IMPROVING DECISION-MAKING EFFICIENCY THROUGH AI-POWERED FRAUD DETECTION AND PREVENTION

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Abstract: The digitization of companies serves as a crucial avenue for their advancement, with investments aiding the integration of AI technologies to address financial challenges and enhance decision-making processes. In conjunction with theoretical discussions, an empirical study surveyed 125 representatives from Serbia's insurance and financing sectors in early 2024. They were to evaluate the impact of AI technologies, funded through their digitization efforts over the past three years, on decision-making efficiency, particularly in fraud detection and prevention. Results showed a positive correlation between these factors and decision-making efficiency, with respondents emphasizing the significant influence, especially within fraud detection. Regression analysis, aided by appropriate analytical software, facilitated thorough data processing. The theoretical and empirical insights from this research contribute to the existing literature on decision-making and digitalization in companies while also fostering further exploration of AI technologies' potential impact on industrial development.

Keywords: *Digitization, Artificial Intelligence (AI) Technologies, Fraud, Financial And Insurance Sectors, Serbia*

1. INTRODUCTION

In today's business landscape, there's a notable paradigm shift underway, termed "digital transformation." This transformation is propelled by cutting-edge technological breakthroughs, empowering enterprises to wholeheartedly embrace digital innovation. However, this transformation has also created new opportunities for fraudsters to perpetrate fraud more easily than ever before. In this digital landscape, the role of AI and machine learning in fraud prevention and detection is crucial in transforming the financial industry by improving efficiency and enabling more effective risk management and decision-making processes (Srebro et al., 2023; Špiler et al., 2023). They offer numerous advantages, including cost reduction, credit scoring and underwriting, and enhanced data security, leading to improved decision-making and risk management by identifying and managing potential risks for an organization proactively (Jevtić et al.,2024;Miškić et al., 2024).

It is because the authors see decision-making in the context of AI, refering to the process by which an artificial intelligence system selects the best course of action or choice from among several alternatives based on available data, rules, and objectives. AI-driven decision-making

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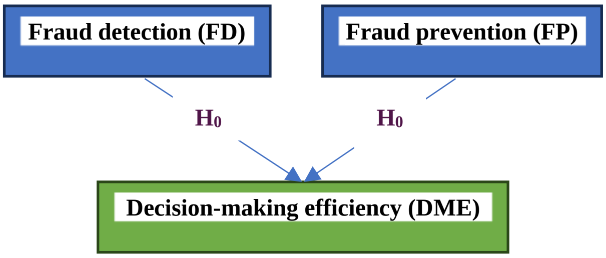
typically involves the following steps: data collection and preprocessing, feature extraction, and selection, feedback, and iteration. AI-driven decision-making aims to leverage data, algorithms, and computational power to automate and optimize decision processes, leading to more accurate, timely, and informed decisions across various domains and applications. The research aims to advance the understanding of how AI technologies can be leveraged to enhance decision-making efficiency in fraud detection and prevention, ultimately leading to more effective and scalable approaches for combating financial crime and protecting organizational assets. That being said, the research question is whether fraud detection and prevention powered by AI can improve the decision-making efficiency of an organization in the financial sector. The paper is structured so that after the introduction, a theoretical framework is presented, along with the results and discussion of empirical research on the topic among 125 representatives of companies from the financial and insurance sectors provided in Serbia in the first quarter of 2024.

2. THEORETICAL BACKGROUND

The United States stands at the forefront of AI research and development, with renowned institutions such as Harvard University. In the United Kingdom, institutions like the University College London (UCL) and the University of Oxford play a vital role in AI and cybersecurity research. Meanwhile, Canada hosts prominent AI research labs such as the Vector Institute in Toronto and the Mila Institute in Montreal, specializing in AI-driven fraud detection and prevention. Israel is esteemed for its expertise in cybersecurity, with advancements in AI technologies for fraud detection and prevention. Similarly, the Netherlands is witnessing a growing AI research community, with institutions like the Delft University of Technology contributing to the development of AI-powered fraud detection methods. Notable studies include Baesens et al. (2015), who explored fraud analytics using descriptive, predictive, and social network techniques, Smith (2023) researched implementing AI for fraud detection, Bolton & Hand (2001) provided a comprehensive review of fraud detection and prevention methods, highlighting research gaps and proposing future research agendas, Abdallah et al. (2016), underscoring the dynamic nature of AI-driven approaches in fraud detection, and Adewumi & Akinyelu (2018). Studies by Dal Pozzolo (2015) also delve into adaptive machine learning for credit card fraud detection, Gupta (2023) explores machine learning and artificial intelligence for fraud prevention, Nguyen, Duong, and Chau (2022) contribute with their study on card fraud detection based on CatBoost and deep neural networks. Respecting the theoretical background, the research question is defined as, RQ: In 2024, what are the perceptions of representatives from financial and insurance companies in Serbia regarding the potential advancements of AI technologies in fraud detection and prevention, particularly in how these advancements contribute to enhancing their firms' decision-making efficiency?. The hypothesis can be defined as: **Ho=**Fraud detection powered by AI (FD) and fraud prevention powered by AI (FP) show no significant impact on decision-making efficiency (DME), and alternative, **Ha=** Both fraud detection powered by AI (FD) and fraud prevention powered by AI (FP) exert a significant influence on decision-making efficiency (DME).The research model is defined in Pictures 1–2 as:



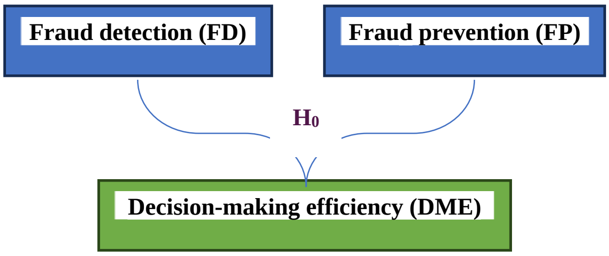


Figure 1. Theoretical system model of research

Figure 2.Derived research model

3. METHODOLOGY

In the empirical research conducted in Serbia for the purposes of this study, during the first quarter of 2024, 125 representatives from the finance and insurance sectors participated. They provided their perspectives on the influence of artificial intelligence (AI) technologies in fraud detection and prevention on enhancing decision-making efficiency within their respective companies via an electronic questionnaire. Most of the participants in the research were directors of the IT department, representing 50 out of the 125 companies surveyed (the others were general managers and owners). In terms of company age, the majority fell within the range of 6–10 years in business (45%).

The demographic characteristics of the research sample are illustrated through further figures (F1–5).

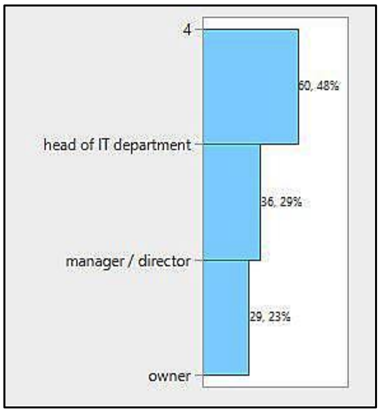


Figure 1. The role of respondent in the company

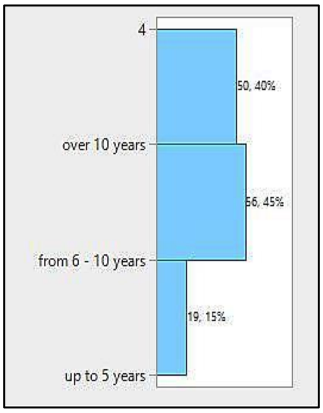


Figure 2: Years inbusiness

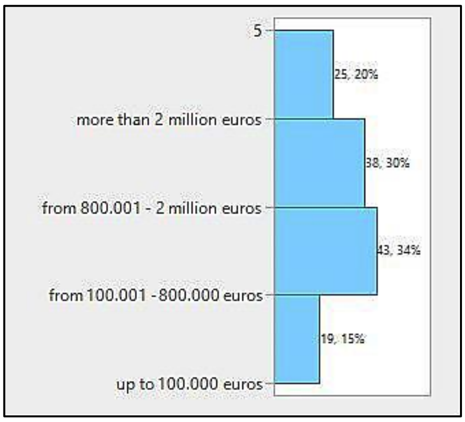


Figure 3: Company revenues in 2023

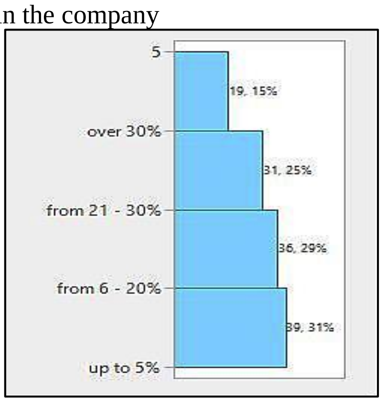


Figure 4. The level of investments in digitization (of the total revenue, in the last 3 years in %)

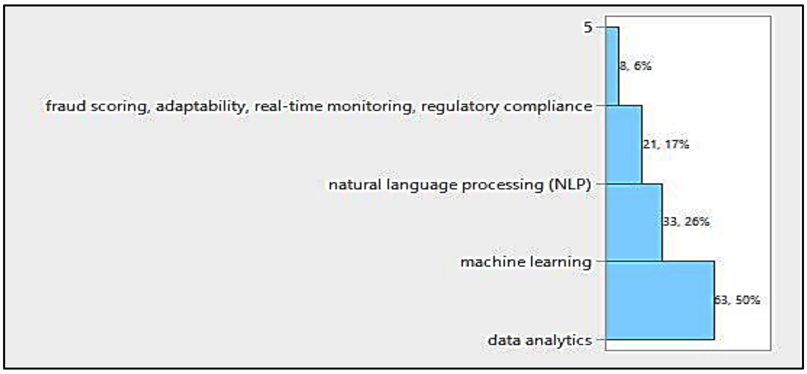


Figure 5. The firm's investments in AI technologies (from digitization funds in the last 3 years)

Concerning revenue, the highest proportion had earnings up to 800,000 euros in 2023. Over the last three years, these companies have allocated their digitization investments as follows: 5% of total revenue for 39 (31%) companies, 6-20% for 36 (29%) companies, 21-30% for 31 (25%) companies, and the remaining 19 (15%) companies invested over 30% of their total revenue. Based on previous investments in digitization, the company's expenditures in AI technologies reveal that the majority of companies allocated funds to the following AI technologies: 35 companies (50%) invested in data analytics, followed by 33 companies (25%) in machine learning, 21 companies (17%) in natural language processing (NLP), and a smaller proportion invested in fraud scoring, adaptability, real-time monitoring, and regulatory compliance, with 8 companies (6%) out of the total of 125 companies. In Table 1, a summary of descriptive statistics is presented.

Table 1. Summary of descriptive statistics

	Role in the company of the representative	**Years in business**	**Company revenues in 2023**	**The level of investments in digitization (% of the total**	**Investments of the company in AI technologies (based on**	**Funds to be invested in AI-powered**

				revenue, in the last 3 years)	**previous funds for digitization)**	**in further 3 years**
Mean	2.248	2.248	2.552	2.24	1.792	2.176
Std Dev	0.8097789	0.7031725	0.979269	1.0579957	0.9443892	0.8986011
Std Err Mean	0.0724288	0.0628937	0.0875885	0.09463	0.0844687	0.0803733
Variance	0.6557419	0.4944516	0.9589677	1.1193548	0.891871	0.8074839
Skewness	-0.484676	-0.389475	0.009226	0.2929823	0.8965023	-0.356343
Kurtosis	-1.308795	-0.917321	-0.996928	-1.148828	-0.310308	-1.678699

The company representatives provided assessments regarding the impact levels of two independent research variables, which are as follows:

1. AI-powered fraud detection (FD)
2. AI-powered fraud prevention (FP),

On a single dependent variable, defined as:

3. Decision-making efficiency (DME).

Their evaluations were based on nine statements and were expressed using a Likert scale ranging from 1 to 5, where 5 indicates the highest level of agreement.

Table 2: List of statements

1.	**Independent variable: AI-powered fraud detection (FD)**
FD1	AI-powered fraud detection systems can identify fraudulent activities in realtime, enabling firms to respond promptly and mitigate potential financial losses.
FD2	AI-powered fraud detection systems help firms comply with regulatory requirements by providing auditable and transparent processes for fraud detection and reporting.
FD3	By automating routine tasks and streamlining fraud detection processes, AI-powered systems improve operational efficiency and reduce the time and resources required for fraud monitoring and investigation.
2.	**Independent variable: AI-powered fraud prevention (FP)**
FP1	AI-powered fraud prevention systems can proactively identify potential fraud risks by analyzing historical data and detecting suspicious patterns before fraudulent activities occur.
FP2	AI algorithms enable real-time decision-making by quickly analyzing incoming transactions and identifying fraudulent behavior as it happens, allowing firms to take immediate action to prevent financial losses.
FP3	AI-powered fraud prevention employs a multi-layered approach, combining various techniques such as anomaly detection, pattern recognition, and machine learning algorithms to create robust defenses against fraudulent activities.
3.	**Dependent variable: Decision–making efficiency (DME)**
DME1	AI-powered detection and fraud prevention systems provide real-time insights into fraudulent activities, enabling timely decision-making to mitigate risks and minimize financial losses.

DME2	AI algorithms help firms allocate resources more effectively by focusing on high-risk areas and minimizing false positives, allowing decision-makers to allocate resources where they are most needed.
DME3	AI-powered systems provide valuable insights into fraud trends and patterns, enabling decision-makers to develop proactive strategies and policies to prevent fraud effectively.

3.1 RESULTS AND DISCUSSION

In Table 3, the frequencies and percentages of representation for Fraud Detection (FD) claims are provided. Statement FD2 connected to the complianceenhancementexhibits the highest mean response value of 4.024, followed by FD3 with 3.944, and FD1 with the lowest mean of 3.712.

Table 3. Assertions and their corresponding values for Fraud detection

Assertions	FD1		FD2		FD3	
	Count	Prob	Count	Prob	Count	Prob
I totally disagree	4	0.03200	1	0.00800	1	0.00800
Partially disagree	15	0.12000	8	0.06400	20	0.16000
Neither agree nor agree	16	0.12800	15	0.12000	7	0.05600
Partially agree	68	0.54400	64	0.51200	54	0.43200
I totally agree	22	0.17600	37	0.29600	43	0.34400
Total	125	1.00000	125	1.00000	125	1.00000

In Table 4, frequencies and percentages of representation for the set of Fraud Prevention (FP) claims are displayed. Statement FP1 exhibits the highest mean response value of 3.792 (continuous monitoring), followed by FP2 with 3.776, and FP3 with the lowest mean of 3.720.

Table4. Assertions and their corresponding values for Fraudprevention

Assertions	FP1		FP2		FP3	
	Count	Prob	Count	Prob	Count	Prob
I totally disagree	1	0.00800	1	0.00800	4	0.03200
Partially disagree	31	0.24800	26	0.20800	15	0.12000

Assertions	FP1		FP2		FP3	
	Count	Prob	Count	Prob	Count	Prob
Neither agree nor agree	9	0.07200	13	0.10400	16	0.12800
Partially agree	36	0.28800	45	0.36000	67	0.53600
I totally agree	48	0.38400	40	0.32000	23	0.18400
Total	125	1.00000	125	1.00000	125	1.00000

In Table 5, frequencies and percentages of representation for the statements regarding Decision-making efficiency (DME) are presented. Statement DM1 shows the highest mean response value of 4.048 (optimizing response time), followed by DME3 with 3.952, and the lowest mean, 3.808, and corresponds to DME2.

Table 5. Assertions and their corresponding values for Decision-making efficiency

Assertions	DME1		DME2		DME3	
	Count	Prob	Count	Prob	Count	Prob
I totally disagree	1	0.00800	1	0.00800	1	0.00800
Partially disagree	11	0.08800	19	0.15200	21	0.16800
Neither agree nor agree	9	0.07200	19	0.15200	10	0.08000
Partially agree	64	0.51200	50	0.40000	44	0.35200
I totally agree	40	0.32000	36	0.28800	49	0.39200
Total	125	1.00000	125	1.00000	125	1.00000

In Table 6, values including Mean, Standard Deviation (Std. Dev), Standard Error of the Mean (Std Err Mean), Variance, Skewness, and Kurtosis are provided for the variables. The variable 'Decision-making efficiency' (DME) exhibits the highest mean response value of 3.936, while the variable 'Fraud detection' (FD) displays the highest Standard Deviation of 0.8896054.

Table 6. Descriptive statistic*s*

	Fraud detection	Fraud prevention	Decision-making efficiency
Mean	3.8933333	3.7626667	3.936
Std Dev	0.8896054	0.7390976	0.6702805
Std Err Mean	0.0795687	0.0661069	0.0599517
Variance	0.7913978	0.5462652	0.449276
Skewness	-0.889043	-0.461398	-0.603085

Kurtosis	0.2143646	-0.312125	0.0361048

The interpretation of the Pearson correlation value offers insights into the opinions and analyses of respondents within the defined research model. All possible connections between the independent and dependent variables show positive directions, indicating a positive correlation between them. The correlation coefficient between Fraud detection powered by AI (FD) and Fraud prevention powered by AI (FP) is 0.8020, indicating a strong correlation. The determination coefficient, representing how accurately Fraud prevention powered by AI (FP) can be predicted based on Fraud detection powered by AI (FD), is 0.6432, equivalent to 64.32%. Similarly, the correlation coefficient between Fraud detection (FD) and Decision-making efficiency (DME) is 0.7789, indicating a strong correlation. The determination coefficient for Decision-making efficiency (DME) in relation to Fraud detection powered by AI (FD) is 0.6066, or 60.66%. Moreover, the correlation coefficient between Fraud prevention powered by AI (FP) and Decision-making efficiency (DME) is 0.8319, reflecting a strong correlation. The determination coefficient for Decision-making efficiency (DME) about Fraud prevention powered by AI (FP) is 0.6920, equivalent to 69.20%. In summary, there exists a strong positive association among all variables, indicating a robust prediction of the dependent variable with the assistance of the independent variables. In Table 7, the extent of contribution from the independent variables, Fraud detection powered by AI (FD) and Fraud prevention powered by AI (FP), in predicting the dependent variable, Decision-making efficiency (DME), is determined. Notably, the independent variable Fraud prevention (FP) demonstrates a greater contribution, measuring at 0.580711, compared to Fraud detection (FD), which stands at 0.313141. The variance increase factor is calculated at 2.8032678.

Table 7. Coefficients for the variables Fraud detection (FD), Fraud prevention (FP), and Decision-making efficiency (DME).

Term	Estimate	Std Error	t Ratio	Prob>|t|	Std Beta	VIF
Intercept	1.0358365	0.165221	6.27	<0.0001	0	.
Fraud detection	0.2359388	0.059678	3.95	0.0001	0.313141	2.8032678
Fraud prevention	0.5266411	0.07183	7.33	<0.0001	0.580711	2.8032678

Based on these findings, the alternative hypothesis **Ha** can be confirmed: *Yes, both Fraud detection powered by AI (FD) and Fraud prevention powered by AI (FP) significantly influence Decision-making efficiency (DME).* A regression equation can be derived from the data provided in Table 4, denoted as Formula 1, which is represented as:

$$\text{Decision} - \text{making efficiency (DME)} = 1.0358365 + 0.2359388 \cdot \text{Fraud detection (FD)} + \\ +0.5266411 \cdot \text{Fraud prevention (FP)} \tag{1}$$

In discussing the final results, the following patterns emerge:As the independent variable Fraud detection powered by AI (FD) increases, there is a significant increase in the dependent variable

Decision-making efficiency (DME). Specifically, for each unit increase in Fraud detection powered by AI (FD), Decision-making efficiency (DME) is expected to increase by approximately 0.5868659 units. Similarly, as Fraud prevention powered by AI (FP) increases, there is a significant growth in Decision-making efficiency (DME). For every unit increase in Fraud prevention powered by AI (FP), Decision-making efficiency (DME) is anticipated to increase by about 0.7544092 units. Additionally, with the growth of both Fraud detection powered by AI (FD) and Fraud prevention powered by AI (FP), Decision-making efficiency (DME) also increases. Consequently, an increase in Decision-making efficiency (DME) could imply higher costs and a rise in the frequency of fraud-related events, while a decrease in Decision-making efficiency (DME) might indicate successful efforts in reducing fraud and associated costs through the implementation of fraud detection and prevention measures.

4. CONCLUSION

In this study on AI-powered fraud detection and prevention, it has been demonstrated that investments in this domain significantly impact the decision-making efficacy of companies. The investigation encompassed several key dimensions: A thorough examination of the existing literature, industry reports, and a case study from Serbia provided insights into the broader landscape of fraud detection and prevention. Although the specific types of fraud were not delineated in this study, the findings offer implications for understanding diverse forms of fraudulent activities, such as identity theft, payment fraud, and insider threats, along with convetional mitigation strategies. By disseminating the findings and insights garnered from this research companies involved in the study can contribute to the collective knowledge base in the field of AI-powered fraud detection and prevention.

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