model. To create the factors, we used principal component analysis for the questions underlying the indexes. The factors formed in this way correlate at least 97% in absolute value with the specific indexes used in the main models, thanks to which the results are highly robust to the use of indexes or factors.
*$P < 0.1$; **$P < 0.05$; ***$P < 0.01$.
Source: Own estimations based on the questionnaire.

make relatively the greatest efforts for personal administration, so the greatest chance of ceasing personal administration and thus possibly being excluded from the formal financial system is in their case, but this can even more likely occur due to some negative development (e.g., the closing of a nearby bank branch).

5. ROBUSTNESS TESTS

In order to further examine the stability of our main results, we performed various robustness tests. In the case of visiting the bank branch, the binary (often or rarely goes to a bank

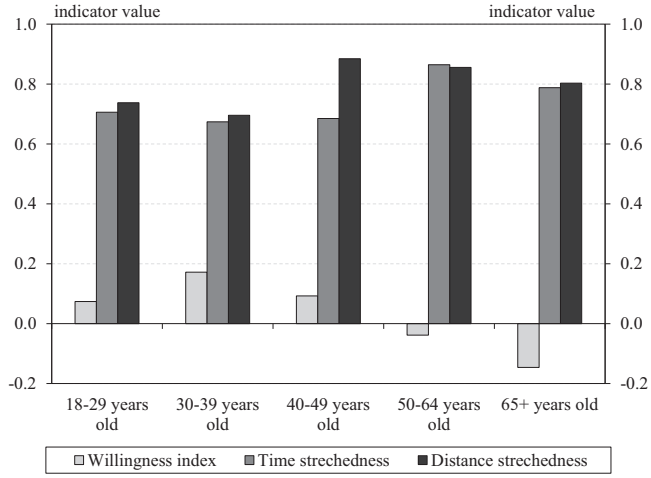

Fig. 3. Averages of the willingness index and the time and distance stretchedness by age groups
Note: The willingness index is the arithmetic average of the standardised values of the time, distance and cost willingness variables. By time (distance) stretchedness, we mean the ratio of the actual time (distance) required to reach the branch and the time (distance) to be done according to the maximum willingness.
Source: Own editing based on the questionnaire.

branch) outcome variable model was supplemented with a multicategory outcome variable multinomial logistic model, while in the case of our models investigating online banking and mobile banking, we expanded the results of the basic model by using the number and frequency indexes as outcome variables. The results of the former can be seen in Table 4, on the basis of which we can see that the robustness test broken down according to the categories of the frequency of going to the bank branch supports our main results and the basic findings made there. The distance from the bank branch and the digital affinity index significantly reduces the frequency of going to the bank branch, while the online banking index has no significant effect on it.

The robustness tests of the online banking models (Table 5) are almost completely identical with the basic results. The digital affinity index significantly increases the use of online banking and mobile banking for all models, while the distance from the branch does not significantly increase the level of online and mobile banking use.[17] In addition, we can observe the significant reducing effect of belonging to age groups over 40 compared to younger age groups.

[17]It even slightly reduces the latter in these models as well.

Table 4. Results of the multinomial logistic model robustness test of the frequency of visits to the bank branch (Eq. (A1))

Model	Variable	Reference: Monthly of more frequently				
		Twice or three times every six months	Every six months	Annually	Less often than annually	Does not go to a bank branch
Model 1	Distance from the branch (minutes)	0.03**	0.028**	0.04***	0.05***	0.05**
	Digital affinity index	0.198	0.765***	0.625***	0.858***	2.045***
	Number of observations	843				
	Pseudo R-squared	0.128				
Model 2	Distance from the branch (minutes)	0.03**	0.028**	0.04***	0.049***	0.054***
	Online banking index (frequency)	0.050	0.128**	0.061	0.084	0.183
	Number of observations	855				
	Pseudo R-squared	0.112				
Model 3	Distance from the branch (minutes)	0.03**	0.027**	0.04***	0.049***	0.051**
	Digital affinity index	0.223	0.789***	0.705***	0.959***	2.073***
	Online banking index (frequency)	−0.018	−0.017	−0.070	−0.089	−0.011
	Number of observations	843				
	Pseudo R-squared	0.128				
Model 4	Distance from the branch (minutes)	0.009	0.034	0.061*	0.09**	0.104
	Digital affinity index	0.085	0.8***	0.743***	1.124***	2.31***
	Digital aff. * Distance from the branch	0.007	−0.003	−0.008	−0.015	−0.018
	Number of observations	843				
	Pseudo R-squared	0.129				

(continued)

Table 4. Continued

Model	Variable	Reference: Monthly of more frequently				
		Twice or three times every six months	Every six months	Annually	Less often than annually	Does not go to a bank branch
Model 5	Distance from the branch (minutes)	0.036	0.033	0.052***	0.067***	0.061**
	Online banking index (frequency)	0.077	0.151	0.117	0.174	0.209
	Online bank. * Distance from the branch	−0.002	−0.002	−0.004	−0.005	−0.002
	Number of observations	855				
	Pseudo R-squared	0.112				
Model 6	Distance from the branch (minutes)	0.004	0.031	0.056	0.086**	0.070
	Digital affinity index	−0.058	0.753**	0.71**	1.134***	2.478***
	Online banking index (frequency)	0.088	0.025	−0.004	−0.035	−0.222
	Digital aff. * Distance from the branch	0.019	0.002	0.000	−0.009	−0.022
	Online bank. * Distance from the branch	−0.007	−0.003	−0.004	−0.004	0.012
	Number of observations	843				
	Pseudo R-squared	0.131				

Note: All models include all categories of gender, age, education, type of settlement, and county variables, the dummy variables of financial training and subjective well-being, as well as the number of people living in the household, bank product index and service index continuous variables. Each column shows the results of a logistic model separately, in which observations belonging to the bank branch visit frequency category indicated at the top of the given column and the reference category (*visits the bank branch every month or more frequently*) are included, the coefficients show how the chance of belonging to the former category is affected by the given variable. The different model versions (Model 1, Model 2, etc.) differ in that they contain a different set of highlighted explanatory variables and their interaction terms. The results are robust if we use factors instead of indexes in the model. To create the factors, we used principal component analysis for the questions underlying the indexes. The factors formed in this way correlate at least 97% in absolute value with the specific indexes used in the main models, thanks to which the results are highly robust to the use of indexes or factors.
*$P < 0.1$; **$P < 0.05$; ***$P < 0.01$.
Source: Own estimations based on the questionnaire.

Table 5. Results of the number and frequency index robustness test of the use of online banking (Eq. (A2) and Eq. (A3)) and mobile banking solutions (Eq. (A4) and Eq. (A5))[18]

Variable	Online banking index (number)	Online banking index (frequency)	Mobile banking index (number)	Mobile banking index (frequency)
Distance from the branch (minutes)	−0.001	−0.006	−0.002*	−0.01*
Digital affinity index	0.159***	1.084***	0.151***	0.998***
Age: 30–39 years old	−0.037	−0.265	−0.040	−0.236
Age: 40–49 years old	−0.052	−0.399**	−0.086**	−0.635***
Age: 50–64 years old	−0.097***	−0.641***	−0.105***	−0.693***
Age: 65+ years old	−0.151***	−1.086***	−0.17***	−1.123***
Constant	0.028	0.406	−0.029	−0.001
Number of observations	844	844	843	844
R-squared	0.441	0.494	0.339	0.349

Note: In the case of online banking, we included the use of both the net banking and mobile banking applications, so if the respondent uses even one of them, it already increases the value of the index. In the case of the age group, the *18–29 years old* group is the reference category. All models include all categories of gender, education, type of settlement, and county variables, the dummy variables of financial training and subjective well-being, as well as the number of people living in the household, bank product index and service index continuous variables. The results are robust if we use factors instead of indexes in the model. To create the factors, we used principal component analysis for the questions underlying the indexes. The factors formed in this way correlate at least 97% in absolute value with the specific indexes used in the main models, thanks to which the results are highly robust to the use of indexes or factors.
*$P < 0.1$; **$P < 0.05$; ***$P < 0.01$.
Source: Own estimations based on the questionnaire.

6. SUMMARY

Based on the attitude of the Hungarian clientele, we examined the relationship between personal contact in a bank branch and the use of online banking solutions. Our results showed that the distance from the bank branch had a significant influence on the frequency of personal contact in a branch, whereas by contrast it had no significant effect on the use of online and mobile banking solutions. In connection with this, we also showed that online banking does not significantly affect visiting the bank branch and does not reduce its frequency, and that this does not depend on the distance from the bank branch, as it remains true even for people who live farther away. Based on all of this, assessing the current consumer habits, it cannot be said

[18]The longer version presenting more variables is available from the authors upon request.

that online banking solutions in Hungary can completely replace personal administration, or replace the benefits of the latter for everyone. In addition to all this, we found that digital affinity is of particular importance in terms of promoting and facilitating the transition to online solutions.

Amidst the trend of bank branch closures in Hungary, our results support the fact that, from a policy point of view, special attention should be paid to consumers typically living in smaller settlements, *1) who do not have a bank branch nearby, 2) who belong to the older age groups, 3) who live in a relatively worse financial situation,* and *4) who are not digitally educated or receptive enough.* Moreover, the members of this group are not mobile due to their age, and in terms of mobility, they are currently more stretched compared to the other respondents. Especially in the case of this group, we have to realise that due to their perceptions, online banking solutions are currently not a full-scale alternative to the shrinking personal banking options in Hungary, so these people can easily be pushed out of the formal financial system. Digital education in general can contribute to solving the above challenges, and through this, increasing digital receptivity. However, digital education is likely to be of low effectiveness in the case of the vulnerable group (elderly people) identified above. For this reason, it is important to strengthen alternative access to banking services for these people like providing enough multi-functional ATMs (which, among other things, are suitable for cash deposits) to manage financial matters or instituting a banking format of postal services.

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APPENDIX

A. Representativeness tables of the sample

Table A1. Distribution of representativeness variables of the questionnaire

Variable	Category	Within-sample frequency	Variable	Category	Within-sample frequency
Gender	Male	476	County	Budapest (capital)	172
	Female	524		Bács-Kiskun	52
Age	18–29 years old	162		Baranya	39
	30–39 years old	161		Békés	35
	40–49 years old	203		Borsod-Abaúj-Zemplén	66
	50–64 years old	234		Csongrád-Csanád	42
	65+ years old	240		Fejér	43
Education	Primary school or lower	194		Győr-Moson-Sopron	47
	Vocational training, vocational school (without high school diploma)	207		Hajdú-Bihar	54
				Heves	30
	High school, vocational high school (high school diploma)	352		Jász-Nagykun-Szolnok	38
				Komárom-Esztergom	31
	University, college (diploma) or higher	247		Nógrád	20
				Pest	130
Type of settlement	Capital city (Budapest)	172		Somogy	32
	County seat, city with county rights	198		Szabolcs-Szatmár-Bereg	55
	Other city with over 8,000 inhabitants	245		Tolna	23
	Other city with a population of 8,000 or less	84		Vas	26

(continued)

Table A1. Continued

Variable	Category	Within-sample frequency	Variable	Category	Within-sample frequency
	Village of over 1,000 people	223		Veszprém	36
	Village with 1,000 people or less	78		Zala	29

Note: In the case of gender, age, settlement type and county representativeness variables, the frequencies of the individual categories were prepared on the basis of the 2020 end-of-year data of the Hungarian Central Statistical Office (HCSO) T-STAR found in the National Regional Development and Spatial Planning Information System (TeIR), as well as the HCSO Detailed gazetteer of Hungary. The education data was based on an estimate using the 2011 census and the 2016 micro-census of the HCSO.
Source: TeIR (2022), HCSO (2022).

Table A2. Multidimensional representativeness dimensions of the questionnaire

Dimension	Category 1	Category 2	Within-sample frequency
Age x type of settlement (narrow)	18–29 years old	Budapest	24
		County seat, city with county rights	30
		Other city	54
		Village	54
	30–39 years old	Budapest	30
		County seat, city with county rights	31
		Other city	52
		Village	48
	40–49 years old	Budapest	36
		County seat, city with county rights	41
		Other city	67
		Village	59
	50–64 years old	Budapest	37
		County seat, city with county rights	46
		Other city	78
		Village	73

(continued)

Table A2. Continued

Dimension	Category 1	Category 2	Within-sample frequency
	65+ years old	Budapest	45
		County seat, city with county rights	50
		Other city	78
		Village	67
Age (narrow) x education (narrow)	18–64 years old	Primary school or lower	84
		Vocational training, vocational school (without high school diploma)	180
		At least a high school diploma (high school, vocational secondary school, higher education)	496
	65+ years old	Primary school or lower	110
		Vocational training, vocational school (without high school diploma)	27
		At least a high school diploma (high school, vocational secondary school, higher education)	103

Note: In the case of age and settlement type representativeness variables, the frequencies of the individual categories were prepared on the basis of the 2020 end-of-year data of the Hungarian Central Statistical Office (HCSO) T-STAR found in the National Regional Development and Spatial Planning Information System (TeIR), as well as the HCSO Detailed gazetteer of Hungary. The education data was based on an estimate using the 2011 census and the 2016 micro-census of the HCSO.
Source: TeIR (2022), HCSO (2022).

B. Formation of indexes and variables

We created different indexes based on the answers to the questions in the questionnaire which related to each other, with the aim that the questions measuring a similar phenomenon can be expressed in one or a few variables and thus become easier to analyse. In the case of bank products, the number of products owned by the respondent or his/her household was divided by the number of products surveyed.[19] In the case of banking services, the number of services used with any frequency was divided by the number of services surveyed.

[19]When we mention "number of products (or anything else) surveyed", we mean the number of questions asked in the questionnaire on the given topic (in this case, of products) to which an analysable answer was received. Analysable answers are understood as the set that includes all answer options other than the "don't know/don't answer" answer option.

In the case of online banking, we also created an index, the numerator of which contains the number of services that the respondent uses with some frequency online (on the net banking or mobile banking interface), and the denominator of which is the number of online banking solutions surveyed. In the case of this set of questions, we also created a binary variable that takes the value 1 if the respondent uses any online banking solution with any frequency, and 0 if not at all. We created the same index and dummy variable for mobile banking, so that the questions only concerned the use of the mobile banking applications.

We also created an alternative index variable for both online and mobile banking, in which the two-dimensional distinction (using or not using) was broken down further, and the frequency of use was also considered. In these groups of questions, we assigned a value to each answer option of the questions, in such a way that the most frequent use meant the most points, and the least frequent use meant the fewest points.[20] For these indexes, the numerator was the sum of the responses, while the denominator was the number of responses that could be analysed.

In addition to all of this, we created a digital affinity index, which measures how comfortable the respondent feels using online banking solutions, how reliable and simple they consider online banking to be, as well as how well they are able to use these digital solutions.[21] To create the index, we assigned values for agreement or disagreement with the given statements.[22] The index was finally formed as an average of the answers that could be analysed, so it ranges from 1 to 4, with higher values indicating respondents who are more digitally receptive, and lower values indicating respondents who are less digitally receptive. Finally, we created a willingness index, which included answers to questions about the maximum amount of time and distance the respondent would be willing to travel to get to a bank branch, as well as the maximum amount of money they would be willing to spend on this trip. The index was created by standardising the answers given in minutes, kilometres and Hungarian forints, and then taking their arithmetic mean.

In order to achieve further manageability of the variables, for some questions, we combined some answer options into relatively homogeneous units, thus reducing the number of values that can be taken by the given variable used in the analysis. We created a binary (dummy) variable based on participation in financial training (in any form), and we also created a dummy variable for subjective well-being:[23] those who declared that they could relatively or very easily cover

[20]Answer options for using the given solution and the values assigned to them: Daily – 10; Several times a week – 9; Weekly – 8; Every two weeks – 7; Monthly – 6; Two or three times per six months – 5; Every six months – 4; Annually – 3; Less often than annually – 2; Never – 1

[21]The statements that belong here: A) Agreeing with statements shows digital affinity: 1. You can manage your finances more conveniently and quickly online. 2. If possible, you would do all your banking online. B) Agreeing with statements shows a lack of digital affinity: 3. Only personal advising can provide adequate information. 4. You do not understand online platforms adequately enough in order to use financial services online. 5. Banking on online platforms is not reliable.

[22]If the statement referred to the existence of digital affinity, we assigned the following values to the answer options: Completely agree – 4; I rather agree – 3; I rather disagree – 2; Strongly disagree – 1. Where the statement referred to a lack of digital affinity, we used reverse scoring.

[23]As expected, many people (237) did not answer the question regarding the objective, specific income level category, while more answers were received to the more subjective, less specific income question, which is why it was necessary to use the latter question and the variable formed from it.

their monthly expenses received a value of 1, those who said they could cover their expenses with moderate or great difficulty, received a value of 0. Regarding the frequency of going to the bank branch, we also created a dummy variable that included the values of frequent (more often than annually) and rare (annually or less often, or never, because he/she manages his/her affairs online). In the case of going to the bank branch, we also created an additional variable in which, due to the low number of items, those who go to the bank branch more often than once a month were combined with those who go to the bank branch once a month (aside from this, we kept the other five categories). In our regression analyses, we used these bank branch visit variables.

Table A3. Presentation of the variables used in the analysis

Variable name	Type	Description
Gender	Categorical	Male or female.
Age	Categorical	Categories: 18–29; 30–39; 40–49; 50–64; 65+
Education	Categorical	Four categories according to education level the respondent attained.
Type of settlement	Categorical	Six categories according to type of settlement the respondent lives in.
County	Categorical	19 Hungarian counties and the capital city.
Frequency of visits to the bank branch	Categorical	Six categories according to the frequency the respondent visits the bank branch.
Number of people living in the household	Discrete	–
Distance from the branch (minutes)	Continuous	The distance of the customer to the bank branch in minutes.
Distance from the branch (km)	Continuous	The distance of the customer to the bank branch in km-s.
Time willingness (minutes)	Continuous	The maximum time the customer is willing to spend to get to the branch.
Distance willingness (km)	Continuous	The maximum distance the customer is willing to cover to get to the branch.
Cost willingness (HUF)	Continuous	The maximum cost the customer is willing to pay to get to the branch.
Online banking (dummy)	Dummy	1 if the costumer uses any online banking service with any frequency, 0 if not.
Mobile banking (dummy)	Dummy	1 if the costumer uses any mobile banking service with any frequency, 0 if not.
Financial training (dummy)	Dummy	1 if the respondent took part in a financial training, 0 if not.

(continued)

Table A3. Continued

Variable name	Type	Description
Subjective well-being (dummy)	Dummy	1 if the respondent's subjective well-being is relatively good, 0 if not.
Frequency of visiting the bank branch dummy	Dummy	1 if the frequency of visits is more frequent than annually, 0 if annually or rarer.
Bank product index	Index	The number of bank products owned by the consumer divided by the number of all products surveyed.
Service index	Index	The number of bank services used by the consumer divided by the number of all services surveyed.
Online banking index (number)	Index	The number of online banking services used by the consumer divided by the number of all online banking services surveyed.
Online banking index (frequency)	Index	An index that, in addition to usage, also takes into account the frequency of use of online banking services.
Mobile banking index (number)	Index	The number of mobile banking services used by the consumer divided by the number of all mobile banking services surveyed.
Mobile banking index (frequency)	Index	An index that, in addition to usage, also takes into account the frequency of use of mobile banking services.
Digital affinity index	Index	An index created using the degree of agreement with five statements measuring digital affinity.
Willingness index	Index	Arithmetic mean of the three standardized willingness variables (time, distance, cost).

Source: Own editing based on the questionnaire.

C. Model equations for robustness tests

Bank branch visit robustness test:

$$\log \frac{P\left(Y_{8,i}=1\right)}{\left(1-P\left(Y_{8,i}=1\right)\right)} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1 x_2 + \beta_5 x_1 x_3 + \overline{\beta}\overline{z}, \tag{A1}$$

for all i, where $i = \{$*Two or three times every six months; Every six months; Annually; Less often than annually, Does not visit a bank branch*$\}$

Online banking robustness test 1:

$$\widehat{y_9} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \overline{\beta}\overline{z} + u, \tag{A2}$$

Online banking robustness test 2:

$$\widehat{y_{10}} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \overline{\beta}\overline{z} + u, \tag{A3}$$

Mobile banking robustness test 1:

$$\widehat{y_{11}} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \overline{\beta}\overline{z} + u, \tag{A4}$$

Mobile banking robustness test 2:

$$\widehat{y_{12}} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \overline{\beta}\overline{z} + u, \tag{A5}$$

for which, in the multinomial logistic regressions, $Y_{8,i} = 1$ denotes the category i of bank branch visiting frequency (compared to the frequency of visiting a bank branch *Monthly of more often*), $\widehat{y_9}$ shows the online banking index (number), $\widehat{y_{10}}$ shows the online banking index (frequency), $\widehat{y_{11}}$ shows the mobile banking index (number), and $\widehat{y_{12}}$ denotes the mobile banking index (frequency). Among our explanatory variables, x_1 is the distance from the bank branch, x_2 is the digital affinity index, x_3 is the online banking index, $\overline{z}$ is the vector of control variables, and u is the error term. In terms of our research questions, the important coefficients are β_1 for the distance to the bank branch, β_2 for the digital affinity index, β_3 for the online banking index, and β_4 and β_5 for the interaction terms of the distance to the bank branch with the digital affinity index and with the online banking index, while $\overline{\beta}$ is the coefficient vector for the control variables $\overline{z}$. These coefficients show the given variable's effect on the result variable. In the case of the model explaining bank branch visiting, we estimated 6 different models for each category of bank branch visiting frequency, which differ in which prominent explanatory variables (and their interaction terms) are included in each model version.