EVALUATING THE PERCEIVED RISKS OF AI IN SOUTH AFRICAN FINANCIAL INSTITUTIONS: A MULTIDIMENSIONAL APPROACH[1]

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ARTICLE INFO

Original Scientific Paper
Received: 06.12.2024
Revised: 14.05.2025
Accepted: 23.10.2025
DOI 10.63356/ace.2025.010
UDK
336.71(680):[005.334:007.52
COBISS.RS-ID 143722241

Keywords:
artificial intelligence, financial institutions, risk perception, AI governance, organisational risk, South Africa

JEL Classification: G20, O33, D81

ABSTRACT

Risk management procedures in financial institutions around the world have been significantly altered by artificial intelligence (AI). However, little is known about the perceived risks of implementing AI, especially in developing nations such as South Africa. The aim of this study is to assess, from a multidimensional perspective, the perceived risks of AI adoption by employees in South African financial institutions. This study employs a mixed-methods approach, using a purposive and snowball sample of 90 survey respondents and semi-structured interviewees from several South African financial institutions. The study revealed a broad spectrum of concerns ranging from AI-induced unemployment to cybercrime vulnerabilities. The analysis provides layered insights into how different departments, including Risk Management, IT, and Operations Management, uniquely perceive and manage AI-related challenges. This study underscores the need for personalised risk management strategies that meet unique departmental concerns, as well as the importance of strategic planning in the integration of AI technology by financial institutions to maximise potential while limiting associated risks. It adds to the growing body of knowledge on AI adoption in emerging markets by providing practical information to practitioners and policymakers.

1. INTRODUCTION

The fourth industrial revolution (4IR), characterised by the fusion of digital, physical, and biological technologies, is transforming humanity and affects many aspects of life, the work environment and social interactions (Skilton and Hovsepian, 2018). To survive today, businesses such as financial institutions need detailed digital strategies. Artificial intelligence (AI) is an essential component of these strategies, acting as a fundamental tool for adapting to the digital environment. The financial sector in several countries experienced significant growth in the use of financial services due to the application of AI (Kshetri, 2021). Although the use of AI has been extensively researched in developed countries, African countries have limited research that focusses on the use of AI in the banking sector (Maouloud et al., 2022). Most studies on African financial institutions focus on the technological and organisational implications of technology (Mariemuthu, 2019; Coetzee, 2019; Akinwale and Kyari, 2022; Qwabaza, 2022). There is a lack of information on the attitudes of these financial institutions' staff regarding the application of AI. It is important to understand the attitudes, fears and sentiments of the workforce to successfully integrate and use AI in financial institutions. Therefore, the purpose of this study is to understand the perceptions of risk of the financial institution workforce about the use of AI in banking.

AI refers to the simulation of human cognitive processes (Qwabaza, 2022), encompassing technologies focussing on machine learning (ML) and natural language processing (IBM, 2024). The computer programmes that these machines use are designed to mimic human cognitive processes (Hind, 2019), including visual perception, speech recognition, decision-making and translation (Wogu et al., 2017).

Financial institutions use artificial intelligence (AI) to automate procedures, improve decision-making skills and provide data-driven insights (Owen-Hill, 2017; Hind, 2019), to increase operational efficiency, generate cost savings and facilitate significant business transformation initiatives (Fountaine McCarthy & Saleh, 2019). This transformation has led to a change in the way client engagement is primarily conducted, with a shift from traditional face-to-face interactions and product-centric strategies toward a stronger emphasis on providing seamless digital consumer experiences (Jeyalakshmi, 2020; Muregess, 2022).

The banking sector in Africa is also significantly impacted by AI. In Ghana (Domeher, Frimpong & Appiah, 2017), South Africa (Mamela and Mukwakungu, 2020) and Nigeria (Ononokpono, Osademe & Olasupo, 2023), AI has been shown to increase banking efficiency, customer satisfaction and improve risk and regulatory management, as well as security (Rahmani, 2023).

Despite the many advantages of AI, it is important to understand the inherent risks associated with its use. Among the primary disadvantages of AI is job displacement, which increases the unemployment rate (Bonorchis & Burkhard, 2016; Manyika et al., 2017; Darangwa, 2021; Fares, Butt & Lee, 2023; Kanupriya, 2024; Molla, 2024) and algorithm bias (Giudici, Centurelli, & Turchetta, 2023; Oğuz, 2024). Recent studies have highlighted ethical and operational challenges (Smith and Jones, 2023), and calls for robust governance are made (Doe, Roe & Poe, 2024). AI also has an impact on salaries. According to Ashta and Herrmann (2021), AI is expected to cause downward pressure on the remuneration of workers in developed nations.

Understanding employee perceptions of these risks is vital for effective AI integration (Klein et al., 2023). A study by McGee (2024) revealed that the perceived risks associated with AI in financial institutions are significant, and there is a varied understanding of AI risks between institutions. This varied perception is also confirmed by studies in Asia (Kaur & Ali, 2021; Boustani, 2022) and globally (Wittmann and Lutfiju, 2021; Sachdeva et al., 2024). Currently, little research is being done in South Africa (Mariemuthu, 2019; Huang and Rust, 2022; Fares Butt & Lee, 2023; Khan and Hagglund, 2025). By examining and documenting the concerns and perceptions of employees in South Africa's financial sector regarding the use of AI in the workplace, this study aims to address the existing knowledge gap.

2. MATERIALS AND METHODS

The study investigated the perceived risks of AI usage in financial institutions in South Africa, using a mixed-methods approach (El Hajj & Hammoud, 2023). A purposive and snowball sampling strategy was used to recruit participants with direct experience from the Risk Management, IT and Operations Management departments. The inclusion criteria require at least two years of departmental experience and familiarity with AI applications. Potential participants were identified through professional networks and industry associations.

The quantitative sample size was calculated using the Cochran (1977) formula, considering a confidence level of 95% and a margin of error of 5%, resulting in a sample of 385 professionals from the Risk Management, IT and Operations Management sectors. The adequacy of this sample size is supported by previous studies, such as Weller and Tikir (2011), who used a sample size of 233 participants, and Thielmann et al. (2016), who employed a sample size of 120 participants.

To obtain an impartial portrayal of the participants and to assess the degree of diversity among them, the study used stratified random sampling, grouping the initial 385 participants into three distinct strata, each representing a specific field of competence, namely Risk Management, IT and Operations Management. Subsequently, the purpose-sampling technique was used for each stratum to choose representatives who meet the inclusion criteria. The final sample size consisted of 90 experts from the three competencies, based on studies conducted by Sekaran (2003) and Roscoe (1975). Similar sample size was used in studies by Weber, Blais & Betz (2002), Hanochm Johnson & Wilke (2002), Harris and Jenkins (2006), and Weller and Tikir (2011).

Studies by Sandelowski (1995), Creswell & Plano Clark (2011), and Van der Merwe and Nell (2013) were used as a guide to determine the qualitative sample size. A final sample size of 18 specialists in three datasets was selected to warrant data saturation, as proposed by Charmaz (2006). The study adhered to all ethical guidelines by obtaining the necessary ethical clearance, and informed consent was obtained from all participants.

3. RESULTS AND DISCUSSIONS

The survey (with an 84% response rate) prompted strong participation from key departments within South African financial institutions. With a response rate of 93.3%, the IT unit formed the largest response group, followed by Operations Management, with a response rate of 90%, and Risk Management, with a lower response rate of 70%. All participants in the Risk Management unit had previous AI exposure, followed by 85.7% with previous AI exposure in the Operations Management unit. Interestingly, only 71.4% of the IT unit reported previous exposure to AI. Most of the respondents had more than five years of experience (32.6%) and an average of 20% of the three subgroups had less than two years of experience.

Insurance companies dominated the responses (26.3%), with retail and commercial banks second with 23.3%, followed by investment banks (13.2%). Other sectors of the financial industry represented include central banks (11%), Internet banks (9.3%) and broking firms (4.1%), indicating different representations. Sectors such as mortgage companies and credit associations were represented less (5.5% or less), ensuring the inclusion of a variety of sectors within the financial industry.

The first set of questions aimed to determine the perceived adoption of AI in various organisational activities and the range of applications by the various subgroups. Activities include the use of AI for customer interaction, external

communication, fraud detection, insurance and underwriting, credit scoring, logistics management, and how claims are processed. Respondents were asked to indicate their perceived use of AI in various functions using a segmentation from 0 to 20% to 81 to 100%. The results are depicted in Figure 1 below.

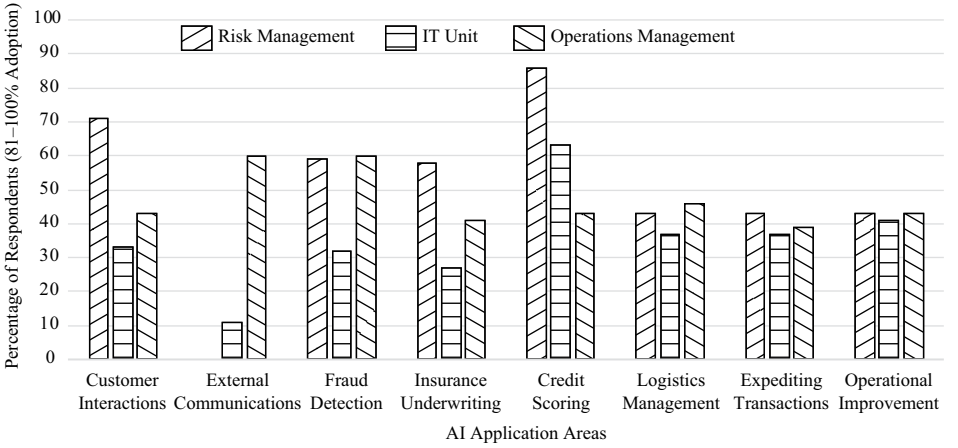

Figure 1: Patterns of AI adoption in units
Source: Authors' calculations

The varied levels of adoption of AI between units in South African institutions, with a focus on high-level applications (81-100%) in domains, show that fraud detection, customer interactions and operational improvement are important. The considerable use of AI, especially in the areas of fraud detection (57.1%) and credit scoring (85.7%), demonstrates the strategic focus of the Risk Management unit on applying AI to improve compliance and financial security. These findings align with studies by Press (2019), which emphasised the value of AI in identifying anomalies and lowering the risk of fraud in financial institutions.

In the Operations Management unit, AI is also frequently used in logistics management (46.2%) and customer interactions (42.9%). Our customer-interaction results mirror those of Muregess (2022), who determined that chatbots are essential for improving customer experience by providing efficient and customised interactions. Furthermore, the IT unit exhibits strong AI integration in areas such as logistics (36.4%) and transaction acceleration (36.4%), which is consistent with research by Manyika et al. (2017) that highlighted supply chain optimisation and logistics as the main benefits of AI-powered ML applications.

Additionally, our findings revealed a broad perception of AI's use in fleet management, transaction acceleration and external device monitoring,

highlighting the various institutions' emphasis on the perceived use of AI for operational efficiency and management procedures. The three departments showed a high perceived use of AI in transaction speeding, external device and system monitoring, and fleet management. These results support the findings by Huang and Rust (2022) that AI can be used by delegating routine tasks to algorithms, freeing human resources for strategic responsibilities. They also underscore the need to take advantage of AI to streamline processes across departments within an organisation.

Despite these perceived adoptions mentioned above, the units show varying acceptance rates for the other variables tested. Only 11.8% of IT respondents reported a high use of AI in external communications, which is quite limited and reflects the reluctance to use AI in public-facing jobs due to algorithm biases and reputational risks. This result is consistent with that of Fares Butt & Lee (2023), who noted similar apprehension in businesses, especially in areas where AI affects the participation of external stakeholders.

The findings indicate that consistent departmental objectives influence the extent of perceived AI adoption. Technical efficiency is given greater importance by the IT unit; customer-facing and logistics procedures are the focus of Operations Management, and security and compliance are the primary focus of the Risk Management unit. These results are in line with research by Boukherouaa et al. (2021), who discovered that company culture and operational priorities have an impact on the adoption rates of AI across industries.

In general, the perceived use of AI by South African financial institutions demonstrates a diverse, yet well-balanced, integration in key operating areas. Although perceived adoption patterns are in line with global trends, the South African environment complicates the implementation of AI technologies due to factors such as labour readiness, departmental objectives, and regulatory challenges and brings complexity to the use of AI technologies. These results highlight the need for customised approaches that align AI integration with organisational goals to achieve optimal effectiveness and impact.

The next set of questions explored how various units within financial institutions, i.e., Risk Management, IT, and Operations Management, perceive risk with the adoption of AI. Our objective is to learn more about the various concerns and goals within the financial sector by examining their responses to questions about possible risks associated with the deployment of AI. Figure 2 highlights the importance of strategic risk management in navigating this transformative era and offers a brief overview of the prospects and difficulties related to the integration of AI in financial institutions.

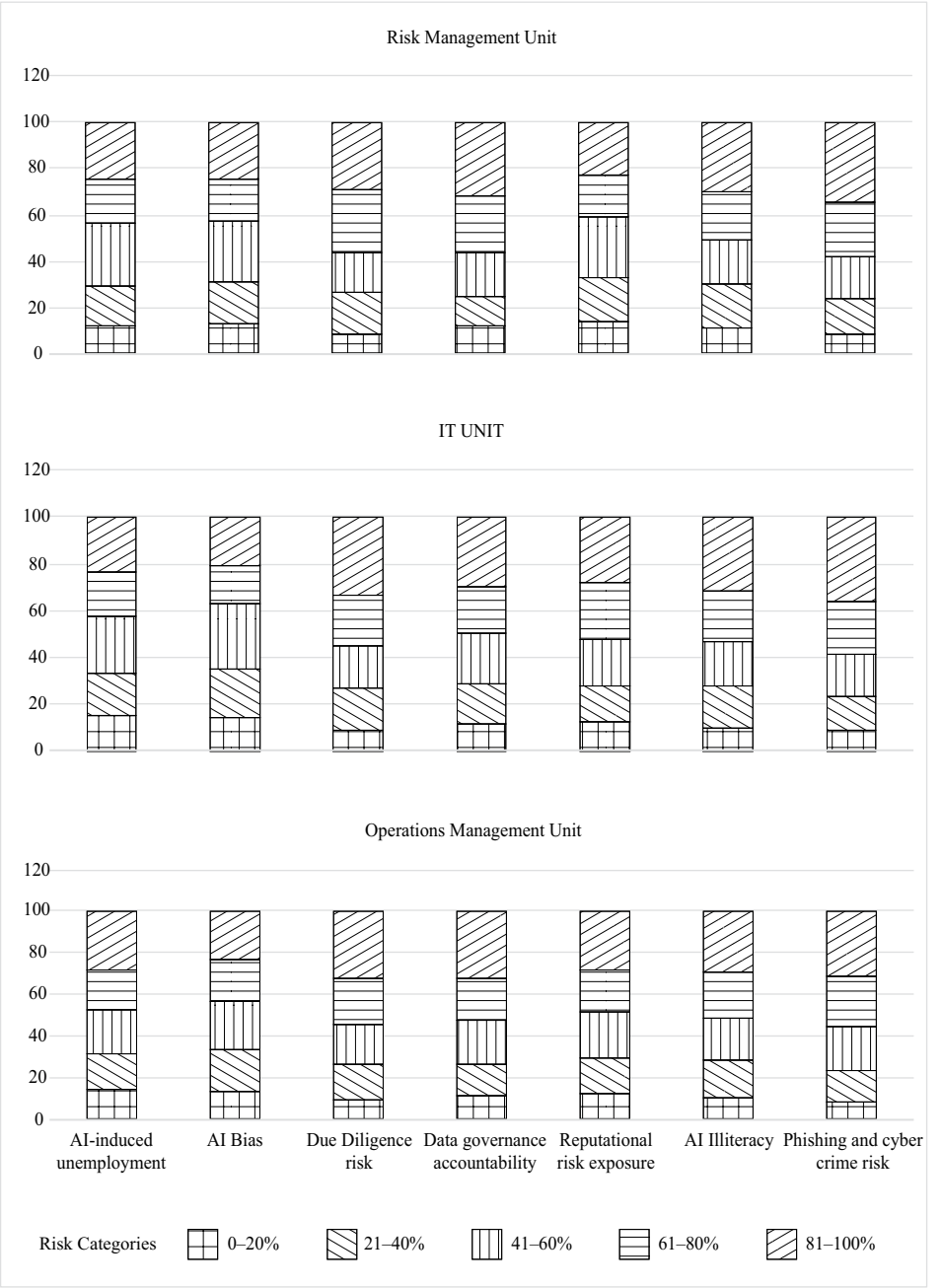

Figure 2: Perceptions of risk associated with AI use per unit
Source: Authors' calculations

Several commonalities become evident when examining the perceived risk responses of the various units. While Darangwa (2021) and Ashta and Herrman (2021) predicted significant workforce reductions, our findings align with Klein et al. (2023), which show department-specific impacts. The anxiety of operations managers about role obsolescence (87% expressed concern) contrasts with the focus of IT on skill adaptation.

Another major perceived risk that we have identified is the risk of AI bias. Many respondents expressed concern about the lack of explainability in AI-driven decision making (for instance, credit scoring or fraud detection algorithms whose inner workings are not transparent). Several respondents from Operations and Risk Management expressed their concern that this can result in reputational risk, as these errors can go undetected until harm occurs. Both units indicated that AI bias is universal risk, categorising it as moderate risk (61-80% risk category). This aligns with the findings of Fares Butt & Lee (2023) who determined that there exists a critical need for fairness in AI systems to mitigate bias in decision-making.

Regarding due diligence risk, 57.1% of the respondents in the Risk Management unit rated it as moderate risk, while 38.5% of the respondents in the IT unit indicated it as high risk (81-100% risk category). These findings echo the recommendations of Huang and Rust (2022), who emphasise the importance of solid governance mechanisms to handle compliance and legal issues in AI implementation.

42.9% of the respondents in the Risk Management unit felt that data governance accountability is a significant risk, while 50% of the respondents in the IT unit felt that data governance accountability is a moderate risk. All units indicated that accountability for errors in nonrepresentative data is a critical concern. The IT unit also indicated that reputational risk is a moderate concern, as stated by 58.3% of the respondents.

A major issue was the lack of proper AI training, especially for the Risk Management unit, where 71.4% of the respondents indicated that the risk was severe (81-100%). Notable concerns were also expressed by the Operations Management unit, which saw AI illiteracy as a critical issue (42.9%). These results are consistent with those of Boukherouaa et al. (2021), who support employee training as a tool to facilitate the successful integration of AI.

The importance of cybersecurity measures was indicated as a concern between units, with 57.1% of the Risk Management respondents indicating it as a critical risk (81-100% risk category), supported by 25% of the IT unit and 30.8% of

the Operations Management unit respondents. These concerns are supported by Faures et al. (2023), who highlighted confidentiality and cybersecurity as key barriers to the widespread adoption of AI in the financial sector, and by Chen et al.'s (2022) model of AI vulnerability that surfaces in financial systems.

The unique priorities and operational challenges of each unit are reflected in the differences in perceived risks between the organisational units. The IT unit stresses cybersecurity and reputational risks, the Operations Management unit raises concerns about workforce-related challenges and fairness in AI systems, and the Risk Management unit concentrates on AI illiteracy, pirating, cybercrime risk and reputational risk exposure. Customised unit-specific risk mitigation strategies that complement the more general objectives of ethical and effective AI integration will be needed to ease these concerns. A blanket approach will not address the perceived risks related to AI in the various units.

The interviews conducted with professionals from South African financial institutions provided useful insights into the perceived risks and challenges associated with the implementation of AI. Data saturation was reached after six professionals were interviewed. They were an investment banker, a senior business analyst, an insurance commission manager, an IT systems administrator, a development manager who oversees system enhancements, and a project manager responsible for IT-related project execution.

The results of the interview reveal a terrain marked by both difficulties and possibilities. Participants unanimously raised concerns about the insufficient preparation for AI implementation, underscoring the need for comprehensive initiatives to address this preparedness gap. The importance of strong measures to protect sensitive information was highlighted, focussing on the primary issues of data security and privacy. The perception of a significant danger in job displacement and workforce changes has highlighted the need to prioritise the development of new skills and the acquisition of additional knowledge to facilitate the transition to a more automated work environment.

The findings suggest that South African financial institutions have both a positive view of the ability to bring about significant changes and a cautious attitude due to concerns about ethical considerations, regulatory compliance, and impact on the workforce. The results indicate that a well-balanced and careful strategy is necessary for the effective integration of AI in the financial sector. This approach should prioritise continuous education, cooperation between organisations and careful risk management.

The themes that emerged from the interviews highlight the complex issues surrounding the use of AI in financial institutions in South Africa. Institutions should adopt a holistic approach that considers increasing organisational readiness (Fountaine, McCarthy & Saleh, 2019), strengthening data governance (Press, 2019), training of the workforce (Manyika et al., 2017), and encouraging ethical AI practices (Fares, Butt & Lee, 2023).

4. LIMITATIONS AND FUTURE RESEARCH

Although this study provided valuable information on perceived AI risks in South African financial institutions, it is important to recognise several limitations. First, the research is limited in scope and focusses geographically only on South African financial institutions, which may limit the generalisability of the findings. Cultural, economic (South Africa being a developing economy with a dualistic nature) and regulatory factors specific to South Africa could influence risk perceptions in ways that are not applicable to other regions. Future research should consider a larger and more varied sample, including financial institutions from other countries and at different levels of economic development. Stakeholder groups could also be expanded to include customers, regulators and fintech entrepreneurs, as these groups may perceive AI risks differently.

The use of self-reported perceptions, which are prone to bias based on optimism or fear, limits our analysis. While some subjectivity was mitigated by anonymity assurances and mixed-methods triangulation, objective indicators of AI adoption and performance should be included in future studies to supplement surveys and interviews. Some indicators to consider are deployment footprint, AI usage intensity, performance and efficiency metrics, risk and compliance data reports, customer-impact measures, human resources effects and financial outcomes. A more comprehensive assessment of AI adoption and its practical consequences will be possible through the collection and analysis of such system-generated metrics than by using perception data alone.

Our study also captured a snapshot in the time of AI perception during a period of rapid technological advancement. The significance of this study may be limited because our data had been collected before some of the most recent advances in AI, which may have excluded concerns such as hallucinations. To investigate the long-term impacts of AI adoption on risk perceptions and organisational outcomes, longitudinal studies are required.

A final limitation of our study was that its scope was based on perceptions rather than objective risk measures. We did not evaluate actual risk management

results or AI-related failures. Future research might integrate objective AI risk assessments (such as algorithm bias audits, security penetration testing results, or incident reports of AI failures) and examine their relationships with perceived risk. Correlating perceived risks with actual risk indicators can reveal where perceptions over- or underestimate real risks. This could help improve risk communication and training.

5. CONCLUSIONS

The purpose of this research was to evaluate the perceived risk attitude in the adoption of AI in South African financial institutions. The study found that several factors influence the adoption of AI in South African financial institutions. These factors include the level of trust in AI technology, understanding its potential and limitations, the regulatory openness of compliance issues, and the ability of financial institutions to adopt modern technologies.

Surprising patterns emerged when perceived risk responses were examined in the various units. While Risk and Operations Management exhibit higher perceived risks, primarily falling within the 81 to 100% range, the IT unit mainly perceives risks in the 61 to 80% range. The level of focus and skill that each unit possesses could be a possible factor contributing to this inconsistency. Given its experience and confidence in handling cybersecurity threats and complex technology systems, the IT unit can identify risks in a range that corresponds to these challenges. However, the Risk Management and Operations Management units, which oversee operational continuity and comply with regulations, could prioritise and see risks differently, which could explain the higher concentration in the 81 to 100% range. The interviews confirmed this as AI literacy emerged as an important element in managing perceived risks.

Although South African financial institutions show increasing interest in implementing AI, the study found that their risk attitudes are still influenced by concerns about data security, ethical implications, and job losses and displacement. This study highlights how crucial it is to address these complex issues to help South African financial institutions implement AI. To effectively manage and reduce perceived risks associated with the adoption of AI technology, a complete approach that combines technological preparedness, regulatory frameworks and a proactive effort to develop trust in technology, is needed.

ACKNOWLEDGEMENTS

An AI generator was used to translate the abstract into Serbian and an AI-powered editing application to refine the grammar of the text.

Conflict of interest

The authors declare that there is no conflict of interest. Furthermore, the authors declare that no funding was received for the study and that the results presented are unbiased.

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ПРОЦЈЕНА ПЕРЦЕПЦИЈЕ РИЗИКА ВЈЕШТАЧКЕ ИНТЕЛИГЕНЦИЈЕ У ФИНАНСИЈСКИМ ИНСТИТУЦИЈАМА ЈУЖНОАФРИЧКЕ РЕПУБЛИКЕ: МУЛТИДИМЕНЗИОНАЛНИ ПРИСТУП

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САЖЕТАК

Процедуре управљања ризиком у финансијским институцијама широм свијета значајно је измијенила вештачка интелигенција (AI). Међутим, мало се зна о перципираним ризицима имплементације AI, посебно у земљама у развоју као што је Јужноафричка Република. Циљ ове студије јесте да, из мултидимензионалне перспективе, процијени перципиране ризике усвајања AI од стране запослених у финансијским институцијама Јужноафричке Републике. Ова студија користи приступ мјешовитих метода, примењујући сврсисходан и узорак сњежне грудве од 90 анкетираних испитаника и полуструктурираних интервјуисања из неколико финансијских институција Јужноафричке Републике. Студија је открила широк спектар забринутости, од отпуштања изазваног AI до рањивости на сајбер криминал. Анализа пружа слојевите увиде у то како различита одјељења, укључујући управљање ризиком, ИТ и управљање операцијама, на јединствен начин перципирају и управљају изазовима везаним за AI. Ова студија истиче потребу за персонализованим стратегијама управљања ризиком које одговарају специфичним потребама одјељења, као и важност стратешког планирања приликом интеграције AI технологије у финансијским институцијама како би се максимизирао потенцијал уз ограничење повезаних ризика. Она доприноси растућем тијелу знања о усвајању AI у земљама у развоју и пружа практичне информације за практичаре и доносиоце политика.

Кључне ријечи: *вјештачка интелигенција, финансијске институције, перцепција ризика, управљање AI, организациони ризик, Јужноафричка Република.*