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TRUST AND AWARENESS IN THE AGE OF ARTIFICIAL INTELLIGENCE-BASED FINANCIAL SERVICES

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INTRODUCTION

"Innovation distinguishes between a leader and a follower."
Steve Jobs

The rapid development of artificial intelligence (AI) has opened new dimensions in many areas of economic and social life that go beyond mere technological progress (Kerényi – Müller, 2019). However, the rise of this technology does not only mean the introduction of new tools and solutions but also poses serious challenges in terms of user trust, acceptance, and adaptation. While AI-based financial applications are rapidly becoming available, not all social groups are responding to these changes in the same way. Technological innovations have always provoked resistance from people – just think of the technophobic *Luddite* movement of the early 19th century[1] or the recently launched *Stop Killer Robots* campaign against autonomous weapons systems.

The use of AI offers many promising opportunities: it increases operational efficiency, enables the development of personalized services, and supports data-driven, faster decision-making. However, the introduction of this technology raises a dilemma in which service providers and users must weigh the benefits of AI against the potential risks. Factors such as the transparency of algorithmic decision-making, data security, ethical compliance, and accountability for errors raise serious concerns. The financial application of artificial intelligence is a particularly sensitive area, as it involves trust-based decisions where data protection, transparency, and responsible operation are fundamental requirements. This contradiction results in *an acceptance paradox*, whereby the very lack of trust prevents the experience necessary to build trust. Since the social, economic, legal, and psychological dimensions mentioned above are all decisive for the financial applications of AI, I believe that this issue can only be examined credibly and meaningfully through an interdisciplinary approach.

Young adults, especially those in higher education, are of particular importance in this context, as they are the first to encounter new financial technologies and will shape the financial decision-making culture of the future in the long term. I therefore conducted the study among Hungarian university students, as this age group is open to technology and is likely to be the one that will come into widespread contact with digital financial services in the near future, meaning that their decisions could fundamentally determine the direction of technology adoption. The study of this target group is particularly justified because it is particularly evident in their case what factors may influence individuals' attitudes toward AI-based solutions in the future, how their trust in digital tools is shaped, and how financial awareness or income status affects all of this.

My dissertation also aims to explore what knowledge, behavioural characteristics, or preferences may encourage or hinder the acceptance of artificial intelligence in everyday financial practices. In addition, I examine what different user groups or

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[1] *The Luddites* were mainly textile workers who feared for their jobs, so they destroyed machines to protest against mechanization and new innovations.

behavioural patterns can be distinguished among the target group based on these factors.

Based on the above, I believe that the acceptance of artificial intelligence in financial services cannot be explained by a single factor. It is not enough to examine how familiar people are with the technology or whether they are willing to use it—underlying attitudes and trust play at least as important a role. In my view, acceptance in this case is based on the combined presence of three key factors: digital and financial literacy, openness to new solutions, and confidence that these systems work reliably. The approach I advocate takes into account not only technological factors, but also individual experiences, emotional reactions, and the social perception of service providers, and interprets technology acceptance as a chain of interrelated cognitive and affective levels.

The main objective of the research

The main objectives of my research aimed at solving the above scientific problem are listed in *Table 1* below.

Table 1. Research Objectives

1) Theoretical model building	My goal is to develop a complex theoretical framework and conceptual model that provides a nuanced picture of the factors influencing the acceptance of artificial intelligence-based financial services through an integrated examination of financial literacy, technology adoption, and trust theories.
2) User segmentation	I examine how individuals' financial knowledge, technological attitudes, and financial behaviour influence their openness to digital financial services and what characteristic user groups (clusters) can be identified among university students based on these factors.
3) Individual decision-making mechanisms	I analyse what knowledge and attitude factors shape university students' decisions regarding artificial intelligence-based digital financial services, focusing on the individual user perspective.
4) Social attitudes	I seek to understand what social attitudes in the rapidly evolving digital environment hinder or promote the adoption of AI-based financial solutions, i.e., what factors support or hinder the integration of these new technologies into everyday financial decisions.

5) Social differences	[2]My aim is to explore the extent to which groups with different demographic and socioeconomic characteristics are open to financial digitization and automated (AI-based) financial systems. In doing so, I aim to contribute to understanding the conditions for inclusive technology use.
6) Formulation of practical recommendations	Based on the results, I intend to formulate practical recommendations to help financial institutions increase trust and acceptance of AI-based financial services.

Source: Own compilation

The socio-economic context of this research is primarily Hungary, where AI-based banking services have already appeared, but user trust and openness are still developing. My thesis focuses more narrowly on the perspective of individual users, i.e., what knowledge and attitude factors shape customers' decisions when it comes to artificial intelligence-based digital financial services. I conducted my questionnaire-based research among Hungarian university students.

I examine separately the role of general knowledge about how the technology works and digital and financial literacy in the adoption of an innovative technology—in this case, artificial intelligence—in the field of financial services. I examine which factors strengthen or weaken trust in such systems and how trust can be influenced by knowledge and knowledge sharing.

My dissertation aims to provide a complex approach to answering how the latest technologies, such as artificial intelligence, can be effectively integrated into the financial sector and how we can contribute to the development of financial culture in the age of technology-based financial services and artificial intelligence. The results of my research are therefore not only of theoretical significance but can also serve as practical guidance for banks and other financial service providers on how to introduce artificial intelligence, as they can provide insights into the key factors of trust and how these can be strengthened among customers. The aim of this dissertation is therefore not only to understand user behaviour, but also to explore how the use of new technologies can be made to reduce rather than increase social inequalities.

[2] In this context, *inclusive* technology use refers to a digital environment that allows groups from different social and economic backgrounds to have equal access to and be able to make meaningful use of digital and artificial intelligence-based financial services.

Hypotheses

The hypotheses formulated during the research are closely related to the objectives of my dissertation. *Table 2* below summarizes the main objectives of my study, the hypotheses assigned to them, and the research methods used.

Table 2. Relationship Between Research Objectives, Hypotheses, and Methods

RESEARCH OBJECTIVE	HYPOTHESIS	METHOD
Theoretical model	H1: The acceptance of artificial intelligence-based services can be interpreted through a complex examination of the dimensions of knowledge, attitude, and trust, as these factors together determine openness to AI and willingness to use it.	Qualitative research methods: - Literature review - Interviews
User segmentation	H2: Users can be clearly distinguished from each other based on their financial awareness, preferences for digital financial services, and attitudes toward technological innovations. The clusters formed in this way can be described with well-defined characteristics.	Quantitative research methods: - Correlation analyses - Principal component analysis - K-means cluster analysis - ANOVA
Individual decision-making mechanism	H3: University students who are open to using artificial intelligence-based solutions more often demonstrate higher financial literacy.	Qualitative research methods: - Content analysis of interviews Quantitative research methods: - Descriptive statistics - Correlation tests - Principal component analysis
Social differences	H4: There is a correlation between financial literacy and income level.	Qualitative research methods: - Literature review - Content analysis of interviews Quantitative research methods: - Correlation tests - K-means cluster analysis - Principal component analysis

Individual decision-making mechanism	H5: Respondents with more thorough financial knowledge are less likely to request personal customer service contact.	<u>Qualitative research methods:</u> - Content analysis of interviews <u>Quantitative research methods:</u> - Descriptive statistics - Correlation tests - Principal component analysis
Social attitudes and individual decision-making mechanism	H6: A more thorough understanding of how artificial intelligence works can promote a more conscious and informed attitude towards AI-based solutions.	<u>Qualitative research methods:</u> - Content analysis of interviews <u>Quantitative research methods:</u> - Descriptive statistics - Correlation analysis - Principal component analysis

Source: Own compilation

The hypotheses formulated in my dissertation are organized according to the main dimensions determining the acceptance of artificial intelligence in *Table 3* below.

Table 3. Hypotheses According to the Dimensions of AI Acceptance

HYPOTHESIS	MAIN DIMENSION	REASON
H	**Knowledge, Attitude, Trust (complex)**	The hypothesis specifically examines the combined effect of all three dimensions on AI acceptance.
H2	**Knowledge, Attitude**	Users are segmented along seven components, in which the dimensions of knowledge and attitude are dominant (the dimension of trust is indirectly present through *digital security*).
H3	**Knowledge**	The hypothesis examines the relationship between financial literacy—particularly its knowledge component—and openness to artificial intelligence-based solutions.
H4	**Knowledge**	The statement focuses specifically on the relationship between financial knowledge and income level.
H5	**Knowledge, Attitude**	This hypothesis examines the relationship between financial knowledge and personal preferences (demand for personal customer service), which affects the use of digital solutions.
H6	**Knowledge, Attitude, Trust (complex)**	By testing this hypothesis, I seek to answer whether knowledge of how AI works reduces fears and thereby increases trust and strengthens positive attitudes toward the technology.

Source: Own compilation

In the qualitative research phase, following a review of the literature, I conducted semi-structured in-depth interviews with eight recognized professionals in the financial sector or education in order to understand the mechanisms of social acceptance of financial AI applications through their own experiences and knowledge. The interview questions were compiled based on the literature and hypotheses.

In the second phase of my empirical research, I conducted a quantitative study: an online questionnaire survey among university students. When compiling the questionnaire, I relied on internationally validated measurement tools. To measure attitudes toward AI, I used *the* General *Attitudes toward Artificial Intelligence Scale (*GAAIS) (Schepman-Rodway, 2020), while for assessing digital and financial literacy, I adapted questions used by the OECD (*Organisation for Economic Co-operation and Development*) (OECD, 2022a), and finally, I included questions from Körber's questionnaire designed to measure trust in automation (Körber, M, 2019) in the questionnaire I compiled. My survey thus provided a comprehensive picture of the digital and financial literacy of the respondents and enabled the identification of groups with similar attitudes and preferences. During the statistical analysis of the data obtained from the questionnaire, I examined the relationships between the variables and identified three new, distinctly separate customer segments using cluster analysis. I evaluated the hypotheses by evaluating the results of the qualitative interviews and statistically processing the data from the quantitative survey.

This combined (*qualitative and quantitative*) methodology ensured that the results of my research were sufficiently reliable and that I could draw well-founded conclusions about the hypotheses.

1. LITERATURE REVIEW

The literature review in my dissertation is based on several pillars, all of which contribute to a deeper understanding and foundation of the research topic and are closely aligned with the interdisciplinary approach represented by my dissertation.

In my dissertation, I first show how national and cultural characteristics influence social openness to financial innovation, which may explain, for example, the different customer behaviours observed in different countries. I then examine the topics of *financial literacy, financial well-being, financial health*, and *financial awareness among young people*, primarily in light of the research results, before moving on to digital development and digital ecosystems, with a special focus on the digitalization of the financial sector. Here, I examine the DESI index (*Digital Economy and Society Index)* and the state of Hungary's digital economy, as this provides an important background to the domestic context of financial digitization. I extend the description of the emergence and characteristics of digital ecosystems to key processes such as the rise of *FinTech (financial technology*) innovations, the emergence of new market players (e.g. *BigTech* companies, i.e. large, global technology companies), as well as the competition they generate and the current regulatory challenges. This section highlights the significant economic and environmental pressures that financial service providers are facing due to the spread of new technologies, and why it has become necessary to rethink their operating strategies in the digitalized economy. I also discuss *what digital financial literacy* means and why it is becoming increasingly important in the use of modern financial services today. The next major topic is the concept *of artificial intelligence* and its application in the financial sector. In this section, I first provide a historical overview of the development of artificial intelligence—and its various approaches—and then examine the role of AI in financial services. I will review the role of *chatbots* and *voicebots*[3] and write about the first domestic AI-based digital financial assistant, which clearly illustrates how artificial intelligence technology is becoming visible to customers in the banking sector. I also discuss the latest trends, such as the rise of *generative artificial intelligence (GenAI)*, including language models representing the new generation of machine learning, and the importance of XAI (short for *Explainable* Artificial Intelligence). The latter is important because the transparency and interpretability of models are closely linked to user trust. An overview of technology acceptance models such as *TAM, TAM2, TAM3*, and *UTAUT* provides an important reference point for understanding testing methods for automated systems. Alongside the presentation of AI technologies, I will discuss previous research results from the field of *AI* on people's *attitudes towards AI*, which provide insight into the current state of the science. In my literature review, I will also discuss the concept of *trust* and its various interpretations. I describe in detail how the topic of trust appears in international and domestic literature, what theoretical models are used to describe

[3] These include programs such as *chatbots*, which communicate with users in writing, and *voicebots*, which communicate verbally.

the nature of trust, what historical and cultural factors influence it, and how trust is interpreted in different fields of social sciences. I discuss trust issues in the digital economy and finance, and how the *FinTech* era—and specifically the emergence of artificial intelligence—affects various aspects of trust. Other topics I will discuss include the role of *ethics* and *transparency* in establishing business trust and the evolution of trust between banks and their customers in the context of digitalization. I also examine the *European Union's* approach to trust and AI, such as the EU's regulatory efforts in the field of artificial intelligence, as legal and social frameworks have a major impact on the extent to which people accept technological innovations. The final subchapter focuses on the values, financial behaviour, and technology usage habits of younger generations, especially *Generation* Z, as they develop in a digital environment, since this age group is also the target group of my study. In this section, I discuss how this generation is adapting to financial digitalization and how it is influenced by the opportunities offered by the online world.

Overall, the main topics of my literature review are the digital ecosystem and *FinTech* environment, digital development and its cultural context, the technological background of artificial intelligence, the theoretical framework of trust, and the digital financial characteristics of young people – are closely aligned with the central questions of the dissertation.

These chapters provide the theoretical foundation on which my research is based and also point out that several factors related to digital financial services, such as the combined effect of *financial literacy*, *attitudes*, and *trust*, have typically been examined separately in different studies. Furthermore, there is a lack of comprehensive research on the social, income, and generational differences underlying trust and rejection of AI-based solutions, especially in the Hungarian context. Another area that has been little explored is how younger, digitally savvy users decide between personal and automated customer service, and how this relates to technological knowledge and digital financial independence.

2. MATERIAL AND METHOD

The main steps of my research are summarized in the following figure (see *Figure 1*) in the appropriate order.

1) DEFINITION OF THE SUBJECT AND OBJECTIVES OF THE RESEARCH

Research topic: Complex analysis of factors determining the acceptance of artificial intelligence-based digital financial services, with a particular focus on financial literacy, technology adoption, individual decision-making mechanisms, and the role of social attitudes.
Main objectives of the research: Theoretical modeling, user segmentation, examination of individual decision-making mechanisms, exploration of the role of social attitudes, analysis of social differences, formulation of practical recommendations.

2) LITERATURE RESEARCH

A critical review of previous relevant research and the development of the conceptual model.

3) HYPOTHESES

Formulation of hypotheses based on the literature and the concept.

4) DEVELOPMENT OF RESEARCH METHODOLOGY

Use of mixed (combined) methodology (semi-structured interviews – qualitative; questionnaire-based data collection and statistical analysis – quantitative).

5) TARGET GROUP SELECTION AND SAMPLING

Identification of a target group consisting of university students.

6) DATA COLLECTION

Conducting semi-structured interviews and collecting data using questionnaires.

7) ANALYSIS

Exploring quantifiable correlations between financial literacy, technology adoption, and various dimensions of trust.

8) COMPARISON OF RESULTS

Integrated interpretation of qualitative and quantitative results, evaluation of hypotheses.

9) NEW RESULTS, FINDINGS, RECOMMENDATIONS

Drawing main conclusions, summarizing new and novel results, formulating recommendations, and determining further research directions.

Figure 1. Presentation of the Research Process
Source: Own compilation

In order to achieve my research objectives, the combined and complex application of several methods is justified, i.e., both qualitative and quantitative methods are necessary to achieve the various objectives, in accordance with the principles of mixed methodology. The methodology of this integrated approach, which I also advocate, recommends the combined use of research methods (Bryman, 2006; Hesse-Biber, 2010). Bryman also argues in favour of integrating qualitative and quantitative research methods when he writes that "the researcher can increase the validity of his or her conclusions if both procedures confirm the results" (Bryman, 2006, p. 374). Since I conducted my research using qualitative (literature review, semi-structured in-depth interviews) and quantitative (statistical analysis of questionnaire responses) methods, I used two samples accordingly. In the following, I will first describe the two methodologies and then the two samples.

2.1. Qualitative research methodology

First, I reviewed the relevant literature in line with the research objectives, then I invited highly experienced professionals who have a good understanding of changes in human behaviour and attitudes in today's significantly transformed social and technological environment to participate in interviews. I compiled the questions based on the literature, my hypotheses, and my own concept. The qualitative phase took more than five months, including organizing and conducting the interviews, preparing the transcripts, and organizing and analysing the data. In this phase of the research, I first selected interviewees with relevant professional backgrounds and sent them the interview questions in advance. The interviews, conducted in person or via *Microsoft Teams*, lasted between 54 and 105 minutes, with one written response. I recorded the conversations digitally and finalized the transcripts by checking them manually, resulting in a total of approximately 80 pages (approximately 264,000 keystrokes) of text. I structured the material into question groups, distinguished the respondents by color coding, and then performed a qualitative content analysis, which I supplemented with a keyword frequency analysis.

I compiled the interview questions based on the literature, research hypotheses, and, in part, my own theoretical framework. After the first three interviews, I modified the order of the question groups to make the conversations flow more smoothly. The main topics of the interview outline are presented in *Table 4* below.

Table 4. Groups of Questions Examined in the Interviews

1. QUESTION GROUP	THE IMPACT OF DIGITAL AND FINANCIAL LITERACY ON THE ACCEPTANCE OF ARTIFICIAL INTELLIGENCE-BASED FINANCIAL APPLICATIONS
2. QUESTION GROUP	THE IMPORTANCE OF MONEY IN LIFE AND PREFERENCES FOR TRADITIONAL ADMINISTRATION
3. QUESTION GROUP	LONG-TERM FINANCIAL PLANNING OF YOUNGER GENERATIONS AND THE IMPACT OF DIGITAL PREFERENCES AND ARTIFICIAL INTELLIGENCE

4. QUESTION GROUP	THE INTRODUCTION OF ARTIFICIAL INTELLIGENCE AND THE DEVELOPMENT OF FINANCIAL AWARENESS
5. QUESTION GROUP	INCOME LEVEL AND FINANCIAL AWARENESS
6. QUESTION GROUP	FINANCIAL AWARENESS AND PREFERENCE FOR DIGITAL TRANSACTIONS
7. QUESTION GROUP	KNOWLEDGE OF ARTIFICIAL INTELLIGENCE AND EMOTIONAL REACTIONS

Source: Own compilation

During the qualitative analysis of the interviews, I focused on recurring attitudes and themes that are related to the key dimensions of the quantitative research. In my research, I interpreted the social acceptance of artificial intelligence not only in terms of general attitudes, but also in line with known empirical models of technology use (e.g., TAM, UTAUT).

2.2. Quantitative research methodology

In order to examine the topic as broadly as possible, I considered it necessary to conduct extensive quantitative research. This consisted of an online questionnaire survey and a detailed analysis using statistical and mathematical methods. Data collection was carried out using the CAWI (*Computer-Assisted Web Interviewing)* method, which involves respondents completing a pre-designed questionnaire independently via an online platform using their own devices. My questionnaire contained a total of 28 question groups and, in addition to sociodemographic questions, included approximately 116 sub-questions, which were primarily intended to validate the correlations identified in the literature and interviews.

- Of the entire questionnaire, 14 sub-questions related to financial and digital financial literacy. These were based on the OECD/INFE international surveys of adult financial literacy (OECD, 2022a, 2023).
- Another 20 sub-questions examined general attitudes towards artificial intelligence. The Schepman-Rodway *General Attitudes towards Artificial Intelligence Scale (GAAIS)* questionnaire was used to measure attitudes towards AI (Schepman, A., Rodway, P. 2024).
- Question 16 of the questionnaire was taken from a questionnaire developed by Moritz Körber, a researcher at the Technical University of Munich, to measure trust in automation (Körber M, 2019).
- I developed the questions in my questionnaire based on themes and attitudes that repeatedly emerged during the interviews. These include questions examining knowledge and trust in artificial intelligence (e.g., questions 15 and 18–22), questions measuring attitudes toward digital financial behaviour (e.g., questions 6–9), and questions exploring personal relationships with money and subjective financial attitudes (e.g., questions 5 and 14).

I examined the responses to the questionnaires using mathematical statistical methods. The analysis was performed using *IBM SPSS Statistics 25*, applying a significance level of 5% (α=0.05) in all tests. *By examining* the *correlations*, I sought to answer two main questions. First, I wanted to determine whether managing everyday finances online is associated with other financial activities (e.g., investments) also being managed on digital platforms. The second question examined the extent to which the transparency, reliability, stability, security, and legal regulation of these methods motivate digital financial management. To explore the relationships between the questions, I also calculated Pearson's correlation coefficients. The PCA (*Principal Component Analysis)* that I used generally had two tasks: on the one hand, it determined the principal components in which the largest part of the variance of the points is found, and secondly, it gave the direction in n-dimensional space where the most information can be read from the set of points in two- or three-dimensional space. According to *the Kaiser criterion*, only those components with *an eigenvalue* greater than 1 were considered relevant. Following the principal component analysis, I used *a rotation method* (*Varimax rotation)* to help give the individual components a clearer structure and make them more distinguishable for me. In the following, I mainly worked with the seven components that appeared to be the most important, which, based on the results, can be identified with the following names and reflect well the content behind them. The principal component analysis reduced the number of variables through aggregation without losing any essential information. Based on a detailed analysis of the *rotated principal component matrix,* I describe the content described by the components below (see *Table 5).*

Table 5. Description of Components

COMPONENT NAME	DESCRIPTION
1. Financial awareness	The *first component* describes financial awareness and knowledge. This dimension mainly characterizes individuals who are familiar with basic financial concepts such as inflation, simple and compound interest, and the EBKM (*Uniform Deposit Interest Rate Indicator*). For them, financial literacy plays an important role, and they accept, for example, taking out a loan if a financial emergency arises. These individuals prioritize financial stability and awareness.
2. Digital banking services	The *second component* focuses on online banking and digital financial transactions. Those who score high on this component prefer online banking services such as money transfers, loan applications, or investment management. This component indicates openness to digital solutions and a preference for online financial management, while also describing technologically competent users.
3. Traditional customer service contact	The *third component* examines whether respondents prefer telephone or in-person customer service. Those who scored high on this component tend to choose traditional methods of administration—rather than telephone or in-person customer service—while being less open to modern technologies. This component also indicates that such individuals are less accepting of cryptocurrencies, for example, which may indicate technological scepticism.

4. Financial planning and foresight	The *fourth component* focuses on financial decision-making and household planning. This dimension mainly characterizes individuals who are actively involved in household financial decisions, closely monitor their finances, and set long-term financial goals. These people are conscious in their financial decisions and carefully consider what they spend their money on.
5. Digital security	The *fifth component* covers the issue of digital financial security. Individuals who score highly in this component pay close attention to the security of digital transactions, data protection, and the use of reliable online financial services. This includes adherence to security standards for digital contracts and the importance of protecting personal data.
6. Preferers of technological developments	The *sixth component* reflects the importance of modern customer service solutions. Such individuals value advanced technologies such as chatbots, digital assistants, or biometric identification, and demand simple, flexible, and convenient administrative solutions. This component is therefore about the acceptance of modern technological developments.
7. Influence	The *seventh component* examines the sources of trust and its social and legal aspects. When this component is highly valued, an individual's trust is influenced by previous personal experiences, the opinions of acquaintances and family members, and legal compliance. This component highlights the key role of reliability and guarantees in financial decisions.

Source: Own compilation

Three additional tests (*Component Transformation Matrix, Component Score Coefficient Matrix, and Component Score Covariance Matrix*) supplemented the results of my principal component analysis, helping to interpret the components and calculate the component scores.

As a result of the principal component analysis, easily interpretable principal components (*factors*) emerged (see *Table 5*), which described the respondents' financial attitudes, knowledge, and technological attitudes. I then performed cluster analysis along these main components, i.e., I grouped the respondents into clusters according to the values they assigned to each factor. I used the *k-means* procedure for cluster formation. Initialization was performed using the *k-means* algorithm. The next step in my method was *iteration*. Iteration is necessary for the initial cluster centres to move toward their optimal positions as the classification of the data increasingly approximates the actual clusters. Finally, I used the ANOVA (*Analysis of Variance)* method to identify differences between clusters along each dimension examined. ANOVA, or *one-way analysis of variance,* is a statistical method that can also be used to compare clusters. My goal with the ANOVA test was to examine the differences between clusters, identify the importance of variables, and check the internal homogeneity of the clusters.

2.3. Qualitative research sample

I asked eight recognized experts to participate in the interviews. I wanted to talk to experts who not only have excellent knowledge of the financial sector but also face the challenges that can arise in the areas of trust, digitalization, financial literacy, and the use of artificial intelligence on a daily basis. It was important to me to get not only theoretical answers, but also insights based on practical experience that would really help me understand how different players—customers, managers, analysts—think in today's rapidly changing environment. During the sampling process, I sought to ensure sectoral diversity, which allowed for the representation of different fields of expertise (see *Table 6)*.

Table 6. Institutional Background and Focus Areas of Interviewees

INSTITUTIONAL BACKGROUND	NUMBER OF PARTICIPANTS	MAIN FOCUS AREA
Commercial bank (senior management)	5	Digital financial innovation, strategic decision-making (4 people), Sales and CRM (1 person)
Central bank advisor	1	Regulation and sustainable finance
International consulting firm	1	Consulting, strategic digitalization
Scientific and research background	1	Artificial intelligence and behavioural science

Source: Own compilation

All participants have at least 12 years of professional experience, with an average of 24.5 years. I have ensured the anonymity of the participants and refer to them in the analysis using the letters shown in Table 7. A brief description of the interviewees is provided in the table below (see *Table 7*).

Table 7. Role of Interviewees in the Research

A) Interviewee A leading financial advisor and educator whose professional career has spanned the transformation of banking in parallel with technological advances. He has outstanding insight into the impact of IT transformations and the organizational and strategic decisions that shape long-term trust in digital financial services. Through his teaching work, his experience with the younger generation's acceptance of technology is particularly valuable to me.
B) Interviewee A senior banking executive in digital channels and CRM, he has decades of experience in developing customer relationship systems and digital experiences, giving him a deep understanding of how technological innovations can win—or lose—customer trust. His career

path also provides insight into the evolution of the relationship between organizational culture and willingness to innovate.
C) Interviewee Banking AI expert and one of the pioneers of generative AI in banking in Hungary. His practical experience is also essential for examining the acceptance of artificial intelligence, particularly in relation to methods for managing employee and customer resistance and alleviating any fears they may have about technological innovations.
D) Interviewee Senior bank executive, CFO (Chief Financial Officer), who has gained professional experience at the highest level of various financial institutions as a senior bank executive, making him one of the best experts on the domestic banking system. He has a unique perspective and critical thinking skills regarding the functioning of the financial sector. Through his combined knowledge of financial strategy, business intelligence, and capital management, he has a good understanding of how artificial intelligence fits into the decision-making and management processes of modern financial institutions and how the introduction of new technologies can be made transparent and credible in Hungary.
E) Interviewee As a senior bank manager and regional sales director, he has practical insight into customer relations and sales practices, which is particularly important to me when examining human factors such as trust, prejudice, and various biases. He is responsible for the development of front-line staff, so he has a clear view of how the relationship between employees and customers is changing as a result of digitalization and the rise of AI.
F) Interviewee A senior economist and project advisor at the central bank, he can provide a macroeconomic and education policy perspective that broadens the focus of my research. I find his experience in raising financial awareness, his high level of publication activity, and his international perspective on sustainable financial systems and the institutional framework for trust particularly valuable.
G) Interviewee Mathematician, psychologist, professor emeritus of AI research, whose interdisciplinary knowledge and deep understanding of decision-making psychology help to understand the mental processes and emotional reactions that influence the acceptance of AI-based financial decisions. Through his scientific credibility and educational work, he enriches my research with a scientific perspective on human factors.
H) Interviewee As a senior bank executive and marketing and communications director at one of Hungary's leading commercial banks, he plays a particularly important role in managing financial trust. Through his knowledge of customer experience, brand loyalty, and digital customer relationship strategies, as well as their practical application, he has gained experience that is essential for a user-centered examination of financial attitudes, customer trust, and the acceptance of artificial intelligence.

Source: Own compilation

The most frequently recurring themes in the interviews are as follows:

- the role and importance of money in an individual's life,
- attitudes towards different forms of administration – digital or traditional
- the applicability of artificial intelligence in financial services,

- customers' digital trust and related fears,
- the role of advice and empathy in complex decision-making situations,
- possible directions for the development of future banking ecosystems.

The most frequently occurring keywords in the interview texts were "*finance/financial*," "*digital*" and *"artificial intelligence*", which were related to awareness, channel usage, and automation, while the other most frequently mentioned terms—such as "*customer*", "*bank*", "*trust*", “*online*”, “*loan*” and *“advice*” appeared in the context of user experience, decision-making, and administrative preferences.
Based on the summary of the interview responses, a vision emerges in which digital and personal channels for financial services are not mutually exclusive, but rather complementary. According to most experts, the service model of the future will not be based on a binary choice (digital channels or personal interaction), but on freedom of choice, i.e. the ability of customers to decide which channel to use depending on their own situation. Maintaining this diversity can not only support the development of financial awareness but also play an important role in strengthening customer trust.

2.4. Quantitative research sample

I conducted the research among students at universities in Budapest because, as this is an innovative technology, I could expect that most of them had already encountered digital financial solutions, were familiar with the concept of artificial intelligence, and were receptive to its use. The generational differences and socio-economic context presented in the dissertation clearly support the conclusion that university students—primarily members of Generation Z—are the most suitable target group for this research.

I conducted the research using *purposive sampling* and an online questionnaire. The aim was to explore the social perception of artificial intelligence applications in finance based on the opinions of competent and informed respondents. Therefore, the sample was not random; I selected the respondents based on predefined professional criteria. The sample included native Hungarian-speaking university students enrolled in full-time programs in Budapest, regardless of their field of study. A total of 867 students completed the questionnaire. The gender distribution in the sample was as follows: 68.3% women (592 respondents) and 31.7% men (275 respondents). According to data from the Central Statistical Office (KSH), 52.1% of full-time students in the 2022/2023 academic year are women (108,070 out of 207,362), meaning that female students are overrepresented in my sample compared to the official national ratio (Central Statistical Office, 2023). Based on geographical distribution, most of my respondents live in Budapest (56.7%), but many also completed the questionnaire in Érd, Cegléd, Miskolc, and Dunakeszi. This means that the majority of respondents come from an urban environment. All respondents have at least a secondary education and 96% are active students. In terms of student numbers, the largest universities were the Budapest University of Technology and Economics, Óbuda University, the Budapest University of Economics, Eötvös Loránd University and Corvinus University of Budapest. The two most represented fields of study were *Business and Management* (21.8%) and *Trade and Marketing* (21.6%), but students from other fields also participated in the survey at a rate of 56.6%. The distribution of the respondents' personal monthly income was as follows (see *Figure 2)*.

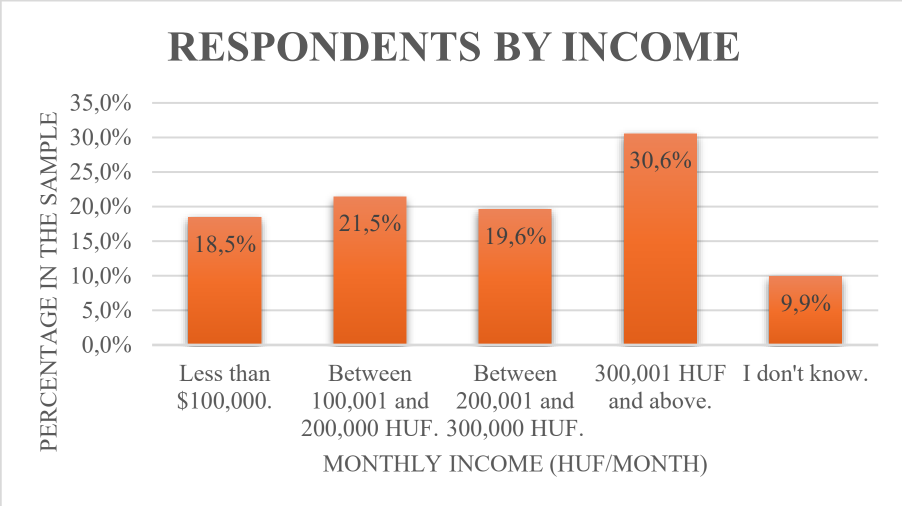

Figure 2. Distribution of Respondents by Income
Source: Own compilation

Forty percent of respondents classified themselves in the two lowest income categories, i.e. with a monthly income of less than HUF 200,000. This is in line with the fact that the majority of students are still pursuing their studies, so their income often comes from scholarships, family support or casual work. At the same time, it is noteworthy that nearly 31 percent of respondents classified themselves in the income category above HUF 300,000. This may indicate that some students have regular employment income or other stable financial resources.

It is important to note that 9.9% of respondents did not provide income data or indicated that they did not know the exact amount. This fact also shows us that the issue of income remains a sensitive topic, even among university students. Based on this, we can see that some respondents are reluctant to share this type of information, which may affect the validity of income-related statements. However, data on savings show that 82.8% of respondents have some amount of money set aside, which indicates a high level of financial awareness among university students. At the same time, the vast majority of respondents, 83.7%, do not have any loans or credit, which can be attributed to their age on the one hand and financial caution on the other. Based on marital status, 52.1% of students live with a partner, while 42.2% said they were single. The proportion of married people is only 4.3%, which realistically reflects the life situation of the age group in the sample. Family statuses such as widowed (0.7%) or divorced (0.5%) occur with low frequency, which also confirms that the majority of respondents are young adults.

According to data from the Central Statistical Office, 207,362 people were enrolled in full-time programs in the 2022/2023 academic year, and the total number of higher education students was 289,991. The sample of 867 respondents in this study thus covers approximately 0.4% of full-time students. Although the sample cannot be considered nationally representative, it provides a sufficient starting point for mapping trends in students' financial attitudes. The proportion of missing values is negligible: a higher rate of non-response was observed in five respondents (0.6%). Missing responses were mainly limited to questions related to internet and mobile banking but were not concentrated on a particular person or group of questions. Taking all this into account, it can be concluded that the sample of respondents provided an adequate basis for the analyses, both in terms of size and composition.

3. RESULTS AND DISCUSSION

To test the hypotheses, I used both qualitative methodology (*interview analysis*) and quantitative statistical methods (*correlation, principal component analysis, cluster analysis, ANOVA*), and where appropriate, I also used relevant literature to evaluate and support the hypotheses.

3.1. Pillars of acceptance (H1)

The literature and in-depth interviews provided me with a sufficient basis for identifying the main factors influencing the acceptance of artificial intelligence, particularly in the field of financial services. By testing H1, my research aims to better understand these factors and identify the dynamic relationships between them.

The principal component analysis and *cluster analysis* conducted during my questionnaire-based research showed that users' technological openness and willingness to accept new technologies can be explained by a group of three factors: digital and financial competencies (*financial awareness, use of digital banking services, financial planning and foresight)*, attitudes (*preference for traditional customer service contact, openness to technological developments)*, and trust factors (*sensitivity to digital security, susceptibility to influence)*. These factors reinforce each other in influencing the adoption of MI applications, which is also supported by other literature, particularly based on integrated interpretations of technology acceptance and trust models. Other studies (e.g., Pavlou, 2003; Gefen et al., 2003) also point out that the combined presence of trust and knowledge is essential for deeper, long-term integration of technology, especially in the case of digital financial services, where risk sensitivity is particularly high. My statistical analyses also support the correlations assumed by the model.

Based on the above, it can be concluded that the level of digital and financial competencies, attitudes toward technology, and the presence or absence of trust are closely interrelated, and these three dimensions together shape individual decisions regarding AI-based solutions. According to my research detailed in the dissertation, these factors were closely related to acceptance even when considered separately, but their combined presence provides the strongest explanatory power. During the *cluster analysis*, clearly distinguishable groups emerged based on attitudes, knowledge, and trust levels related to acceptance, with all three factors showing significant differences between the clusters. This also statistically confirmed that acceptance is multifactorial and that these variables together shape users' technological openness. However, it has been proven that this complex relationship is not static, but a constantly evolving process built on social and individual experiences, which is also influenced by changes in the technological environment, regulatory frameworks, and the development of digital culture. The model I have created (see *Figure 3.*) reflects my finding that the acceptance of artificial intelligence in financial services does not stem directly from knowledge of the technology but is the result of a gradually evolving process. The first step is knowledge, which enables an understanding of how the technology works. Understanding, especially when combined with positive experiences, promotes trust, which is a prerequisite for users to become open to accepting and using new solutions.

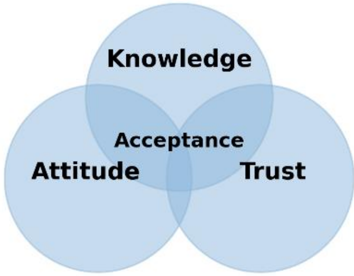

Figure 3. Conceptual Model of Artificial Intelligence Acceptance
Source: Own compilation

The model thus interprets technology acceptance as a chain of interlinked stages in which cognitive and emotional factors both play a role, and the individual stages can either reinforce or inhibit each other's effects.

Based on the findings of my research and the correlations identified in the literature, I consider the thesis that the social acceptance of artificial intelligence in financial services cannot be explained by a single factor, such as technological knowledge or willingness to use, but rather by the dynamic interaction between the three factors of knowledge, trust, and attitude, which supports hypothesis H1. trust, and attitude, which validates hypothesis H1. The prerequisites for acceptance are therefore the existence of financial and digital competencies, an open attitude towards new technologies, and increased trust in the system. I therefore accept hypothesis H1.

3.2. Clusters in the digital environment (H2)

The aim of the cluster analysis was to identify user groups with different attitudes toward digital financial solutions based on individual attitudes and behavioural patterns, which is the subject of hypothesis H2. Statistical analyses revealed significant differences between respondents, which allowed us to identify three distinct, coherent, and meaningful clusters. The centres of the clusters (standardized average scores) show the average degree of deviation of the respondents in each cluster from the sample average along the given dimensions. Positive values indicate that the group is above average in the given dimension, while negative values indicate scores below average. Based on the data, each cluster was characterized in detail, taking into account these central indicators (see *Figure 4.*).

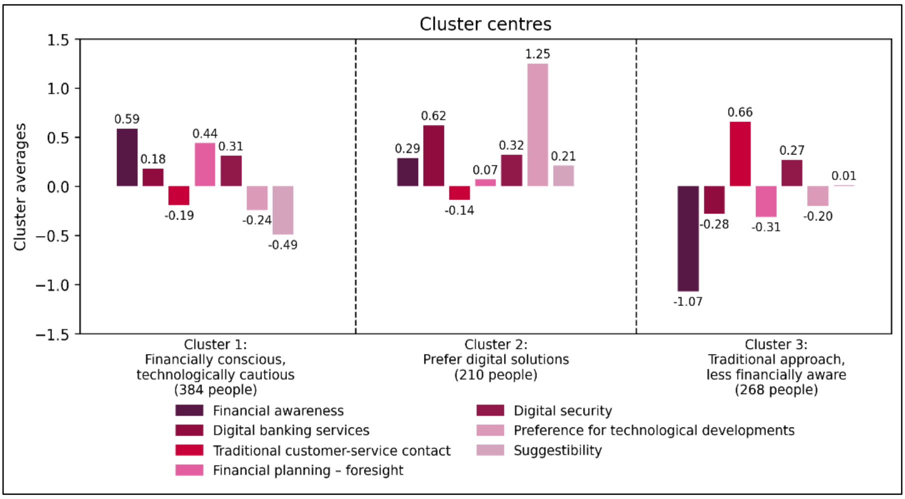

Figure 4. Cluster Centre Averages

Source: Own compilation

These factors thus clearly described the different attitudes and behavioural patterns between the clusters. Members of the *financially conscious and technologically cautious cluster* stand out in their conscious financial decisions, while *those who prefer digital solutions* show a high affinity for technological innovations. Thus, the three clusters were well separated from each other and each showed clear distinctive patterns (see *Table 8)*. The algorithm did not classify five respondents into any cluster.

Table 8. Characteristics of Clusters

Cluster	Key characteristics	Strengths	Areas for improvement	Number of respondents
1. Financially conscious, technologically cautious	Responsible, conscious, planning	High financial awareness, foresight, difficult to influence	Do not prefer technological innovations	384 (44.5
2. Those who prefer digital solutions	Technology-oriented, digital	Openness to modern banking solutions and technological developments	Medium financial awareness, moderate foresight	210 (24.4)
3. Traditional attitude, less financially aware	Conservative, traditional	Strong preference for traditional customer service	Very low financial awareness, not forward-thinking, reject modern technology	268 (31.1

Source: Own compilation

My findings in the sample show that nearly half of university respondents are financially aware and technically cautious, while one-third are explicitly conservative about finances. However, only one- of respondents preferred digital solutions. The differences emerging from the results can help to develop personalized approaches for each target group. According to these results, it is worth offering customized digital services to the first and second clusters, while the third cluster should be targeted with financial education and simple solutions. Technological innovations are particularly important for the second cluster, so it is worth targeting them with this in mind. In summary, the results of the cluster analysis confirm hypothesis H2. I therefore accept hypothesis H2.

3.3. Digital choice based on financial awareness (H3)

Hypothesis H3 assumes that openness to AI-based solutions is related to users' level of financial awareness. The interviews revealed that key issues related to the financial application of artificial intelligence *include access to financial information, opportunities for raising awareness,* the *paradoxical effects* of *technological convenience, differing impacts across income groups,* the *responsibility dilemmas of advisory services,* and *sustainability and ESG considerations.* Based on the responses to question 19 of the questionnaires, which measured trust in AI systems, it can be observed that the level of trust increases with financial awareness. Among the most aware respondents, 45.7% gave a positive assessment (i.e., a score between 5 and 7 on a 7-point scale), while among the less aware, this proportion was only 28.0%. In contrast, low response values indicating distrust (scores between 1 and 3) appeared in 41.0% of respondents with low awareness, while this figure was only 15.5% among those with high awareness. The correlation between the two variables is moderate (Pearson $r = 0.226$ $p < 0.000$). There was a weaker correlation between general attitudes toward the use of MI financial customer service (question 20) and financial awareness ($r = 0.153$). In contrast, the frequency of internet banking use, as an indicator of digital financial activity, showed a slightly stronger correlation with financial literacy ($r = 0.351$). Based on *principal component analysis* (PCA) and *cluster analysis*, digital banking and technological openness do not automatically correlate with higher financial literacy. The first principal component, which represents financial literacy, does not correlate significantly with MI acceptance or digital device use. Thus, in this approach, the relationship is not linear, and it is not clear that MI increases financial literacy. In addition, AI is less accessible or less effective among lower-income users. Summarizing the results of the two methods, we can say that artificial intelligence-based solutions can support the development of financial literacy, mainly through information transfer, visualization, and automated advice. However, this effect is not automatic and depends heavily on individual attitudes, income, trust, and behaviour patterns. The quantitative results of my research confirm the correlation, but it can be considered weak (Pearson $r = 0.226$), so my hypothesis cannot be clearly confirmed. Therefore, AI is a useful tool, but its effectiveness is not guaranteed in all cases. Although the quantitative results do not clearly confirm the H3 hypothesis, a significant proportion of the interviewees explicitly emphasized the role of MI-based tools in promoting awareness (e.g., respondents B, E, and F). From a qualitative perspective, this supports the existence of a relationship, although it is not measurable in all cases. I therefore partially accept hypothesis H3.

3.4. Financial background and financial awareness (H4)

In the next hypothesis, I sought to answer the question of what relationship exists between an individual's income level and their financial awareness. Among my quantitative results, cluster analysis showed that *financial awareness* is one of the strongest dimensions in distinguishing between clusters ($F = 485.78$; $p = 0.000$). Taking into account the analysis of variance (ANOVA) performed on the data, the results do not show a statistically significant relationship between the variables ($F(2, 315) = 2.402$; $p = 0.092$).

My main findings suggest that financial literacy does not depend solely on income level. Higher-income individuals often outsource decisions, while lower-income individuals may be more conscious out of necessity, and quantitative data suggest that other factors also influence financial literacy (such as social background, level of education, digital skills, and access to financial services). This hypothesis is also supported by research findings that it is not only the absolute level of income, but also the way in which income is earned and the context in which it is earned (learning, attitude, access to information, and the service environment) also determine financial awareness and openness to digital financial solutions. These observations cannot be considered proven causal relationships, but they can be treated as theoretically relevant hypotheses for a later study. <u>I therefore rejected hypothesis H4.</u>

3.5. Digital independence (H5)

With the spread of digital financial services, it is becoming increasingly important to understand which channels users prefer to use when managing their finances and what role financial literacy plays in this. Hypothesis H5 examines whether there is a correlation between financial literacy and the demand for personal customer service. In addition, I analyzed how higher financial literacy contributes to trust in artificial intelligence-based services.

Cluster analysis in relation to hypothesis H5 showed that 70% of the financially conscious cluster uses digital channels, compared to 90% of those who prefer digital solutions, as opposed to the less financially conscious group, where 80% prefer traditional customer service.

My main findings are that financial literacy increases confidence in digital channels and reduces the need for personal service, but trust and prestige continue to play a role in choices. Financially aware customers are indeed more likely to choose digital banking because they are more confident in their financial decisions. However, for larger investments or more complex financial transactions, some of them may still require personal service, perhaps simply for reasons of prestige. There are attitudinal and trust-related reasons for this phenomenon. Overall, the hypothesis is increasingly supported by the spread of digital channels. Based on principal component analysis, an inverse relationship can be observed between financial literacy and preference for personal customer service (component weight: –0.697). More financially conscious individuals tend to choose digital channels, while those with lower financial literacy typically rely on personal or telephone customer service. <u>I therefore accept hypothesis H5.</u>

3.6. Knowledge as a Trust-Enhancing Factor (H6)

User attitudes and decisions regarding artificial intelligence can be influenced by a number of factors, including the level of knowledge about how the technology works. Hypothesis H6 examined whether there is a correlation between a more thorough understanding of how AI works and a more conscious and informed attitude towards the technology. Based on the interviews, the acceptance of AI-based financial solutions is hampered by regulatory, technological, organizational, customer trust, and knowledge gaps, which require comprehensive preparedness and transparent communication. The seventh component of the PCA is the *trust component,* which shows that technological knowledge and regulatory knowledge can reduce fear and uncertainty. Based on *principal component analysis*, a positive relationship was found between *knowledge of AI* and *trust*, and AI acceptance is significantly related to variables indicating digital literacy ($r = 0.72$; $p < 0.01$). Based on my quantitative data, the correlation between several variables of AI acceptance and indicators of digital literacy was moderate or stronger (e.g., $r = 0.30–0.42$, $p < 0.01$), meaning that technological knowledge does indeed increase the acceptance of financial applications of artificial intelligence. The correlations between the components also show that higher AI knowledge is positively correlated with digital trust and reduces technological fear. This result is a direct quantitative confirmation of the hypothesis. Higher financial and technological knowledge reduced fear and uncertainty about the future of AI. Statistical analysis shows that those with higher knowledge of how AI works feel less uncertain about the systems. Knowledge of AI regulation also provides a similar sense of security.

My main findings are that higher AI knowledge and technological knowledge increase digital trust and reduce fears, while attitudes, experiences, and the regulatory environment also have a significant impact on attitudes toward AI. Knowledge about AI can therefore reduce uncertainty and increase acceptance. Those with a deeper understanding of how artificial intelligence works are generally less prone to irrational fears, which is why experts are often less afraid of artificial intelligence because they are aware of its limitations and possibilities. <u>I therefore accepted hypothesis H6.</u>

4. CONCLUSIONS AND RECOMMENDATIONS

The results of my research partially confirmed the correlations found in the literature but also revealed new perspectives in several areas. *The social embeddedness* of *digital and financial literacy* and *trust* in artificial intelligence, as well as *the significance of attitudes*, paint a more nuanced picture than expected, which is also supported by the analysis conducted among Hungarian higher education students.

According to the results of my research, *digital literacy* has a positive impact on the acceptance of AI-based financial solutions, while the impact of *financial literacy* is mixed. A similar opinion was expressed by Venkatesh and Davis (2000), who argued that technology acceptance (TAM model) largely depends on *perceived usefulness* and *ease of use,* which are reinforced by digital literacy. In his study examining the adoption of online banking, Ryu (2018) showed that digital competencies are directly related to the use of financial technologies. At the same time, the literature also presents findings that indicate that more financially literate users are often more cautious about new technologies because they are aware of the potential risks (Gursoy et al., 2019; Arner et al., 2019; Gomber et al., 2017). Based on the results, digital and financial literacy are inseparable but differently weighted components of AI acceptance.

My findings also confirmed that *customer experience* plays a key role in building *trust* in AI. Users' trust in a digital system is often based on previous experiences (Gefen – Straub, 2004; Lemon – Verhoef, 2016). According to Gursoy et al. (2019), the successful use of AI-based chatbots increases user trust in digital financial advice. At the same time, several authors emphasize that overly automated customer service systems can reduce trust, as users continue to demand human interaction (Huang – Rust, 2018; Lemon – Verhoef, 2016). My interview experience also supports that the lack of transparency of AI – its *"black* box" nature – is a significant factor in mistrust, as emphasized in the literature on XAI (*Explainable Artificial Intelligence)* (Doshi-Velez – Kim, 2017).

Attitudes toward services and *acceptance* are also influenced by *income level* and *social status*. Vives (2019) found that higher-income and wealthier customers are more likely to choose *personal banking services*, especially for larger decisions. Fernandes et al. (2014) also confirmed that those who attach greater value to financial decisions are more likely to seek personal advice. In line with this, my own findings also show that those for whom money is of paramount importance are more likely to choose traditional forms of banking. At the same time, Philippon (2019) and Gomber et al. (2017) also showed that *digital banking* is growing in popularity among wealthier customers, as technology offers fast and convenient options, and the spread of online financial management services is increasing the acceptance of self-service solutions even among conservative customers. However, the dominance of *self-service* solutions is particularly noticeable among younger, technologically open customers. According to Venkatesh et al. (2012), younger customers have a higher acceptance rate for self-service technologies, which is related to their digital skills and independence. Oliveira and his co-authors (2016) pointed out that customer demand for speed and convenience is one of the main drivers of the spread of online banking services. At the same time, Meuter et al. (2000) warn that older customers find it more difficult to adapt to self-service systems and therefore tend to seek traditional solutions. Lee and Shin (2018) emphasize that personal advice remains a decisive factor in more complex and complicated financial decisions.

My research among younger customers, especially university students, showed that while *digital skills* and *openness to technology* are high, *financial literacy* and long-term financial planning are often lacking (Lusardi – Mitchell, 2017; Goyal et al., 2021). According to the literature (Tang et al., 2022; Kaur – Arora, 2021), this is mainly a consequence of generational differences, which can be partly explained by socialization in the digital world and the increased interest of younger people in new forms of investment (e.g., cryptocurrencies). The results of my cluster analysis also confirm that the financial behaviour of young Hungarian adults cannot be treated as homogeneous but can be divided into three distinct groups.

My findings are comparable in some respects to those of Németh, Zóler and Luksander (2017), which was based on a representative sample of 1,000 people and mapped the financial culture of 18–35-year-olds using OECD methodology, where respondents were also classified into three distinct attitude groups based on cluster analysis. The "*cautious and* prudent" group (45%) was characterized by conscious budgeting, knowledge of financial products, and forward-looking financial decisions. The members of the "*conscious* risk-taker" cluster (31%) were young people with good financial knowledge, a risk-taking and planning mindset, while the "*worried,* spendthrift" segment (24%) was characterized by low financial awareness, low propensity to save, and emotionally based decision-making. In my own research, I also identified three clusters, but in addition to *financial attitudes, technological affinity* and *attitudes toward artificial intelligence (AI)* also played a role in the segmentation. The largest group in my study was "*financially aware, technologically* cautious" students (44.5%), which is close to the "*cautious and* thoughtful" group identified by Németh et al. However, according to my research, these students are also cautious about digital and AI-based solutions, which indicates a lingering mistrust despite the technological advances of the past decade. The second cluster consists of "*digital solution* preferers" (24.4%), which is lower than Németh's "*conscious* risk takers" cluster (31%). This may indicate that technological openness does not necessarily go hand in hand with advanced financial awareness or conscious risk taking. The third group in my study consisted of respondents with a "*traditional attitude and financial* awareness" (31.1%), which represents a significantly higher proportion than Németh's "*worried,* spendthrift" group (24%). This difference le to conclude that, despite the development of financial technologies, the number of young people who make conscious financial decisions but have strong reservations about digital financial services remained stable or even increased slightly in the period between the two surveys (approximately 7–8 years). In summary, although the study by Németh et al. (2017) also identified three distinct types of financial attitudes, my own research has reinterpreted the segmentation of this age group by incorporating the dimension of technological and AI acceptance. This provides a more up-to-date and practically relevant foundation for designing targeted strategies in digital financial education. Based on my findings, one of the major advantages of AI-based financial advice is that it can support personalized decision-making, but some of the respondents remain sceptical about the use of such technologies. One reason for this mistrust is limited trust in technological systems, which the literature partly explains by a lack of human empathy and personal relationships (Langer et al., 2022). In contrast, if AI provides accurate and reliable information, it can improve user satisfaction (Huang & Rust, 2018; McLean & Osei-Frimpong, 2019) and reduce customer uncertainty.

Based on the results of my research, I have formulated thirteen recommendations in my dissertation that can help MI-based financial solutions gain wider acceptance and greater trust.

It is important that financial and digital literacy, attitudes towards technology, levels of trust and socio-cultural factors are not treated separately, but in conjunction with each other in efforts to strengthen the acceptance of digital financial technologies. The three user groups I have identified require different approaches, so service providers should tailor their communication, education, and service offerings to them in order to develop more effective strategies. Strategies should also take income differences into account, with cost efficiency and increased access being attractive for lower income groups, and personalized, high-quality solutions for higher income groups. Financial education should be supplemented with digital and AI skills, while communication should be as personalized as possible. Trust is greatly enhanced when the AI used by organizations is transparent and explainable. It is also important that digital platforms are modern, easy to use, self-service, and support user learning. Efforts should be made to ensure access for all, thereby promoting social equality. Building trust requires emphasizing ethical conduct, data protection, and transparency, as well as a clear, flexible, and user-friendly regulatory environment. In the future, it will be worth monitoring how user attitudes change and mapping the distribution of different attitude groups through representative research. Finally, it is justified to develop an objective measurement method that provides an accurate picture of how well AI solutions meet user expectations and needs.

5. NEW SCIENTIFIC RESULTS

1) In my dissertation, I approached the acceptance of artificial intelligence in finance from not only a technological perspective, but also from a social and psychological one. As a result of my research, I developed *a conceptual model for the acceptance of artificial intelligence,* according to which people's decisions regarding artificial intelligence are not only influenced by their knowledge or previous experiences, but also, and to an equal extent, by how much they trust these solutions and the emotions that a particular technological innovation evokes in them. This model also highlights that technology acceptance is a complex, multi-level process in which cognitive and *emotional factors* build on each other and constantly interact. Positive experiences or increased trust can facilitate acceptance, while uncertainty or negative emotions can hinder it. With this approach, financial education and regulatory strategies can also be placed on a more personal and realistic footing.

2) Due to its *complexity*, the topic I have examined *requires a novel scientific approach.* I have found that trust in AI technology and its social acceptance are not based solely on technological knowledge but are also influenced by other factors such as users' emotional reactions, experiences, and perceptions of organizations that use AI, which together shape attitudes. The combined use of the GAAIS scale to measure attitudes toward AI has opened a new level of analysis.

3) In my research, I identified *three new consumer clusters* along *digital and financial attitudes* in today's ever-changing FinTech ecosystem. I named them as follows:
    1. *Financially conscious, technologically cautious group*. They typically exhibit responsible financial behaviour, are forward-thinking and difficult to influence, but are less open to using innovative technologies.
    2. *Digital solution preferers*. Members of this group are strongly technology-oriented and open to digital financial innovations, but their financial awareness is moderate, and they are less likely to plan for the long term.
    3. *Traditional, less financially aware group*. This group is conservative, strongly attached to personal service, and has low financial awareness and little openness to technological innovation.

    These clusters provide strategically important information for service providers in product development and customer communication.

4) My results show that in the student sample examined, which consisted mainly of university students under the age of 25 studying at higher education institutions in Budapest, *attitudes toward digital financial services* vary significantly, which confirms that digital affinity is not necessarily determined by age group. In the sample examined, a more conservative, cautious attitude towards technological innovations proved to be dominant (75.6%).

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