ARTIFICIAL INTELLIGENCE WAVES IN FINANCIAL SERVICES INDUSTRY: AN EVOLUTION FACTORIAL ANALYSIS

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Abstract

Artificial intelligence (AI) has gained prominence in the financial industry. Thus, it is particularly interesting to address the financial services where AI-based systems are mainly used, the reasoning for their use, risks, and evolution potentialities. This research explores the viewpoints of professionals inside and outside the European Union area on AI-based services in the financial industry, aiming to analyze their current position and conceptualize their evolution through an integrative method study. The analyzed data pertain to 523 professionals (out of 740 contacted) who have compiled an online questionnaire related to four study pillars, such as AI-based systems use in financial services (A), the reasoning for their use (B), their risks (C) and evolution potentialities (D). Then, we examine how AI-based systems impact the evolution of AI in financial services (D) use in financial services (A), the reasoning for their use (B), and their risks (C). The study argues that to encourage a sustainable future of AI evolution in the financial sector, the risk management approach is a crucial aspect that regulatory bodies should consider accurately. According to the field professionals' collected opinions in this study referring to their gender and age, special attention should be paid to these risks: AI limitations in forecasting market uncertainties, their lack of ethical values and explainability, as well as their no-audited versions. Therefore, academia and field professionals recommend the establishment of regulatory standards that, compared to risk management approaches, leave enough space even for AI innovation.

Keywords: artificial intelligence, financial services industry, fintech, risk management
JEL classification: G21, G22, G23

1. Introduction

Human intelligence expresses the mental ability to reason, problem-solve and learn. It comprises cognitive functions such as memory, language, planning, attention, and perception (Colom et al. 2022).

Over the years, human intelligence has exploited technology to support and complement human cognitive functions, also known as Intelligence Augmentation (IA) (Kyllonen, Roberts, and Stankov 2010). In this way, IA is typically focused on building systems that put humans and machines to work together. Further advancements in this matter have brought about artificial intelligence (AI applications/models/systems/platforms), also known as machine intelligence. This technology is focused on the complete outsourcing of intellectual tasks (making predictions, recommendations, or decisions) to machines (Turing 1950). The AI uses massive amounts of alternative data sources and data analytics called ‘Big Data.’ The last ones feed Machine Learning (ML) models, which can learn from data sets and surpass human intelligence in executing determinate tasks without being explicitly programmed by humans (Tzimas 2021).

Recent statistics show that revenues from AI-based products worldwide are expected to reach 126 billion dollars by 2025 (statista.com). Furthermore, the percentage of organizations employing AI-based systems grew 270% over the past four years (gartner.com). Meanwhile, in 2025, 95% of customer interactions are expected to be powered by AI (servion.com).

Thus, it can be confirmed that AI has gained a prominent position (Panetta et al. 2018) and has attracted the attention of various financial services (Lin, 2019), such as asset management

(Gupta 2020), algorithmic trading (Cohen 2022), credit underwriting (Brotcke 2022) or blockchain-based financial services (Smith 2019).

AI-based tools in finance are not limited to a few applications but are diversely used and consistently gaining popularity. These tools range from those enhancing financial education, automating administrative tasks for educators, creating innovative content for lessons, providing voice assistance, to implementing hyper-personalization techniques for student follow-up processes (Alenezi and Faisal 2020). Social media platforms also leverage unique AI algorithms to deliver relevant financial content. For instance, Facebook's DeepText tool adeptly understands conversations and translates posts into different languages, while Twitter uses AI to combat inappropriate remarks.

Instagram, a popular social media platform, leverages big data and AI to enhance user experience and optimize financial target advertising. Another noteworthy AI application, 'RegTech', is employed for meeting regulatory and compliance requirements and for reporting purposes (De Lis 2016). Authorities also utilize an application called 'SupTech' for regulatory, supervisory, and oversight tasks (Di Castri et al. 2019).

In addition, AI chatbots comprehend natural language and respond to people online who use the "live chat" feature that many insurance companies provide for customer service (Onyuma 2019). The chatbots powered by Natural Language Processing (NLP) are also used in other financial services such as personal finance (for financial health management purposes), consumer finance (fraud and cyber-attacks prevention), and corporate finance (predict and assess loan risks, perform advanced fraud detection and spot anomalous activities) referring to Insider Intelligence 2022 data.

Nonetheless, the researchers affirm that AI-based tools have issues of uncertainty risk (Wu et. al., 2014), cybersecurity, and systemic risks (Lee 2021). They also suffer from a lack of explainability (Giudici and Raffinetti 2022; Holzinger 2018), ethics, equity, bias, and reliability risk (Biolcheva 2020). In other words, various risks may arise while implementing these AI-based tools to facilitate our financial activities while reducing information, communication, analysis costs, and related risks.

Therefore, this paper tries to contribute to the existing literature in three different ways: This study addresses the financial services where AI-based systems are mainly used, the reasoning behind their use, their risks, and their evolution potentialities. This research helps fill the literature gap on this topic.

Employing a comprehensive mixed method, this research thoroughly explores the perspectives of professionals within and outside the European Union on AI-based services in financial services. The aim is to provide a robust analysis of their current status and potential evolution.

This paper captures and presents valuable findings and insights to policymakers, regulators, and professionals in the FinTech industry, with the goal of supporting and promoting the use and evolution of responsible AI.

2. Literature review

Today, the AI approaches have revolutionized how modern economies and societies serve thoughts, behaviors, research, and do business (Abrardi, Cambini, and Rondi 2019; Bolton et al. 2018; Boyd and Holton 2018). In finance, they provide relevant legal, accounting, tax, and auditing knowledge (Faina, Alturas and Almeida 2020; Smith 2019). They also detect possible fraud (Potamitis 2013) or suspicious activity. Another AI is represented by NLP, also known as Automatic Speech Recognition (ASR). They analyze human languages (sentences) using algorithms to translate the human sentences and, thus, automatically proceed to a given task (Yu and Deng 2016). The NLPs and chatboxes in the insurance sector communicate and convey products to customers (Onyuma 2019).

Further development of AI is evidenced in the banking sector, which benefits from using advanced mathematical and statistical models like predictive analysis, artificial intelligence, and data mining (Shakya and Smys 2021). For example, machine learning (ML) models offer a higher customer default forecasting accuracy for credit scoring purposes than standard statistical models (Albanesi and Vamossy 2019).

AI solutions and ML are increasingly being used in the financial services sector, particularly in improving operational efficiency. This trend has garnered significant interest in recent years, with a focus on enhancing performance, managing risks, and improving customer experience (Ogege and Bolouprемо 2020; Lundberg and Lee 2017). In portfolio allocation and stock selection activities, AI is making significant strides. In trading activities, AI algorithm techniques such as evolutionary computation, deep learning, and probabilistic logic are used for predictions, decision-making, and trade execution (Metz 2016).

In the insurance sector, AI adoption has improved the performance of back-office operations and customer approach (Lee, Floridi, and Denev 2021). These businesses implement AI-based solutions while demanding a competitive market advantage (Žigienė, Rybakovas, and Alzbutas 2019; Gandomi and Haider 2015).

AI is also implemented in financial education and incorporated into administration, teaching, and learning issues (Chassignol et al. 2018). In social media, AI technologies are highly effective monitoring processes (Sterne 2017). Thus, AI helps understand how people interact in social networks and discuss a given topic, as well as concerns that are further explored for financial business purposes. Text mining and analyzing social media posts and tweets through NLP algorithms can inform trading decisions in this context. It occurs as NLP uses these data to identify certain market behaviors.

Foremost in the research field, AI-based solutions that provide complex calculations have increasingly gained popularity during the last few years (Li et al., 2021; Li and Xu 2021; Lin 2021; Moskowitz et al. 2006).

However, there is a controversial debate over the financial risks in AI-driven solutions (i.e, exacerbate illegal practices in trading aiming to manipulate the markets) and the limitations of AI (Azzutti 2022; Azzutti, Ringe and Stiehl 2021; Jarco and Sulkowski 2023). Despite these debates, the European GDPR EU (2016) regulation requires that AI systems carry meaningful information about the logic involved in the automated decision-making process and act according to legal dispositions in force. This regulation, in fact, paves the way for AI to make problem-solving in finance easier and faster, offering a more optimistic perspective (Chen et al. 2019).

Comprehensively, the idea that the presence of various risks evidences financial AI is supported (Mohamed et al. 2013). For example, uncertainty risk makes developing optimization models more difficult (Wu, Chen and Olson 2014). Many other issues related to AI are related to ethics, equity, bias, and decision-making reliability (Biolcheva 2020; Boyd and Crawford 2012). Meanwhile, with the popularity of advances in financial AI services, cybersecurity and systemic risks have increased (Lee 2021; Abawajy, Kelarev and Chowdhury 2014). Another major issue in this field emerges concerning AI operations, where these systems need more explainability, and this becomes difficult in the auditing process (Giudici and Raffinetti 2022; Fritz-Morgenthal, Hein and Papenbrock 2022; Holzinger 2018). Correspondingly, in the coming years, the primary commitment will be to conduct a more profound analysis of AI developments concerning their risk management approaches. Thus, as a comprehensive regulatory framework, the EU AI Act (2023) embodies the EU's commitment to address the ethical, legal, and societal challenges precipitated by AI technologies (Musch, Borrelli and Kerrigan 2023).

The study of Balavenu et al. (2022) proposes that AI approaches can also be used in regulating the financial sector. In this context, the crucial role of national competent authorities is underscored. They are tasked with supervising and enforcing the EU AI Act's (2023) provisions within their respective jurisdictions, thereby playing a pivotal role in the successful implementation of the Act (Musch et al., 2023).

Other researchers, Azzutti et al. (2023), inspired by the EU AI Act (2023), have investigated the advantages of a 'rule-based' and 'risk-oriented' regulatory approach. They claim a combination of ex-ante and ex-post regulatory measures must be put into perspective with the 'AI life cycle'.

Critics argue that stringent regulatory requirements for high-risk AI systems might shrink innovation by imposing onerous compliance burdens on developers. In other words, this means less AI research and development for small and medium-sized enterprises (SMEs) by favoring established entities with more significant resources ((Musch, Borrelli and Kerrigan 2023). Additional research in compliance with the EU AI Act (2023) argues for establishing

AI Law Audit model departments within financial companies using AI functions (Doekes 2023).

However, further studies argue that a human being should always decide which model should be used, which one needs to be reviewed, and which models should be discontinued (Fritz-Morgenthal, Hein and Papenbrock 2022).

It is worth noting that the existing literature lacks comprehensive studies that analyze attitudes toward the use of AI in financial services while also highlighting their risks and potential for evolution. This study's novelty lies in its unique approach to determining professional viewpoints through a mixed-method study.

3. Methodology

3.1. The methodological research design

This research study uses an online questionnaire to collect professionals' opinions concerning various aspects of AI use in the financial services industry.

The questionnaire, a comprehensive tool, is structured into two sections. The first section focuses on the demographic background of the respondents, encompassing gender, age, country, employment position, and educational/academic qualifications. The second section, the core of the questionnaire, explores the four pillars of AI use in the financial services industry, each containing four elements. These pillars are ***A. The use of technology as a financial service through AI-based functions; B. Reasons for using or not using AI; C. The main risks that AI faces; and D. The evolution of AI in financial services.***

We apply an integrative method study. Concretely, we use the quantitative method (questionnaire) numerical data and qualitative methods (focus groups: field professionals, their gender and age) descriptive data to test a hypothesis-based approach. Thus, we test whether the use of technology as a financial service through AI-based functions (A), considering the reasons for using or not AI (B), as well as the main risks that AI faces (C), impact the evolvement of AI in financial services (D). The research study hypothesis is specified below:

Ho: $D= \beta 0+\beta 1*A +\beta 2*B + \beta 3*C + \mu t.$ (1)

3.2. Participants and data

In this research study, 523 professionals out of 740 were contacted, and 15.3% were young (18-25 years old). The participants' nationalities (see Table 1) in percentage are Albanian (31.35%), Czech (6.88%), German (10.7%), Hungarian (8.6%), Italian (6.11%), Kosovo (6.69%), North Macedonian (8.41%), Portuguese (8.6%), Romanian (6.5%) and British (6.11%). The majority of study participants are female (65.8%). Meanwhile, more than 8.22% of the participants involved in the study are researchers and members of Cost-Action (CA) field programs. In general, the participants of the study are university academic staff (16.6%), certified accountants (8.4%), economists (20.2%), employees in the financial sector (10.9%), IT specialists (13.9%) and university students (30%) inside and outside the European Union area. All of them have used AI functions in the financial services industry.

The university students in the study are primarily from bachelor's (65.4%), professional (5%), Economists in the study hold bachelor's degrees (20.7%), professional master's (47.1%), scientific master's degrees (26.5%), and the rest (11.1%) are Ph.D. candidates, demonstrating a high level of academic achievement.

The certified accountant study participants hold even a Ph.D. degree. The employees in the financial services industry hold a bachelor's degree (31.6%) and a professional master's degree (24.6%), and the rest hold a scientific master's degree (43.8%). The IT specialists hold professional master's degrees (73.3%), and the rest hold full professor titles (26.7%).

The academic staff have a scientific master's degree (26%) or are Ph.D. candidates (6.2%), in addition to those who possess Ph.D. degrees (34.6%), the associate professor title (22.2%), and the full professor academic title (11%).

Table 1. Study participant`s data

		Environment		Age					
The demographic information	**Total**	**CA**	**No CA**	**18-25**	**26-34**	**35-44**	**45-54**	**55-64**	**+65**
Base size	523	43	480	80	101	69	122	100	51
Albanian participants	164	14	150	38	29	17	56	16	8
Czech participants	36	6	30	0	10	6	7	6	7
German participants	56	6	50	12	5	8	13	12	6
Hungarian participants	45	5	40	2	4	1	15	21	2
Italian participants	32	0	32	6	1	6	8	6	5
Kosovo participants	35	0	35	10	4	5	3	13	0
North Macedonia participants	44	4	40	6	9	4	8	12	5
Portuguese participants	45	0	45	0	12	16	5	2	10
Romanian participants	34	0	34	1	21	3	4	5	0
British participants	32	8	24	5	6	3	3	7	8

Source: Questionnaire data

3.3. Research method

The online questionnaire (see Table 2) to explore professionals' opinions concerning AI functions used in the financial services industry was delivered through their official e-mail addresses. The questionnaire evaluation uses the Likert scale from 1 (one) to 5 (five), meaning: 1= Strongly disagree (Sa); 2=Disagree (D); 3 = Undecided (U); 4=Agree (A) and 5= Strongly agree (Sa). The SPSS 20 (SPSS Inc., Chicago, IL) statistical program is used to analyze the data and further test the below research hypothesis:

$$Ho: D= \beta 0+\beta 1*A +\beta 2*B + \beta 3*C + \mu t. \quad (1)$$

The results of the Shapiro-Wilk test (1968) indicate that the key elements of the Likert scale data from the questionnaire do not follow a normal distribution. Thus, in order to test whether the use of technology as a financial service through AI-based functions (A), considering the reasons for using or not AI (B), as well as the main risks that AI faces (C), impact the evolvement of AI in financial services (D) we use both ordinal regression analysis and ordinal logistic regression that does not assume normality.

First, we apply ordinal regression analysis. This approach is used to understandthe relationship between the independent variables (A, B, and C) and an ordinal dependent variable (D). It allows for modeling the probabilities of the different categories of the ordinal outcome (D), providing insights into how the predictor variables (A, B, and C) influence the likelihood of being in a higher or lower category.

Then, we apply ordinal logistic regression analysis, a specific type of ordinal regression that assumes a proportional odds model. This method is particularly useful when the assumption of proportionality holds, meaning that the relationship between each pair of outcomes is the same. This method estimates the odds of being in a higher category versus all lower categories combined, which can be particularly informative for our hypothesis testing.

By applying both analyses, we can cater to different assumptions and thoroughly examine the research hypothesis. This dual approach allows for a comprehensive understanding of the data, accommodating various modeling needs and enhancing the reliability of our findings.

Table 2. Likert scale questionnaire

			Rating 1-5				
			Sd	D	U	A	Sa
			1	2	3	4	5
The use of technology as a financial service through AI functions	A1	AI is mostly used in financial and banking services					
	A2	AI is mostly used in insurance, accounting and auditing services					
	A3	AI is mostly used in financial education and scientific research services					
	A4	AI is mostly used in social media (Facebook, Twitter and YouTube) for financial advertisement purposes					
Reasons for using or not AI (B)	B1	AI provides cheaper, faster, larger, more accessible, more profitable, and more efficient services in many ways					
	B2	AI solves Strategic Decision Problems and Effectively forecasts					
	B3	AI cannot help in prediction of outcomes, problem solving in investment management (IMT), fraud detection (FDT), algorithm trading (AT), and correct underwrite loan and insurance products (LIU)					
	B4	AI does not always operate in alignment with laws and regulations and the privacy of customers isn`t guaranteed					
The main risks that AI face (C)	C1	AI is limited in capturing all that is happening in the marketplace (market uncertainties) and cannot judge what has not happened yet					
	C2	AI operates based on historical discriminatory practices, lack ethical values and explainability					
	C3	AI is vulnerable to cybersecurity risks					
	C4	AI cannot be always audited					
The evolvement of AI in financial services (D)	D1	The development of responsible AI enhances financial services and improves regulatory compliance					
	D2	The growth of digital economy will facilitate the expansion of AI-based functions in financial services					
	D3	Policymakers and financial regulators should deeply analyze the risk management issues of AI to provide more transparent and auditable versions					
	D4	The overregulation in AI use in financial services might impede the innovation in the field					

Source: Questionnaire results

The data collected per each pillar element (A/B/C and D from 1-4) are evaluated using average ratings. Decimal values are rounded to the nearest value. This first transformation is advisable because most information users need help figuring out how to use Likert Scales, such as the 5-point scale.

4. Results and discussions

Only 70.7% of professionals contacted by e-mail completed the questionnaire. According to these data, 37.5% of the elements evaluated in this questionnaire were rated 4 (participants agree with AI use in the financial services industry), and the rest of 62.5% were rated 3 (participants are undecided about AI use in the financial services industry; see Table 3).

Table 3. Likert scale general questionnaire results

		1	2	3	4	5
A1	AI is mostly used in financial and banking services			X		
A2	AI is mostly used in insurance, accounting and auditing services			X		
A3	AI is mostly used in financial education and scientific research services			X		
A4	AI is mostly used in social media (Facebook, Twitter and YouTube) for financial advertisement purposes				X	
B1	AI provides cheaper, faster, larger, more accessible, more profitable, and more efficient services in many ways				X	
B2	AI solves Strategic Decision Problems and Effectively forecasts			X		
B3	AI cannot help in prediction of outcomes, problem solving in investment management (IMT), fraud detection (FDT), algorithm trading (AT), and correct underwrite loan and insurance products (LIU)			X		
B4	AI does not always operate in alignment with laws and regulations and the privacy of customers isn`t guaranteed			X		

		1	2	3	4	5
C1	AI is limited in capturing all that is happening in the marketplace (market uncertainties) and cannot judge what has not happened yet			X		
C2	AI operates based on historical discriminatory practices, lack ethical values and explainability			X		
C3	AI is vulnerable to cybersecurity risks				X	
C4	AI cannot be always audited			X		
D1	The development of responsible AI enhances financial services and improves regulatory compliance				X	
D2	The growth of digital economy will facilitate the expansion of AI-based functions in financial services				X	
D3	Policymakers and financial regulators should deeply analyze the risk management issues of AI to provide more transparent and auditable versions				X	
D4	The overregulation in AI use in financial services might impede the innovation in the field			X		

Source: Questionnaire results

Table 3 data shows that the elements mostly rated with 4 pertain to pillar D: evolvement of AI in financial services 3 out of 4. Meanwhile, the other study pillars, such as A: The use of technology as a financial service through AI-based functions; B: Reasons for using or not AI; and C: The main risks that AI faces, are generally rated at 3 (3 out of 4 elements in these pillars are rated 3).

Referring to the evolvement of AI in financial services pillar D, the elements where the participants agree toward the use of AI in financial services are:

D1-The development of responsible AI enhances financial services and improves regulatory compliance;

D2 - The growth of the digital economy will facilitate the expansion of AI-based functions in financial services;

D3-Policymakers and financial regulators should deeply analyze AI risk management issues to provide more transparent and auditable versions.

The D1 is rated highly by Romanian participants (with 5), followed by Portuguese participants (with 5), Hungarian participants (with 4), British participants (with 3.7), Italian participants (with 3.6), and Albanian participants (with 3.5). D2 instead is rated mainly by Romanian participants (with 5), Italian participants (with 4.5), Hungarian and Portuguese participants (with 4), and Albanian participants with (3.6). At the same time, D3 results were highly rated by Romanian and Portuguese participants (with 5), followed by British participants (with 4.25), Hungarian, Italian, Kosovo, and North Macedonia participants (with 4), and Albanian participants (with 3.5).

Generally, pillar D is rated on average by university academic staff with 4.02, certified accountants with 3.7, economists with 3.6, employees in the financial sector with 3.5, IT specialists with 3.02, university students with 3.3, and the researchers engaged in Cost Action programs with 3.3. This distribution of values demonstrates that professionals inside and outside the European Union share different opinions concerning AI functions used in the financial services industry.

Accordingly, it is essential to understand how to improve AI evolution in financial services (D). Thus, we test whether the use of technology as a financial service through AI-based functions (A) also considering the reasons for using or not AI (B) as well as the main risks that AI faces (C) impact the evolvement of AI in financial services at 95% confidence level, as in following:

$$Ho: D = \beta 0+ \beta 1 *A +\beta 2 *B + \beta 3 *C + \mu t. \quad (1)$$

The analysis demonstrates that the Likert scale data for the A, B, C, and D pillar elements are not normally distributed, as the Shapiro-Wilk test significance is lower than 0.05, referring to the above ordinal regression variables at a 95% confidence level (see Table 4).

Table 4. Ordinal regression variables tests of normality data

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
A	0.098	523	0.000	0.958	523	0.000
B	0.131	523	0.000	0.948	523	0.000
C	0.130	523	0.000	0.954	523	0.000
D	0.109	523	0.000	0.935	523	0.000

Source: Author`s calculations

In addition, through the test of parallel lines, the ordinal regression model significance is estimated 0.000 (lower than 0.05). It confirms that location parameters (slope coefficients) are the same across response categories in D variable (see Table 5).

Table 5. Test of parallel lines

Model	2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis General	2061.589 920.429	1141.160	42	0.000

Source: Author`s calculations

Thus, we proceed with the Generalized Linear Model (ordinal logistic regression analysis) to estimate whether the use of technology as a financial service through AI-based functions considering also the reasons for using or not AI as well as the main risks that AI faces impact on the evolvement of AI in financial services at 95% confidence level. The omnibus test demonstrates that the Generalized Linear Model used to test our hypothesis described above (see Table 6) fits well. The Chi-square significance is 0.000 (lower than 0.05). Also, the test of model effects confirms the omnibus test results as the significance of A (37.429), B (20.282), and C (92.719) is 0.000 (lower than 0.05).

Table 6. Omnibus Test

Likelihood Ratio Chi-Square	df	Sig.
515.487	3	0.000

Dependent Variable: Evolvement of AI in financial services (D)
Source: Author`s calculations

The Generalized Linear Model (ordinal logistic regression analysis) parameters presented in Table 7 confirm that each study pillar A, B, and C impacts the evolvement of AI in financial services (pillar D) and is statistically significant at a 95% confidence level.

Table 7. Generalized Linear Model Parameters Estimation

			95% Wald Confidence Interval		Hypothesis Test			
			Lower	Upper	Wald Chi-Square	df	Sig.	
Parameter	B	Std. Error						Exp(B)
A	0.620	0.1027	0.418	0.821	36.406	1	0.00	1.858
B	0.613	0.1375	0.343	0.882	19.856	1	0.00	1.845
C	1.379	0.1475	1.090	1.668	87.380	1	0.00	3.969
(Scale)	1							

Dependent Variable: Evolvement of AI in financial services (D)
Source: Author`s calculations

In addition, Spearman`s correlations (see Table 8) confirm that pillars A (0.641), B (0.616), and C (0.701) have a moderate and statistically significant correlation with D.

Table 8. Spearman`s Correlations

		A	B	C	D
Spearman's rho	A Correlation Coefficient	1	0.585	0.627	0.641
	Sig. (2-tailed)		0	0	0
	N	523	523	523	523
	B Correlation Coefficient	0.585	1	0.721	0.616
	Sig. (2-tailed)	0		0	0
	N	523	523	523	523
	C Correlation Coefficient	0.627	0.721	1	0.701
	Sig. (2-tailed)	0	0		0
	N	523	523	523	523
	D Correlation Coefficient	0.641	0.616	0.701	1
	Sig. (2-tailed)	0	0	0	
	N	523	523	523	523

Source: Author`s calculations

5. Conclusions

This study analyzed the viewpoints of professionals inside and outside the European Union area on AI-based services in the financial industry, aiming to understand their current position and conceptualize their evolution. Some of the study professionals are also researchers and members of Cost-Action programs in the field. The last ones have rated the study elements concerning the evolvement of AI in financial services (pillar D), such as D1 with 3, D2 with 3.4, D3 with 3.45, and D4 with 3.4. At the same time, the other study professionals (non-Cost Action program members) have rated D1 with 3.5, D2 with 3.6, D3 with 3.5, and D4 with 3.2.

In this light, it should be stated the fact that researchers were less confident in comparison with other study professionals referring to the following elements:

D1-The development of responsible AI enhances financial services and improves regulatory compliance;

D2-The growth of the digital economy will facilitate the expansion of AI-based functions in financial services;

D3-Policymakers and financial regulators should deeply analyze AI risk management issues to provide more transparent and auditable versions.

The vice versa occurs for D4-The overregulation of AI use in financial services might impede innovation in the field; the researchers are more confident in this point (rated it with 3.4) than the rest of the study participants (with 3.2).

From a gender context, instead, the results confirm that males have rated, on average, pillar D with 4 and females have rated it with 3. Thus, it means that males trust the current evolution of AI in the financial services industry, while women are more demanding.

While referring to age, all the professionals who participated in the study rated pillar D on average at 3, meaning they are undecided.

In general terms our analysis demonstrates that the current use of technology as a financial service through AI-based functions (A) considering also the reasons for using or not AI (B) as well as the main risks that AI face (C) help in the evolvement of AI in financial services (D). Statistically based, the ordinal regression analysis route-one results confirm that for every unit of improvement in:

- The use of technology as a financial service through AI-based functions (A), there is a predicted increase of 0.620 in the log odds of being at a higher level of the evolvement of AI in financial services (D);
- The reasons for using or not AI (B), there is a predicted increase of 0.613 in the log odds of being at a higher level of the evolvement of AI in financial services (D);
- The main risks that AI faces (C), there is a predicted increase of 1.379 in the log odds of being at a higher level of the evolvement of AI in financial services (D).

The ordinal logistic regression analysis route-two results show that the odds ratio of being in a higher level of evolvement of AI in financial services (D) increases by a factor of:

-1.858 for every one unit increase in the use of technology as a financial service through AI-based functions (A);

-1.845 for every one unit increase on the reasons for using or not AI (B);

-3.969 for every unit increase on the main risks that AI faces (C).

Thus, according to professionals' points of view independent of their profile, it can be deduced that much more should be done to manage the main risks that AI faces (pillar C), such as:

C1. AI is limited in capturing everything happening in the marketplace (market uncertainties) and cannot judge what has yet to happen (rated on average at 3.27). Therefore, it is crucial to support the research on correctly using AI to forecast market uncertainties. This support can enhance investors' trust in financial markets, business growth by collecting additional funds, and new product delivery by positively impacting the financial industry. Finally, the overall economy can benefit.

C2. AI operates based on historical discriminatory practices, lacks ethical values, and is not explainable (rated on average at 3.41). The development of fair and ethical AI emerges as an industry-wide objective. Correspondingly, regulatory standards can overcome these issues only by establishing bridges of dialogue with the industry.

C3. AI cannot always be audited (rated on average at 3.17). This is another point considered emergent by the professionals. Regulators should ensure the establishment of independent audit bodies for AI systems. In this way, more reliable and improved AI versions can be achieved.

Furthermore, the results confirm that the continuous use of technology as a financial service, facilitated by AI-based functions for various reasons, contributes to the evolution of AI in the financial services sector.

The study results also highlight that a robust risk management approach is essential for regulatory bodies to consider in order to foster extensive use and ensure a sustainable future for AI in the financial sector. At the same time, in the context of developing the first AI legislative act, academics and industry professionals advocate for establishing standards that balance risk management with the need to support AI innovation. It is worth noting that this study focuses only on professionals' viewpoints on the potential evolution of AI-based systems within the financial services industry. Future research endeavours could explore diverse viewpoints and assess the impacts of the EU AI Act on specific segments of the financial industry.

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