

Midocean University

College of Management

Department of Risk Management



The Impact of The Artificial Intelligence on The Risk Management of the Organizations at the Private Sector in Saudi Arabia

**أثر الذكاء الاصطناعي على إدارة المخاطر في منظمات في القطاع
الخاص في المملكة العربية السعودية**

Student Name:

Abdalmohsin Mohammed Bin Kelaib

Student ID: 222000928

Supervised by:

Dr. Walid Soliman

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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

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Dedication

I thank God Almighty first and foremost for the great grace that He has bestowed upon me, then I thank those who favored them. My beloved parents do not cease to me for all their efforts from the moment of my birth to these blessed moments. For everyone who advised me, guided me, contributed, or directed me with me in preparing this research and connecting me to the required references and sources at any of the stages it went through, and I especially thank the distinguished professor Walid Soliman for helping me Supporting me and guiding me with advice, education, correction, and all that he did with me.

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Abstract

This current research aims to identify the impact of the artificial intelligence on the credit risk management, operational risk management, and enterprise risk management of the organizations at the private sector in Saudi Arabia. The research conceptual model developed for this research, whereas the independent variable (IV): “Artificial Intelligence (AI)”. Also, the dependent variable (DV) “Risk Management”. The deductive quantitative approach will be used to understanding the relationships between the research variables. The main data for the research will gather using a Google Forms survey. It will use the non-probability sampling technique through using a convenience sampling for all employees at the private sector in Saudi Arabia via an online questionnaire. The research data will be analyzed using SPSS software. The research analysis will be done quantitatively. Hence, the findings of this research are that hypotheses (H1, H2, H3) are satisfied.

Keywords: *“Artificial Intelligence (AI)”, “Risk Management”, “Credit Risk Management”, “Operational Risk Management”, “Enterprise Risk Management”.*

Chapter One

Introduction

1.1 Introduction

In the current technological development, Artificial Intelligence (AI) has seen rapid growth and application in a variety of domains. AI has a major impact on institutions and policies. AI is playing increasingly important roles in different sectors as a result of the growth and applications of AI (Naim, 2022). AI is based on the replication of human intelligence concepts (Aldahwan & Alsaeed, 2020). The goal of AI is to create machines that can perform tasks that are normally performed by humans. There are many well-known and advanced areas of AI, including Expert Programs, Fuzzy Logic, Genetic Analytics, Language Analysis, and Logic Programming (Castaño et al., 2020). As a result of AI's innovative and strong applications and benefits, AI is presented as the most effective and innovative tool for other disciplines. In the present scenario, this technology is the only one that can be compared with the intelligence of humans and can be trusted for its results (Naim, 2022).

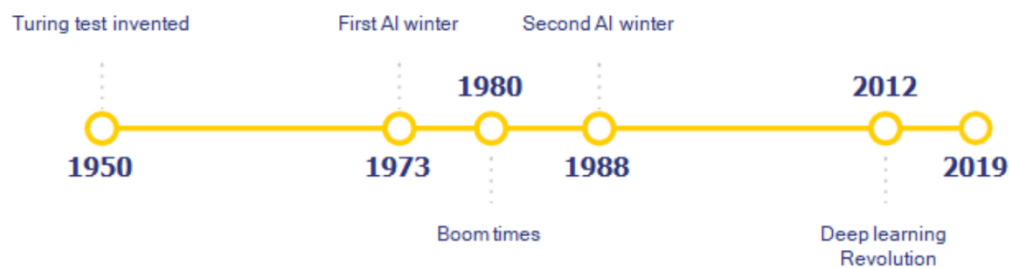


Figure (1): Growing role of AI, taken from (Naim, 2022).

Using AI enables the integration of technology and concepts and provides a better return on investment, as well as other tangible and intangible benefits. The advantages may include risk assessment. Through the application of AI, Risk Management's (RM's) competencies have been enhanced. Moreover, AI has many benefits, but there are also some concerns as well. The rise of artificial intelligence has exacerbated ethics issues, increased digital divide, and led to biased decisions. AI should also be monitored for strategic planning at organizational and industrial levels (Naim, 2022). By analyzing large amounts of data, identifying patterns and trends, and making predictions based on historical data, AI can provide valuable insights and improve risk management. It's important to note, however, that AI is not a silver bullet, and must be used alongside human expertise and judgment to be effective (Velibor Bozic, 2023).

Further, risk managers should position themselves as value drivers within their organizations and as AI risk advisers to the board and senior management. Risk managers are typically not

technical experts. By combining risk management skills with an understanding of the organization and broad digital understanding, this person will be able to add value. A risk manager will also require a minimum level of digital knowledge, which will need to be updated on a regular basis. Risk management across various industries relies heavily on artificial intelligence (AI). Organizations can identify, analyze, and mitigate risks more efficiently and effectively by using advanced algorithms and machine learning techniques (Naim, 2022). Additionally, risk management is among the most critical factors affecting the competitiveness of small and medium-sized enterprises (SMEs) (Žigienė et al., 2019). In spite of the potential benefits AI can bring to Saudi Arabia, there are also potential risks, such as job displacement, discrimination, and cybersecurity threats that may impede Saudi Vision 2030's economic progress (Al Anezi, 2021).

Therefore, the Saudi Data AI Authority (SDAIA) and international companies could establish partnerships to support AI research by continuing to employ AI applications in their businesses. The scope of AI will almost certainly increase after 2030 when it affects the economy and society. The contributions of AI to the Saudi Arabia's economy will reach USD 135.2.2 billion by 2030. All future projects and cities in the Kingdom of Saudi Arabia will be based on AI technologies, and the Kingdom intends to invest heavily in this promising field with high profits (Aljohani & Al bilwi, 2022). The use of artificial intelligence has been demonstrated in a variety of fields in South Africa, including engineering, economics, manufacturing, education, and medicine (Ashehri, 2019).

This current research aims to identify the impact of the artificial intelligence on the risk management of the organizations at the private sector in Saudi Arabia. Moreover, this research proposal discussed the research background, the research questions, and the objectives. Further, the hypothesis regarding the relationship between the research variables “Artificial Intelligence (AI)”, and “Risk Management” are also formulated. Furthermore, the significance of the research is also provided. The research problem statement is also addressed, as well as ethical considerations. Finally, the content of this research is outlined.

1.2 Problem Statement

The Fourth Industrial Revolution (4IR) has resulted in numerous technology developments that enable enterprises to switch from conventional brick-and-mortar operations to operations with digital capabilities. AI is one such technology. Credit risk, market risk, operational risk, and enterprise risk are the four main AI applications for risk management that have been found by researchers (Aziz & Dowling, 2018). According to the investigations, businesses are

spending money on AI technologies to automate repetitive operations and boost productivity. However, according to (Lee et al, 2020), the adoption of AI technology into risk management procedures has been slow. Data accessibility, openness, and ethical considerations when using digital tools like artificial intelligence provide difficulties for risk functions (Aziz & Dowling, 2018). Due to these difficulties, decision-making in risk management has historically been primarily subjective. This needs to change to data-driven decision-making, which is methodical. So, this study aims to identify the impact of the artificial intelligence on the risk management of the organizations at the private sector in Saudi Arabia, Also, identifying the risks that can be resulted from the AI implementation in risk management.

1.3 Study Purpose/Objectives

This research has the following objectives:

1. Identify the impact of applying artificial intelligence on the credit risk management.
2. Identify the impact of applying artificial intelligence on the operational risk management.
3. Identify the impact of applying artificial intelligence on enterprise risk management.
4. Identify the risk resulted from implementation AI in risk management.

1.4 Research Importance

There are main reasons for this research, as outlined below:

- 1- There is a lack of the literature reviews in the research topic in Saudi Arabia, the research's results are important in order to provide a deep understanding for the impact of the artificial intelligence on the risk management of the organizations at the private sector in Saudi Arabia. Further, this research has been tested the conceptual framework in a new context in Saudi Arabia.
- 2- This research is crucial for many employees as it will provide the best guide to using artificial intelligence if employees understand its advantages. According to Naim, (2022), there is a growing recognition of AI's potential. A growing number of people are becoming aware of the potential of artificial intelligence. In the context of risk management, key benefits will include data processing; the use of structured and unstructured data in massive amounts; combining datasets and updating patterns; increasing and enhancing efficiency by automating day-to-day guidance and assistance; a real-time and predictive approach such as being aware of new exposures, increasing risk prevention advices, and responding quickly to critical situations.

- 3- Furthermore, the managers will be able to make better decisions, and keep improving their skills, thus they can perform better. According to (Naim, 2022), risk managers can use AI to identify key areas where AI can be applied. Risk management steps that need to be improved, claims occurring, lines of business, and total cost of risk (TCOR), risk managers can use this matrix in accordance with their organization's specific needs and benefits.

1.5 Research Questions

The research main questions are addressed as the following:

Q1. What is the impact of applying artificial intelligence on the credit risk management in Saudi Arabia's private organizations?

Q2. What is the impact of applying artificial intelligence on the operational risk management in Saudi Arabia's private organizations?

Q3. What is the impact of applying artificial intelligence on the enterprise risk management in Saudi Arabia's private organizations?

1.6 Research Hypotheses

As the following, the research hypothesis is determined below:

H1: The Artificial Intelligence Has a Positive Impact on The Credit Risk Management.

H2: The Artificial Intelligence Has a Positive Impact on The Operational Risk Management.

H3: The Artificial Intelligence Has a Positive Impact on The Enterprise Risk Management.

1.7 Theoretical Model

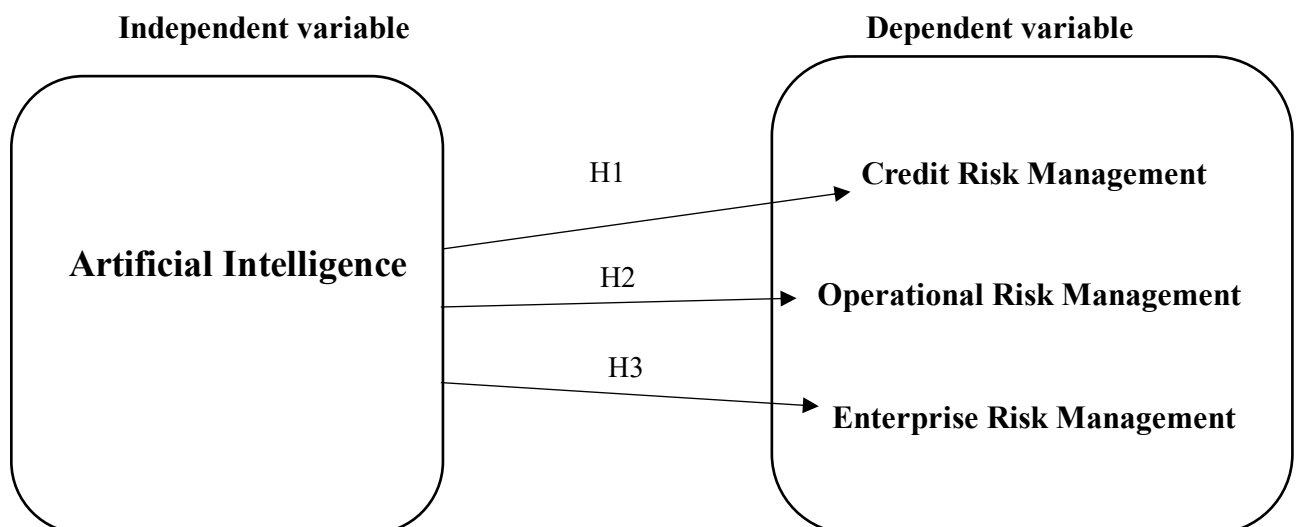


Figure 2. Research Model has been created for the research's purpose.

1.8 Research Limit:

- **Human:** This research will focus on the employees at the private sector in Saudi Arabia.
- **Spatial:** This research will be in Saudi Arabia.
- **Temporal:** This research will be conducted in 2024.

1.9 Research Terminologies:

- **Artificial Intelligence AI:** “is the use of algorithms, the term algorithm refers to a specific instruction for solving a problem or performing a calculation” (Sheikh et al., 2023).
- **Risk Management:** “Risk management is the systematic application of management policies, procedures, and practices to the tasks of analyzing, evaluating, controlling and monitoring risk (the effect of uncertainty on objectives), and it is the identification, assessment, and prioritization of risks followed by coordinated and economical application of resources to minimize, monitor, and control the probability and/or impact of unfortunate events or to maximize the realization of opportunities” (Nichols, 2011).
- **Credit Risk Management:** “Credit risk management is a structured approach to managing uncertainties through risk assessment, developing strategies to manage it, and mitigation of risk using managerial resources, the strategies include transferring to another party, avoiding the risk, reducing the negative effects of the risk, and accepting some or all of the consequences of a particular risk” (Achou & Tenguh, 2008).
- **Operational Risk Management:** “Operational risk is the risk of losses arising from the materialization of a wide variety of events including fraud, theft, computer hacking, loss of key staff members, lawsuits, loss of information, terrorism, vandalism and natural disasters, while Operational risk management is an activity that banks, and firms in general, have indulged in for a long time “ (Moosa, 2007).
- **Enterprise Risk Management:** “process, effected by an entity’s board of directors, management and other personnel, applied in strategy setting and across the enterprise, designed to identify potential events that may affect the entity, and manage risk to be within its risk appetite, to provide reasonable assurance regarding the achievement of entity objectives” (Beasley et al., 2005).

1.10 Research Structure

There are five chapters in the research as below:

Chapter One: It covers an overview of the research, the problem, the objectives, research importance, research model, the research question and hypotheses, the research terminology, the content of the research, and the ethical consideration.

Chapter Two: A critical literature review relevant to this research is presented in the second chapter; it summarizes the literature previously published in highly ranked academic journals, identifies gaps, and provided the relationship between the research variables.

Chapter Three: Research methods and methodology are discussed in the third chapter. The research design, research approach, research population, research sample, and analysis are discussed.

Chapter Four: The results are presented in the fourth chapter. Analyzing the research data and testing hypotheses are described in tables and figures.

Chapter Five: In this chapter, it includes a summary of the findings, discussion, implications, limitations for this research, and further recommendations for future researchers.

Chapter Two

Literature Review

2.1 Introduction

Organizations are continually seeking effective strategies to identify, assess, and mitigate risks that threaten their continuity. According to (Jackson et al., 2023), AI has become a transformational force in tackling these issues. Artificial Intelligence (AI) in risk management signals a revolutionary change toward more complex, data-driven decision-making processes in the credit, enterprise, and operational domains, this chapter serves as the theoretical basis for the investigation, with a particular emphasis on the connection between risk management and artificial intelligence (AI). It looks at the ways that artificial intelligence (AI), a potent and cutting-edge technology, interacts with different risk management techniques to improve operational efficiency, detect fraud, and make better decisions. The chapter looks at how AI is changing traditional risk management techniques in several industries, emphasizing how it affects risk identification, assessment, and mitigation. This part lays the groundwork for comprehending the dynamic interaction between AI technologies and risk management procedures through a survey of the literature and theoretical frameworks.

2.2 Dependent Variables:

2.2.1 Artificial Intelligence (AI)

Artificial intelligence (AI) is the only technology that can be compared to human intelligence and has a degree of reliability in its findings. It is portrayed as the most powerful and inventive tool for other disciplines, with many beneficial uses (Naim. 2022). Artificial Intelligence (AI) encompasses a wide range of technologies, including machine learning algorithms, natural language processing (NLP), data analytics, and predictive maintenance systems (Kalogiannidis et al., 2024).

According to (Naim, 2022), Artificial intelligence (AI) is essential to risk management in many different types of businesses. By using complex algorithms and machine learning techniques, artificial intelligence (AI) may help businesses discover, analyze, and mitigate risks more effectively and quickly. AI improves risk management by: - Identifying risks from multiple data sources, enabling proactive mitigation. - Determining the likelihood and severity of risks in order to allocate resources and set priorities. - Using pattern recognition to detect

fraud in order to stop losses and safeguard reputation. - Controlling credit risk by forecasting the probability of borrower default and making better lending decisions. Improving cybersecurity to safeguard sensitive data by identifying anomalies and threats.

According to (Bozic, 2023), Artificial Intelligence (AI) can play a significant role in enhancing integrated risk management practices. In Risk Identification and Assessment: AI is capable of analyzing enormous volumes of data from several internal and external sources to spot possible threats and evaluate their effects. AI helps firms proactively manage risks by using machine learning algorithms to find patterns, anomalies, and correlations that human analysts might miss. In predictive analytics: artificial intelligence (AI) may create predictive models by combining real-time data with historical data. By predicting possible dangers and their chance of happening, these models help businesses spend resources wisely and take preventative action. Algorithms driven by AI, for instance, might examine consumer behavior, market trends, and economic data to forecast financial hazards or spot new cybersecurity dangers. In Cybersecurity: Artificial Intelligence is a vital component of cybersecurity protection. It is capable of continuously observing system logs, user activity, and network traffic in order to identify and address possible security risks. Artificial intelligence (AI)-enabled systems are able to recognize trends that point to malevolent activity, like malware infections or illegal access attempts, and can then set off automated reaction systems or instant notifications. In Fraud Detection: Artificial Intelligence (AI) has the potential to detect fraudulent activity and irregularities in financial transactions, insurance claims, and procurement procedures. AI systems are able to identify suspicious activity by evaluating vast amounts of data and using pattern recognition techniques. This lowers the possibility of monetary losses and harm to one's reputation. In Compliance Monitoring: By automating the monitoring of enormous volumes of data, AI can assist enterprises in adhering to rules and guidelines. It could examine emails, documents, and transactions in order to spot possible infractions including insider trading, money laundering, and breaches of data privacy. AI can also help in enacting regulatory changes and evaluating the efficacy of internal controls. In Decision Support: AI can offer insightful analysis and helpful suggestions to enhance risk management decision-making procedures. AI algorithms can provide risk scenarios, evaluate their possible impact, and recommend the best course of action for mitigating risks by evaluating large, complicated data sets. This can increase risk allocation, assist firms make better decisions, and improve the effectiveness of risk management as a whole.

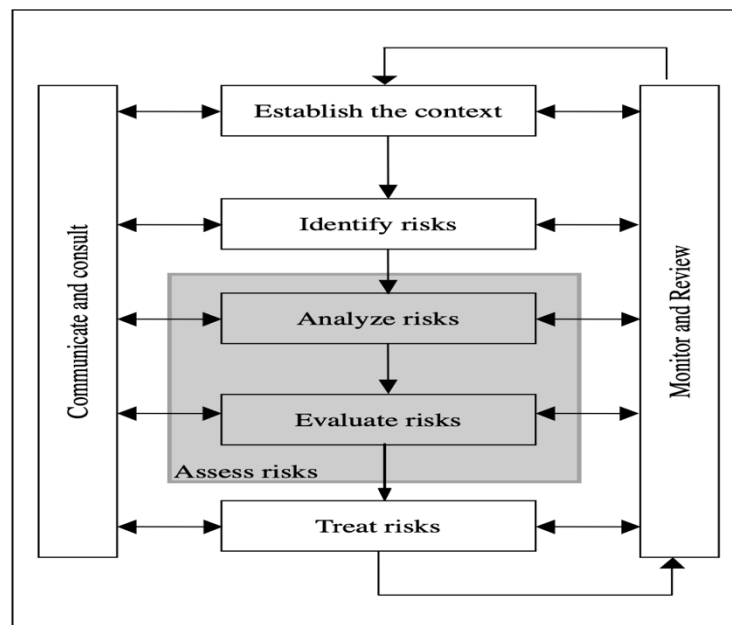
2.3 Independent Variables:

The research independent variables are determined as the following:

2.3.1 Risk Management

Unexpected circumstances can occur in projects and lead to outcomes that deviate from the plan, either positively or negatively. While unfavorable outcomes result in a loss, favorable outcomes present opportunity. Risk management is about preventing losses from unforeseen circumstances (Ahmed et al., 2007). According to (Risk Management Standard AS/NZS 4360, 1999), the risk management process is the systematic process of identifying flaws in the techniques employed in product development so that prompt mitigation activities are taken to minimize risk, transfer risk, reduce risk likelihood, or lessen risk effect as shown in (FIG 1).

Integrated risk management (IRM) refers to the coordinated and strategic approach to identifying, assessing, and mitigating various risks across an organization. It involves combining different risk management disciplines, such as operational risk, financial risk, compliance risk, and strategic risk, into a unified framework (Bozic, 2023).



Figure(3):Representation of the risk management process (Ahmed et al., 2007).

2.3.1.1 Risk Management Strategies

Risk-informed, cautious/precautionary, and discursive techniques are the three main approaches that are frequently employed to manage risk (Aven, 2016). Another name for the precautionary/cautionary approach is a robustness and resilience strategy. The best course of action would typically involve combining these three tactics: First, the "risk-informed

strategy" describes how risk is handled using either an absolute or relative risk assessment method for risk avoidance, reduction, transfer, and retention (Aven, 2016).

Second, the precautionary/cautionary approach emphasizes features such as containment, the creation of alternatives, safety considerations, redundancy in the design of safety devices, immune system strengthening, diversification of methods for achieving similar or identical goals, flexible response options in system design, and enhanced emergency management and system adaptation conditions. The capacity to correctly interpret signals and the early warning signs of major occurrences is crucial in this situation. These concepts form the foundation of all risk rules in order to address uncertainties, hazards, and the possibility of surprises (Aven, 2016).

Third, the discursive strategy employs steps to increase confidence and dependability, including facts clarification, the removal of doubts and ambiguities, the involvement of those who will be impacted, accountability, and discourse (Aven, 2016).

2.3.1.2 Risk Management Categories

- ***Credit Risk Management:***

Credit risk is one of the most significant subjects in banking and finance since the loan application procedure demands careful consideration to determine the likelihood of repayment (Mhlanga, 2021). It is important to use caution and attention to prevent needless losses. Financial institutions should consider the debtor's past and present circumstances before making a loan. Credit risk can take many different forms, and it always depends on the kind of debtor and the financial instrument's class (Gu et al., 2018). For example, different debtors have distinct features, such as the government, private corporation, and individual. Furthermore, the processes involved in providing a loan and trading financial derivatives are entirely dissimilar (Mhlanga, 2021).

- ***Business / Enterprise Risk Management (ERM):***

There are two fundamentally distinct approaches that an enterprise can take to risk management: (1) managing one risk at a time, in a highly segmented and decentralized manner; or (2) managing all risks collectively within a coordinated and strategic framework. The term "enterprise risk management," or "ERM," is frequently used to refer to the latter strategy. (Nocco & Stulz, 2006) argues that businesses which are successful in establishing an efficient ERM will have a sustained competitive advantage over those that handle and track

risks on their own. So, any organization can enhance its ability to execute its strategic plan by assessing and controlling its risks in a systematic and consistent manner, as well as by providing its business managers with the knowledge and motivation to maximize the trade-off between risk and return (Nocco & Stulz, 2006).

- ***Operational Risk Management:***

Operational risk management (ORM) is critical for any organization, The largest category of risks is by far operational risk. It is defined as everything that is not credit or the market in its fullest sense. It might include anything from a shift in the payment terms on a foreign exchange transaction to a natural disaster that results in the loss of a major trading facility. It covers things like fraud, legal and regulatory concerns, insufficient systems, improper supervision, improper controls, incorrect organizational structure, and human mistake. Portfolio, organizational, strategic, people, change management, operations, currency, country, credit rating shift, reputation, taxation, legal, business continuity, and regulatory or compliance risks are all examples of operational risk (Namazian & Eslami, 2011).

2.4 Pervious Studies

Companies and governments need to identify various models and theories to develop risk management strategies. Artificial intelligence assists in managing risk factors by implementing theories and models in the risk management process. The purpose of this paper is to provide an assessment of certain theories and models that businesses can use to develop risk management strategies. An analysis of the iceberg model of risk, stakeholder theory, and agency theory is included. Furthermore, an analysis of AI risk allows an organization to detect fraud processes (Al balooshi, 2018). Additionally, in order to manage risk effectively, organizations must analyze stakeholders based on the stakeholder theory (Citron & Pasquale, 2014). While in this theory, problems or issues relating to agency are assessed. An agency problem occurs when principles and agents have conflicts of interest, as suggested by New et al., (2015).

This paper (Al balooshi, 2018) explores the relationship between AI and risk management as well as developing an understanding of artificial intelligence. This paper examines how businesses and governments are impacted by artificial intelligence and its challenges. A primary qualitative data analysis and a secondary thematic analysis were used for the purposes of this study. As part of the primary data collection method, the researcher interviewed senior level employees of leading organizations, including the research department and risk analytics

department. The majority of participants displayed a positive attitude toward artificial intelligence. An organization's risk management framework can be enhanced with artificial intelligence, according to the majority of respondents.

A study by Barta & Göröcsi, (2021), the paper analyses the nature of risks AI can bring to corporations and countermeasures that should be implemented using an overview of general IT risk assessment processes and stages of intelligent systems development. Furthermore, the article provided guidelines for implementing business processes to address risks associated with intelligent decision making through frameworks for AI risk management.

A study by (Naim, 2022), this paper also describes three cost modeling methods and challenges using AI techniques. Cost estimation and modelling can be done in three ways: Analog, Analytic, and Parametric. The results suggest strategies and applications of AI for financial risk management. It has been suggested that there is a need to enhance the application of artificial intelligence to financial risk management by investing in R&D and applications of encryption technology for user information.

In (Bozic, 2023) study, investigated the use of artificial intelligence (AI) in hospital operational risk management. The study found that AI-powered predictive analytics can forecast and reduce operational risks like staff shortages and supply chain disruptions by analyzing historical data and external factors like weather patterns or disease outbreaks. Also, by anticipating patient admissions, ER visits, and the need for particular medical services, machine learning algorithms can improve the distribution of hospital resources. AI can also automate and streamline logistics and scheduling procedures, increasing operational effectiveness and lowering the possibility of mistakes or delays.

(Danielsson et al., 2022) study stated that artificial intelligence (AI) is revolutionizing the financial sector by improving operational efficiency and helping with risk management, however, because of procyclicality and the requirement to trust AI systems, it may also create new risks and amplify those that already exist.

A study by (bin Al-Dhab, 2023)¹ aimed to highlight the most important applications of artificial intelligence and machine learning in the detection of fraud on credit cards, and to

¹ -بن الضب، علي، (٢٠٢٣). دور الذكاء الاصطناعي وتعلم الآلة في تعزيز كشف الاحتيال على البطاقات الائتمانية. صندوق النقد العربي،

compare the results of supervised machine learning algorithms, by application to the Python programming language, using synthetic data created in a random way by simulating random numbers of a sample consisting of 200 thousand credit cards, and 20 variables as characteristics of the credit card holder using four algorithms represented in: the algorithm of logistics regression, the nearest neighbors, linear discriminant analysis and the decision tree. The study concluded that machine learning algorithms contribute to enhancing credit card fraud detection with a predictive capacity of more than 94 percent, and the linear learning algorithm was better than the rest of the used algorithms, which supports the use of modern machine learning techniques, and opportunities to benefit from many algorithms. The study recommended the need to use artificial intelligence in general, and machine learning in particular in the analysis of fraud on credit cards in the Arab countries, which helps financial institutions and supervisory, regulatory and supervisory bodies to manage risks and reduce the costs resulting from these operations, especially with the eye of many fraudsters to the use of modern technologies, which requires keeping abreast of current global developments in this field.

(Bussmann et al., 2020), mentioned that In order to better forecast future behavior, explainable AI models—which provide insights into AI predictions based on comparable financial features of borrowers—are being developed for credit risk management. (Milojević & Redzepagic, 2021), asserted that AI and machine learning have the ability to greatly enhance banking risk management, assisting with strategies to mitigate the effects of current global financial and economic issues, such as the COVID-19 problem. (Xie, 2019), confirmed that Macroeconomics and microeconomics have been impacted by the development and use of AI and machine learning in the financial system, which has resulted in the creation of novel financial services and made the development of effective AI use techniques for financial risk management necessary.

(Berrada et al., 2022), discussed the advantages of artificial intelligence (AI) for credit risk assessment, with particular attention to its uses in fraud detection, customer support, and segmentation. For improved service and loss prevention, it emphasizes the developments in deep learning and machine learning methodologies. (Widagdo et al., 2023), addressed the use of AI in quantifying credit risk with a forward-looking approach, contrasting with traditional methods, it examines a number of research to reach a consensus on the potential of AI to increase financial inclusion and prediction power, but it also highlights obstacles to lowering costs and simplifying the technology.

(Ahmed, 2017)² research aimed to develop a proposed model to predict the occurrence of financial risks using information technology based on artificial intelligence through the method of neural networks to support the ability to plan to confront them, the proposed model has been applied to the Egyptian banking sector in light of the current global financial crisis. This model for predicting and managing financial crises in commercial banks was proposed using neural networks as the most important applications of artificial intelligence and their management using information technology, and the proposed model was judged by specialists. The study showed the most important obstacles to the use of information technology to cope with crises in commercial structures, is the lack of appropriate software, followed by insufficient resources and equipment. The study also showed that artificial neural networks are a powerful tool that can be used in the processes of predicting the crises facing commercial banks, and they are characterized by their ability to learn, and thus grow and experience to take the most appropriate decisions in light of the emergency circumstances. This study agrees with (Maryam & Abdul Rahim, 2022)³ study who aimed to estimate the credit risk in Algerian banks and make the right lending decision using the RBF radial basis function artificial neural network model, so, they formed a database of financial and qualitative variables for 100 of borrowing institutions From the CPA bank, this sample divided into 50 good Borrower institutions and 50 other bad borrower institutions. To create the RBF model, they used SPSS(V25) program. Their results showed that the artificial neural networks model had shown an accuracy in classification at 100%, which would help Algerian banks to predict credit risks and make wise and speed lending's decision more than the classic models, but these modern approaches require robust technologies devices and quantitative and

² -أحمد، حسين مصيلحي سيد، (٢٠١٧). نموذج مقترح لإستخدام الشبكات العصبية في التنبؤ بالأزمات المالية " دراسة تطبيقية على البنوك

التجارية". مجلة كلية الاقتصاد والعلوم الإدارية، مج(١٨)، ع(١).

³ -مریم، حویاد و عبد الرحیم، شیبی، (٢٠٢٢). تقدير مخاطر الائتمان المصرفي باستعمال نموذج الشبكة العصبية الاصطناعية ذات الدالة الشعاعية

(RBF): دراسة حالة بنك القرض الشعبي الجزائري. مجلة الامتياز لبحوث الاقتصاد والإدارة، مج (٦)، ع(٢)، ص ص ٤٨٥-٥٠٤.

statistical methods. Also, these results are supported by (Sabrina, 2023)⁴ study, which aimed to study the possibility of applying the artificial intelligence methods to estimate the creditworthiness of Algerian banks, through modelling the artificial neural network and the systems expert method, based on a sample of 145 enterprises. The study concluded that there is a statistically significant relationship between the model of the artificial neural network and expert system and the creditworthiness estimation.

(Reis & Quintino, 2023), examines the performance of statistical and artificial intelligence (AI) predictors in credit risk analysis, and it concludes that AI techniques—such as neural networks and random forests—predict default risk better than statistical ones. (Ghodselahi, 2011), used ensemble learning to create a hybrid model for credit scoring that outperforms existing approaches in terms of accuracy and performance. It highlights how important it is to select the most appropriate classification model in order to lower credit scoring errors.

(Carvalho et al., 2022), addressed the application of artificial intelligence (AI) technologies to operational risk management, emphasizing the shortage of funding and data on AI technology advancements relevant to operational risk controls. It identifies challenges to operational risk management automation, including under capabilities in human resources and giving other industries priority.

(Azvine et al., 2007), examined the function of real-time business intelligence (RTBI) in operational risk management and makes the case that RTBI is essential for comprehending real-time company performance and risk posture and, as a result, for controlling operational risks. (Grover et al., 2020), explored the use of artificial intelligence (AI) in manufacturing and supply chains, as well as other areas of operations management, within businesses. It focuses on six aspects, such as job-fit and complexity. (Banja, 2020), examined the ethical issues that AI applications, such as system failures and privacy issues, may provide to risk management. It emphasizes how crucial it is for risk managers and technology specialists to work together to successfully manage these risks associated with AI.

⁴ - صيرينة، بنية، (٢٠٢٣). نمذجة طرق الذكاء الاصطناعي لتقدير الجدارة الائتمانية بالبنوك الجزائرية. مجلة دفاتر بواذكس، مج(١٢)، ع(١)، ص

A study by (Ali et al., 2022)⁵ aimed to identify the role of artificial intelligence in the performance of banking services, as technology is one of the most important components of the business environment in our contemporary time, as it constitutes the cornerstone in enhancing opportunities for survival, growth and continuity, and as a result of the rapid and continuous development of modern technological technologies, which helped to innovate new means and methods in providing banking services to customers. Artificial intelligence programs have emerged that are based on advanced modern technologies. The research found that the application of artificial intelligence in many areas of banking services helped develop the performance of banks by improving the quality of banking service, controlling costs, mitigating risks, increasing revenues, and raising the level of competition. Many banks have worked on artificial intelligence strategies, including Nasser Social Bank, to use technology and employ it in various banking services to achieve customer satisfaction and gain more of them. The bank has been keen to achieve the factor of diversification in the methods of offering the service through the multiple banking channels adopted by banks during the past periods, including traditional channels, ATMs, mobile phones, digital screens, the Internet, in addition to developing payment tools and means to become suitable for the nature of modern transactions and in line with the electronic business environment. The service provided bank cards, electronic checks, and electronic money, all of which is focused on achieving one goal, which is to achieve the wishes and needs of customers and gain their satisfaction on the other hand. In conclusion, the research recommends the importance of applying more artificial intelligence programs and applications at the level of various banking services, and seeking to follow up and develop those programs, and stressed the importance of holding the necessary training programs for employees in banks for how to deal with these programs and to achieve the strategic goals of banks.

(lamjd, 2016)⁶ research study provides a risk management model that integrates the quantitative analysis of risks related to economic institutions and artificial intelligence

⁵ -علي، منذر محمد وآخرون، (٢٠٢٢). أثر تفعيل تقنيات الذكاء الاصطناعي على تعزيز أنشطة المراجعة الداخلية "دراسة ميدانية". مجلة

الإسكندرية للبحوث المحاسبية، مج(٦)، ع(٣).

⁶ -المجد، بوزيدي، (٢٠١٦). دور الذكاء الاصطناعي في التوقع والتحليل الكمي للمخاطر في المؤسسة الاقتصادية. مجلة أبعاد اقتصادية، ع(٦)، ص

ص ٢٢٥-٢٤٥.

according to a clear scientific methodology, by integrating the mechanisms of artificial intelligence and probability methodologies, supporting the decision-making process of discovering and addressing the various risks associated with the business environment, and strengthening the role that different statistical and mathematical tools and methods can play in enhancing and strengthening decisions related to how and ways to deal with the various risks posed by the economic environment with its various components. The study findings showed the importance of using artificial intelligence, statistical and mathematical methods in risk management within economic institutions. It turns out that these tools enable decision makers to predict the behavior of risks and develop scientific strategies to deal with them, leading to their control and reduction. The study recommended to focus on the use of these advanced methods in forecasting and addressing risks, in addition to building a clear risk management strategy based on accurate analysis and visualization of future scenarios, and developing methods and procedures using Modern technology, the establishment of a system of strategic vigilance to analyze developments and anticipate risk in the business environment.

- **Summary of Past Studies:**

Table 1.1: Summery Of Literature Review

No.	Title	Objectives	Results	Authors
1	Role of Artificial Intelligence in Business Risk Management	Describe cost modeling methods and challenges using AI techniques	Suggests strategies and applications of AI for financial risk management, emphasizing the need for enhanced AI application through R&D and encryption technology for user information.	(Naim, 2022)
2	Integrated Risk Management and Artificial Intelligence in Hospital	Investigate AI in hospital operational risk management.	AI predictive analytics forecast and reduce operational risks. AI improves resource distribution and automates logistics, increasing operational effectiveness.	(Bozic, 2023)

3	Artificial Intelligence and Systemic Risk	Explore AI's impact on the financial sector	AI revolutionizes operational efficiency but may create or amplify risks due to procyclicality and trust requirements.	(Danielsson et al., 2022)
4	Explainable machine learning in Credit Risk Management.	Develop explainable AI models for credit risk management	Explainable AI models provide insights into predictions, aiding in better forecasting of borrower behavior based on financial features.	(Bussmann et al., 2020)
5	Prospects of Artificial Intelligence and machine learning application in Banking Risk Management	Assess AI and machine learning in banking risk management,	AI and machine learning enhance banking risk management, mitigating effects of financial and economic issues like COVID-19.	(Milojević & Redzepagic, 2021)
6	Development of artificial intelligence and effects on financial system.	Examine AI and machine learning in economics and financial systems,	AI and machine learning impact macro and microeconomics, creating new financial services and necessitating effective AI use in financial risk management.	(Xie, 2019)
7	A review of Artificial Intelligence approach for credit risk assessment,	Discuss AI for credit risk assessment, Focus on deep learning and machine learning methodologies.	The study Highlights AI's role in fraud detection, customer support, and segmentation for credit risk assessment.	(Berrada et al., 2022)
8	Artificial Intelligence in credit risk: A literature review.	Use AI in quantifying credit risk with a forward-looking approach	AI increases financial inclusion and prediction power, though challenges exist in cost reduction and technology simplification.	(Widagdo et al., 2023)
9	Evaluating classical and artificial intelligence	Compare statistical and AI predictors in credit risk analysis.	AI techniques like neural networks and random forests, AI	(Reis & Quintino, 2023)

	methods for credit risk analysis		techniques predict default risk better than statistical methods.	
10	Contributions of artificial intelligence in Operational Risk Management	Application of AI in operational risk management, and Analysis of challenges in automation and the technology's relevance to operational risks,	The study Identifies challenges in automation due to under capabilities in human resources and prioritization of other industries.	(Carvalho et al., 2022)

2.5 Theoretical Framework

2.5.1 The Process of Risk Management

Organizations face an increasingly uncertain future, and in order to remain competitive, they must achieve a delicate balance between pursuing opportunities with a higher return, and keeping exposure to risks at an acceptable level, staying in a dynamic environment requires good preparation, in which the need to develop strategies and assess risks never ends both closely and integrated, as the concept of risk management refers to that approach or scientific approach to dealing with risks through anticipation, control and control Potential losses, as well as the design and implementation of procedures that will minimize the possibility of loss or the financial impact of losses occurred. Therefore, the management of these risks requires a clear methodology, based on scientific foundations (lamjd, 2016). According to (lamjd, 2016), the risk management process includes:

Risk identification: The most important element in any risk management process is the risk identification process, as failure to identify risks certainly means not taking appropriate action to deal with various risks, as at this stage the various possibilities of risk exposure are discovered, which can result in losses affecting processes, systems and products. By relying on several methods, including checking lists, brainstorming methodology, risk workshops, risk self-assessment... etc.

Risk Analysis: The risk analysis process is carried out in a systematic manner, to ensure the analysis of all risks and losses resulting from them, in addition to identifying the changes associated with those risks and classifying them according to importance, the purpose of risk analysis and control is to present the risks that are evaluated in a clear systematic manner, and there are several methods used to analyze the risk and give a comprehensive picture, including: Matrix Approach, Fault Tree Approach and (FEMA).

Risk assessment: The risk assessment process should be based on identifying two important indicators: the likelihood of the risk occurring and the degree of its impact. The first indicator refers to the criterion of uncertainty and the surrounding coincidences in the environment, considering that its conditions have become enveloped in variables that are difficult to predict or fully encompass the interaction of its elements and components. This makes determining the likelihood of any risk occurrence require scrutiny of its circumstances. As for the second indicator, it expresses the expected outcome of the occurrence of the sudden risk, namely determining the severity of the event's impact on the activities within the organization, which leads to achieving the loss factor.

Risk Verification & Monitoring: Considering that risk management is an ongoing process, it requires monitoring its operations and reviewing the extent to which the institution implements appropriate control and risk management measures and absorbs them. This involves preparing what is known as a recovery plan because verifying some risks with significant loss potential can affect the safety of various activities and operations throughout the entire institution.

Risk Planning: Risk planning involves identifying and designing a clear strategy that reflects the implementation approach of all stages. The risk management cycle within the institution is considered a guiding program or a formal process that constitutes internal commitment by planning the necessary resources and identifying the roles and responsibilities of each member of the risk management team. It outlines various tasks and operations that must be deployed for success.

Risk Control: This represents the recovery plan aimed at ensuring the implementation of various procedures or means necessary for risk management. The success of the risk management process control phase is closely linked to the earlier stages of risk management because it relies on the data from these stages most of the time. We monitor the

implementation of treatment methods on one hand and the evolution of risk behavior on the other. Therefore, organizations should adopt these steps in an organized and clear manner, ensuring effective handling of risks systematically and scientifically, ultimately positioning them as a strong force in their environment, capable of facing various changes and disruptions in the business environment.

2.5.1 AI Techniques Used in Risk Management

According to (De marco, 2023) study, there are many AI techniques used in risk management as follows: -Artificial Neural Networks (ANNs): recognized for their ability to find patterns in intricate, nonlinear data. They are especially renowned for outperforming conventional linear regression models in terms of accuracy in risk prediction and project failure mitigation. Superior risk prediction rates are provided by the innovative approach of ANN integration in risk management. Their benefits include parallel processing, fault tolerance, machine learning capabilities, and network-wide information storage (De marco, 2023).

High Order Neural Networks (HONNs): These networks, which were initially intended for nonlinear discrimination, use neuronal feedback loops to enable both forward and backward information transmission. HONNs based on the Hopfield model, are good at combinatorial optimization issues because they converge to a local minimum that represents an ideal solution (De marco, 2023).

Fuzzy Logic and Fuzzy Cognitive Maps: These tools are used to mimic the risk and uncertainty that are present in projects. Fuzzy Cognitive Maps are a useful tool for visual modeling, simulation, and prediction. They reflect causal reasoning by extending cognitive maps with fuzzy graphical features (De marco, 2023).

Monte Carlo Simulation (MCS): MCS is well-known for its use in quantitatively evaluating risk in construction projects. It analyzes stochastic behavior and the relationships between project resources and activities, especially in relation to cost estimation and the effects of schedule delays (De marco, 2023).

Support Vector Machine (SVM): SVMs are useful for categorizing and predicting results based on the similarity of input properties, notwithstanding their complexity. They are preferred because of their aptitude for handling uncertain data and because of their potential in the finance and construction cost estimation domains (De marco, 2023).

Genetic Algorithms (GAs): GAs are adaptable, emulating natural evolutionary processes, and can be used in conjunction with other heuristic techniques for optimization. They can be used for a variety of issues, including risk simulation and project planning (De marco, 2023).

K-means Clustering: A popular data clustering technique used for grouping data based on characteristics, though it may not guarantee optimal convergence (De marco, 2023).

Less Considered Models: Includes Bootstrap Technique, Bayesian Belief Networks, Fast Messy Genetic Algorithm (FmGA), Expert Systems (ES), Analytical Network Processing (ANP), Structural Equation Modeling (SEM), and Case-based Reasoning (CBR). These models have several benefits when it comes to tackling intricate network interdependencies, replicating expert judgment, and estimating quantities (De marco, 2023).

Hybrid and Nature-Inspired Algorithms: Mentioned are Particle Swarm Optimization, Ant Colony Optimization, Artificial Fish Swarm, Bees Colony, Firefly, Bat Algorithms, and Shuffled Frog-Leaping Algorithm. These are renowned for their ability to improve the efficiency of project management by addressing the factors of cost, time, and risk with cutting-edge AI tools and methodologies (De marco, 2023).

2.5.2 AI Methods Used in Risk Management

- **Cost Modeling Methods**

A three-stage model (input, process, output) for project cost estimation incorporates data on costs, evaluations, productivity, and safety. Artificial Neural Networks (ANNs) are utilized for forecasting costs, like those of reinforced-concrete structures, and for monitoring project productivity and safety. ANNs provide reliable and predictable cost estimation over time. The integration of ANNs in Watson allows for the analysis of large datasets from over six hundred projects, enabling precise project duration predictions and risk identification, significantly outperforming traditional spreadsheet methods (De marco, 2023).

- **Time Modeling Methods**

The dynamic Project Duration Prediction (DPDP) method employs machine learning to predict project durations based on a dataset of project features. This approach is flexible, accommodating various project types and organizational biases, and optimizes ANN models for accuracy (De marco, 2023).

- **Risk Modeling Methods**

AI applications in risk management offer direct benefits (cost, people, product) and indirect benefits (process management, optimization, decision-making). The process includes risk identification (analyzing databases and conducting semantic analysis), risk assessment (evaluating the frequency and impact of potential risks using AI), and risk treatment (managing assessed risks with AI's help to suggest mitigation strategies). Risk monitoring involves continuous surveillance of risk parameters, utilizing AI to adapt to changes in the project environment or risk status (De marco, 2023).

- **Hybrid Models**

Hybrid models combine features of different AI techniques to leverage their strengths and mitigate weaknesses (De marco, 2023), notable examples include:

-Fuzzy Hybrid Methods (FHMs): Combine fuzzy logic with other AI methods to address project risk uncertainties.

- Fuzzy-Analytical Network Processing (FANP) and Fuzzy Monte Carlo Simulation (FMCS): Integrate fuzzy logic to improve risk analysis and prediction under uncertainty.

-Fuzzy-Artificial Neural Network (FANN): Merges ANN's predictive capabilities with fuzzy logic's ability to handle linguistic uncertainty, enhancing decision-making in risk identification and modeling.

-Evolutionary Fuzzy Neural Inference Model and Evolutionary Fuzzy Hybrid Neural Network: Incorporate genetic algorithms and fuzzy logic with neural networks for optimization and uncertainty management.

-Bootstrap aggregating and Adaptive boosting neural networks: Utilize multiple ANN classifiers to improve prediction accuracy through techniques like voting systems and iterative weight adjustments.

Chapter Three

Research Methodology

3.1 Introduction

In This chapter has been used a quantitative research methodology to evaluate artificial intelligence's (AI) effects on the risk management. To comprehend causal links, trends, and the efficacy of AI in risk management across a range of industries, including banking, healthcare, manufacturing, and information technology, this chapter seeks to collect and analyze numerical data. Additionally, this research used a structured online questionnaire approach to get quantitative feedback from experts who have integrated AI into their risk management procedures. Various facets of risk management, including credit, operational, and enterprise risk management, are included in the questionnaire's instruments. An understanding of how AI helps with risk management is provided by statistical methods for both descriptive and inferential analysis, in addition to highlighting the technology's effectiveness, efficiency, and stakeholder satisfaction.

3.2 Research Design

Research designs can be used for a variety of research projects. Choosing the right design depends on the research objectives and the problems they pose. The type of data that is generated by each type of research design can be collected and analyzed using a variety of research methods. Research designs can be categorized into the following types such as historical, descriptive, correlation, comparative, experimental, simulation, evaluation, action, and ethnological, feminist, and cultural (Walliman, 2021). A descriptive analytics approach examines and interprets past data to determine what has happened in an organization or business. In order to understand patterns, trends, and relationships, historical data is collected, summarized, and presented in a way that enables businesses to identify patterns and trends (Wolniak, 2023). The quantitative approach is used to investigate causal relationships, average, identify trends, summarize, average, and extrapolate findings to larger populations. It enables us to rate priority, calculate effect sizes, assess the strength of relationships, and evaluate the quality of the evidence supporting efficacy. (Rana et al., 2021).

In this research, it has been adopted a quantitative descriptive analysis for the collected data through an online questionnaire. Also, the method will be adopted using a survey as the main means of gathering information to comprehend Artificial Intelligence's (AI) effects on risk

management. With this strategy, quantifiable data on the efficacy, efficiency, and stakeholder satisfaction of AI in risk management may be gathered. The survey's design aims to gather a diverse range of replies, facilitating statistical examination of AI's effects on various businesses.

3.3 Population of The Study

The study's objectives provide clarification regarding which group the research findings can be generalized for or applied to. In study, this kind of group is called a population (Shukla, 2020). In this study the population consists of individuals working for companies in a variety of industries who have integrated AI into their risk management procedures. This reflects the widespread use of AI in risk management initiatives and spans a range of industries, including finance, healthcare, manufacturing, and information technology.

3.4 Sample Characteristic

A sample is a part of the population that fully represents the population. This means that the units chosen as a sample from the population must encompass all the various characteristics of the various kinds of population units (Shukla, 2020). To ensure a variety of perspectives on the application of AI in risk management, the sample will be comprised of a wide spectrum of participants. Characteristics will consist of:

- Industry Sector: A wide range of industries recognized for having adopted AI at rapid rates.
- Role in Organization: Diverse roles involving IT personnel working with AI systems, risk management specialists, and decision-makers.
- Experience with AI: Participants' levels of familiarity with AI will range from beginners to seasoned experts.

In this research, the sample size can be computed to guarantee the statistical power of the study. 100 employees from the private sector in Saudi Arabia were determined to be the sample size. However, the completed answers are only 84 respondents.

3.5 Sample Size Determination

There are many different types of sampling techniques, however they can be broadly divided into two groups: probability sampling methods and non-probability sampling methods (Alvi, 2016). Convenient sampling, sometimes known as accident or opportunity sampling, is a noteworthy idea in the field of non-probability sampling. Instead of choosing participants at random, this method allows researchers to choose people based on factors like accessibility

or simplicity of approach. It is especially helpful in situations when the target population falls into a large group or when random sampling is not feasible due to logistical issues (Alvi, 2016).

3.6 Data Collections Procedures

Data collection is the process of gathering and measuring information on variables of interest, in an established systematic fashion that enables one to answer stated research questions, test hypotheses, and evaluate outcomes (Kabir, 2016). Therefore, this research has been conducted the primary data through an online questionnaire, by Google Forms. It has been distributed through an online questionnaire in Saudi Arabia. While the research secondary data is conducted by online articles, journals via the internet.

In this research, the questionnaire consists of a list of open-ended or closed-ended questions with responses from the respondents. A questionnaire will be completed over the online distribution via WhatsApp. The research's questionnaire questions include 4 sections:

- Demographic information: like, age- gender- year of experience- employment status.
- Questions about the impact of AI on credit risk management, taken from (Mesihovic & Nordström, 2021).
- Questions about the impact of AI on operational risk management, taken from (Kalogiannidis et al., 2024).
- Questions about the impact of AI on enterprise risk management, taken from (Kalogiannidis et al., 2024).

3.7 Method of Analysis

Researchers use SPSS v.27 software to analyze the data collected in order to answer the research questions and test the research hypotheses. Descriptive statistics are used to test hypotheses and answer research questions.

The following descriptive and inferential statistics used to test hypotheses:

- 1- Descriptive Statistics (Means and standard deviations).
- 2- Frequencies and percentages.
- 3- Cronbach's Alpha test to measure reliability .
- 4- A non-parametric Kruskal-Wallis test
- 5- Kolmogorov-Smirnova normal test.

3.8 Measurement's Scale

In statistics, a measurement scale indicates the type of information provided by numbers. Different types of information are provided by each type of scale (nouns, ordinals, intervals, and ratios). The measurement process involves assigning numbers to people, objects, and events in a meaningful manner, and understanding measurement scales is vital to interpreting these numbers (Lee, 2022). The current research measurement scale is Five Likert Scale starting from (5=Strongly agree, 4=agree, 3=neutral, 2=disagree, 1=strongly disagree), while other instruments have a multiple choice. The research instruments in the Appendix.

3.9 Pilot Study

The pilot study is a crucial initial step in research, helping researchers evaluate and refine their study instrument before applying it to the main sample. Conducted on a smaller scale, it enhances the quality and efficiency of the main study. This preliminary phase is valuable for assessing treatment safety, examining random sample representation, increasing researcher familiarity with methods and interventions, and providing estimates for calculating the sample size (In, 2017). In the present study, it focused on 30 persons in Saudi Arabia to validate and establish the reliability of the chosen instrument.

3.10 Validity and Reliability Tests

- **Validity Test**

A validity test is a process or evaluation that is used, usually in the context of research or assessment, to determine if a measure or instrument is valid. The degree to which a test or measurement accurately captures what it is intended to capture is referred to as validity. Thus, the purpose of a validity test is to ascertain whether a given tool or measure measures the intended construct or notion in an effective manner (Sullivan, 2011).

The validity of the questionnaire means that it represents the population studied well, as the answers we get from the questionnaire questions give us the information for which the questions were developed. As for the stability of the questionnaire, it means that if we redistribute this questionnaire to another sample from the same population and the same sample size, the results will be close to the results we obtained from the first sample, and the results between the two samples will be equal with a probability equal to the reliability coefficient. nally 1979). A value of Cronbach's alpha between 0.6 and 0.8 is acceptable (Wim

et al, 2008). Moreover, Robinson (1991) recommends that, in an empirical approach and as a rule of thumb, if the score of the item-to-total correlations is more than 0.50 and the inter-item correlations exceeds 0.30, the construct validity is satisfied (Hajjar, S. T. ,2018). To measure the construct validity in an empirical approach the rule of thumb item-to-total correlations, and the inter-item correlations are adequate. Cohen (1988) states that if inter-item correlation lies within 0.10 and 0.29 ,then there is a weak correlation for both positive and negative values, and when inter-item correlation lies within 0.30 and 0.49 a medium correlation, and lastly if inter-item correlation is between 0.50 and 1.00 a strong correlation. It has been verified the validity of the questionnaire as the following:

Table 3.1: Coefficient Of Correlation Between the Degrees Of Each Statement Of Artificial Intelligence Has Positive Impact On Credit Risk Management.

Statements	Pearson	Sig.
you use credit scoring models.	.691**	0.000
your credit scoring models based on AI and Machine learning solutions.	.835**	0.000
you use AI and Machine Learning solutions to a higher degree today than 5 years ago when it comes to corporate credit risks.	.791**	0.000
AI and machine learning solutions helped you mitigate errors and faultiness when it comes to corporate credit risks.	.818**	0.000
you base your strategic decisions on machine learning analytics.	.753**	0.000
AI and ML driven solutions complement your risk management process.	.837**	0.000
you have an established credit scoring model for predicting and identifying credit risks among corporate clients.	.785**	0.000
you are able to make predictions regarding potential bankruptcies (corporate) with the help of AI and ML driven solutions.	.723**	0.000
it is a goal for your organization to further develop your AI and ML solutions within risk management.	.709**	0.000

The table (3.1) shows that the correlation coefficients between each statement of the first dimension (Artificial intelligence has positive impact on credit risk management), where the value of the correlation coefficient are between (0.691 – 0.837) which is a positive correlation. The Sig value of each statement is less than 0.05 and thus considered to be honest and intended to measure.

Table 3.2: Coefficient Of Correlation Between the Degrees Of Each Statement Of (Artificial Intelligence Has Positive Impact On Business Risk Management)

Statements	Pearson	Sig.
AI integration in incident response planning has significantly reduced business disruptions.	.809**	0.000

The use of AI in incident response contributes to quicker recovery from unexpected incidents.	.771**	0.000
AI tools aid in accurately predicting the impact of potential incidents on business operations.	.773**	0.000
The integration of AI has improved the coordination and management of incident responses.	.938**	0.000
AI-enhanced incident response plans are more comprehensive and effective than traditional plans.	.823**	0.000
The use of AI in incident response planning has increased the resilience of our business.	.901**	0.000
I am confident in the ability of AI-integrated plans to handle future business disruptions effectively.	.797**	0.000

The table (3.2) shows that the correlation coefficients between each statement of the second dimension (Artificial intelligence has positive impact on business risk management), where the value of the correlation coefficient between (0.771– 0.938) which is a positive correlation. The Sig value of each statement is less than 0.05 and thus considered to be honest and intended to measure.

Table 3.3: Coefficient Of Correlation Between The Degrees Of Each Statement Of (Artificial Intelligence Has Positive Impact On Operational Risk Management)

Statements	Pearson	Sig.
AI-driven predictive maintenance has noticeably reduced the frequency of operational downtime.	.794**	0.000
The predictive alerts provided by AI systems are accurate and timely.	.866**	0.000
The use of AI for maintenance has led to cost savings in equipment repair and replacement.	.902**	0.000
Predictive maintenance using AI is more efficient than traditional maintenance approaches.	.872**	0.000
The implementation of AI in maintenance has improved overall operational efficiency.	.921**	0.000
I am satisfied with the role of AI in predictive maintenance within our organization.	.734**	0.000

The table (3.3) shows that the correlation coefficients between each statement of the third dimension (Artificial intelligence has positive impact on operational risk management), where the value of the correlation coefficient between (0.794– 0.921) which is a positive correlation. The Sig value of each statement is less than 0.05 and thus considered to be honest and intended to measure.

- **Reliability Test**

A reliability test is a method used to assess the consistency and stability of a measurement instrument or scale over time and across different conditions, The degree to which a measurement tool yields dependable and consistent data is referred to as reliability (Sullivan, 2011). Reliability means that a measure or questionnaire should consistently reflect the construct that it is measuring (Field, A,2009)

Reliability is used to measure the same scale items multiple times, ensuring that the same result is found every time, as long as the underlying phenomenon is not changing. Reliability is also a measure of internal consistency between different items of the same construct. When a multiple-item scale is provided to respondents and yields a similar score every time even if it is completed at two different points in time, this is a reflection of internal consistency. Therefore, it can be said that reliability can be estimated in terms of average inter-item correlation, average item-to-total correlation, or more commonly, Cronbach's alpha (Bhattacharjee, A. ,2012). The alpha coefficient value depends on the number of items on the scale. In general, reliability of less than 0.6 is considered poor, the 0.7 range, accepted, and over 0.8 good (Sekaran, U. ,2003).

In a reliable scale all items should correlate with the total. So, if items don't correlate with the overall score from the scale with their values being less than about 0.3 it means there are problems, as a particular item does not correlate very well with the scale overall. Items with low correlations may have to be dropped (Field, A. ,2009).

In this research, the reliability of each scale has been tested through Cronbach's alpha to identify the internal consistency of the scale. The alpha coefficient value depends on the number of items on the scale. In general, reliability of less than 0.6 are considered poor, the 0.7 range, accepted, and over 0.8 good. Also, the reliability of each scale has been tested through Cronbach's alpha to identify the internal consistency of the scale . The following table summarizes the reliability test results for the study variables. All the variables show an alpha coefficient of more than 0.6.

Table 3.4: Cronbach's Alpha Coefficient for the main dimensions

The dimension	Cronbach's Alpha	No. of Statements
Artificial intelligence has positive impact on credit risk management	0.914	9
Artificial intelligence has positive impact on business risk management	0.924	7

Artificial intelligence has positive impact on operational risk management	0.921	6
All the dimensions	0.963	22

Table (3.4) summarizes the reliability test results for the questionnaire dimensions. All of the dimensions show an alpha coefficient equals 0.939, this result indicates that the research dimensions will give the same results if re-applied to the same sample and test stability using Cronbach alpha coefficient, The Cronbach alpha for Artificial intelligence has positive impact on credit risk management is 0.914, Artificial intelligence has positive impact on business risk management is 0.924, and Artificial intelligence has positive impact on operational risk management is 0.921, that means that the dimensions of the survey have good reliability.

3.11 Chapter Summary

The preceding section outlines the methodology employed in this chapter. It encompasses a comprehensive elucidation of the research approach. The sampling methodology, as well as the delineation of the population under study are clearly defined. The data collection methods are meticulously detailed, with a specific emphasis on the utilization of an online questionnaire for data gathering. Additionally, the data analysis process was executed through the utilization of SPSS software, version 27. Rigorous validation and reliability tests were carried out to ensure data integrity. Furthermore, this section elucidates the statistical tools utilized for data analysis.

Chapter Four: Results, Discussion, And Conclusion

4.1 Introduction

The central aim of this study is to identify the impact of the artificial intelligence on the credit risk management , operational risk management, and enterprise risk management of the organizations at the private sector in Saudi Arabia. In pursuit of this goal, a combination of descriptive and inferential statistical techniques was employed to assess participants' responses concerning the research tool items and to scrutinize the relationships between independent and dependent variables. To facilitate data analysis, the research employed the use of Statistical Package for Social Science (SPSS) version 27. This software facilitated data processing and allowed for the validation of research hypotheses through the comprehensive analysis of results. In the forthcoming sections, the methodology employed in this research will be elucidated, providing insight into the approach and tools utilized for a rigorous investigation into the specified research objectives.

4.2 Research Findings

The Sample Description is determined as follow:

Table 4.1 Demographic Variables of Respondents

Variables	Groups	Frequency	%
Gender	Female	30	36%
	Male	54	64%
Age	20 Less than 30	28	33%
	31 Less than 40	45	54%
	41 Less than 50	10	12%
	51 Less than 60	1	1%
Education level	Bachelor's degree	55	65%
	Diploma	1	1%
	Doctorate degree	1	1%
	High School	3	4%
	Postgraduate	24	29%
Employment status	Employed full-time	78	93%
	Employed part-time	1	1%
	Other	3	4%
	Student	1	1%
	Unemployed	1	1%
Industry/Field of work (if applicable)	Education	14	17%

	Finance/Banking	3	4%
	Government	14	17%
	Healthcare	4	5%
	Manufacturing	2	2%
	Other	13	15%
	Technology	34	40%
Total		84	100%

The table shows us that 64% of the sample are male, 36% of the sample are female, according to age, 27% of the sample are 20 Less than 30, 54% are 31 Less than 40, 12% of the sample are 41 Less than 50, according to Education level, 65% of the sample have Bachelor's degree, 29% of the sample have Postgraduate, 4% of the sample have High School, according to Employment status, 93% of the sample are Employed full-time, 1% are Employed part-time, according to Industry/Field of work, 40% worked in Technology, 17% worked Government, and 17% worked in Education sector.

4.3 Analysis of The Dimensions

For analysis of the questionnaire statements, we depend on the mean and standard deviation for each statement.

1. Descriptive Statistics for Credit risk management.

Table 4.2: Mean Std. Deviation, The Rank For (Credit Risk Management)

Statements	Mean	Std. Deviation	Degree
you use credit scoring models.	3.69	1.02	agree
your credit scoring models based on AI and Machine learning solutions.	3.56	0.95	agree
you use AI and Machine Learning solutions to a higher degree today than 5 years ago when it comes to corporate credit risks.	4.07	0.93	agree
AI and machine learning solutions helped you mitigate errors and faultiness when it comes to corporate credit risks.	3.98	0.90	agree
you base your strategic decisions on machine learning analytics.	3.49	0.98	agree
AI and ML driven solutions complement your risk management process.	3.67	0.92	agree
you have an established credit scoring model for predicting and identifying credit risks among corporate clients.	3.57	0.84	agree
you are able to make predictions regarding potential bankruptcies (corporate) with the help of AI and ML driven solutions.	3.54	0.90	agree
it is a goal for your organization to further develop your AI and ML solutions within risk management.	3.80	0.90	agree

Credit risk management	3.71	0.93	agree
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The responses of the sample of the study sample showed a general trend towards approving for Credit risk management, where mean is 3.71 while its standard deviation is 0.93 and that means that sample of the study has a moderate agreement towards the Credit risk management dimension.

2. Descriptive Statistics for Enterprise risk management.

Table 4.3: Mean Std. Deviation, The Rank For (Enterprise Risk Management)

Statements	Mean	Std. Deviation	Degree
AI integration in incident response planning has significantly reduced business disruptions.	3.86	0.88	agree
The use of AI in incident response contributes to quicker recovery from unexpected incidents.	3.87	0.86	agree
AI tools aid in accurately predicting the impact of potential incidents on business operations.	3.92	0.78	agree
The integration of AI has improved the coordination and management of incident responses.	3.95	0.79	agree
AI-enhanced incident response plans are more comprehensive and effective than traditional plans.	3.90	0.89	agree
The use of AI in incident response planning has increased the resilience of our business.	3.95	0.86	agree
I am confident in the ability of AI-integrated plans to handle future business disruptions effectively.	3.92	0.82	agree
Enterprise risk management	3.91	0.84	agree

The responses of the sample of the study sample showed a general trend towards approving for Enterprise risk management, where mean is 3.91 while its standard deviation is 0.84 and that means that sample of the study has a moderate agreement towards the Enterprise risk management.

3. Descriptive Statistics for Operational risk management.

Table 4.4: Mean Std. Deviation, The Rank For (Operational Risk Management)

Statements	Mean	Std. Deviation	Degree
AI-driven predictive maintenance has noticeably reduced the frequency of operational downtime.	3.83	0.88	agree
The predictive alerts provided by AI systems are accurate and timely.	3.75	0.88	agree
The use of AI for maintenance has led to cost savings in equipment repair and replacement.	3.79	0.84	agree
Predictive maintenance using AI is more efficient than traditional maintenance approaches.	3.79	0.78	agree

The implementation of AI in maintenance has improved overall operational efficiency.	3.86	0.81	agree
I am satisfied with the role of AI in predictive maintenance within our organization.	3.80	0.83	agree
Operational risk management	3.80	0.83	agree

The responses of the sample of the study sample showed a general trend towards approving for Operational risk management, where mean is 3.80 while its standard deviation is 0.83 and that means that sample of the study has a moderate agreement towards the Operational risk management.

4.4 Testing the Research Hypotheses

As the following, the research hypothesis is determined below:

H1: The Artificial Intelligence Has a Positive Impact on The Credit Risk Management.

H2: The Artificial Intelligence Has a Positive Impact on The Operational Risk Management.

H3: The Artificial Intelligence Has a Positive Impact on The Enterprise Risk Management.

It has been presented the correlation matrix of the main dimensions as following:

Table 4.5: The Correlation Matrix of The Main Dimensions

		Artificial intelligence	Credit risk management	Enterprise risk management	Operational risk management
Artificial intelligence	Pearson Correlation	1	.854**	.613**	.549**
	Sig. (2-tailed)		0.000	0.000	0.000
	N	84	84	84	84
Credit risk management	Pearson Correlation	.854**	1	.786**	.710**
	Sig. (2-tailed)	0.000		0.000	0.000
	N	84	84	84	84
Enterprise risk management	Pearson Correlation	.613**	.786**	1	.870**
	Sig. (2-tailed)	0.000	0.000		0.000
	N	84	84	84	84
Operational risk management	Pearson Correlation	.549**	.710**	.870**	1
	Sig. (2-tailed)	0.000	0.000	0.000	
	N	84	84	84	84

From the correlation matrix we can find how are the relationships between the main dimensions as following:

- There is a strong and positive significant relationship between Credit risk management and Artificial intelligence, as Pearson Correlation = 0.854, and the sig value = 0.000.
- There is a strong and positive significant relationship between Enterprise risk management and Artificial intelligence, as Pearson Correlation = 0.613, and the sig value = 0.000.
- There is a strong and positive significant relationship between Operational risk management and Artificial intelligence, as Pearson Correlation = 0.549, and the sig value = 0.000.

Thus, there is a statistically significant impact for the Artificial Intelligence on Credit risk management, Enterprise risk management, Operational risk management. Moreover, it has been identified the simple linear regression to test the hypothesis as follows:

H1: The Artificial Intelligence Has a Positive Impact on The Credit Risk Management.

Table 4.6: The Correlation Matrix of The Main Dimensions

	Coefficients	R	R2	t	Sig.
(Constant)	1.245	.854 ^a	0.729	7.30	0.000
Artificial intelligence	0.679			14.85	0.000

From the above table it is clear that total correlation (R) equal (0.854) and the coefficient of determination (R^2) equal to (0.729), and this indicates that the independent variables explain (73%) of any change in the dependent variable (Credit risk management), also the sig value = (0.000) is less than (0.05), there is a statistically significant impact for Artificial intelligence On Credit risk management, and the value of independent variable coefficient equal (0.679) ,when the independent variable (Artificial intelligence) increases by one unit, the dependent variable (Credit risk management) will increase by (0.401) unit.

H2: The Artificial Intelligence Has a Positive Impact on The Operational Risk Management.

Table 4.7: The Correlation Matrix of The Main Dimensions

	Coefficients	R	R2	t	Sig.
(Constant)	2.308	.549 ^a	0.301	8.93	0.000
Artificial intelligence	0.412			5.95	0.000

From the above table it is clear that total correlation (R) equal (0.549) and the coefficient of determination (R^2) equal to (0.301), and this indicates that the independent variables explain (30%) of any change in the dependent variable (Operational risk management), also the sig value = (0.000) is less than (0.05), there is a statistically significant impact for Artificial intelligence On Operational risk management, and the value of independent variable coefficient equal (0.412) when the independent variable (Artificial intelligence) increases by one unit, the dependent variable (Operational risk management) will increase by (0.412) unit.

H3: The Artificial Intelligence Has a Positive Impact on The Enterprise Risk Management.

Table 4.8: The Correlation Matrix of The Main Dimensions

	Coefficients	R	R2	t	Sig.
(Constant)	2.174	.613a	0.376	8.56	0.000
Artificial intelligence	0.479			7.03	0.000

From the above table it is clear that total correlation ($R=0.613$) and the coefficient of determination ($R^2= 0.376$), and this indicates that the independent variables explain (38%) of any change in the dependent variable (Enterprise risk management), also the sig value = (0.000) is less than (0.05), there is a statistically significant impact for Artificial intelligence On Enterprise risk management, and the value of independent variable coefficient equal (0.479), when the independent variable (Artificial intelligence) increases by one unit, the dependent variable (Enterprise risk management) will increase by (0.479) unit.

Table 4.9 : A summary of the research hypotheses' results

Hypotheses	Supported
H1: The artificial intelligence has a positive impact on the credit risk management.	supported
H2: The artificial intelligence has a positive impact on the operational risk management.	supported
H3: The artificial intelligence has a positive impact on the enterprise risk management.	supported

Source: The table was created for this research.

4.5 Recommendations

First, the sample size could be greater than the current' research sample size. The second is that further research may be needed to develop more precise frameworks and empirical tests in Saudi Arabia's public sector as well. Third recommendation is establishing other data collection methods such as interviews. Fourth, testing new variables that may affect risk management such as diversity management, and employee engagement as moderating variable. Lastly, future studies must focus on adding more items or statements in the questionnaire for other types of questions such as opinions.

4.6 Research Implications

As part of the study, the literature pertaining the research topic was applied to the context of a large private sector organization in Saudi Arabia to investigate how the Ai affect the risk management in the Saudi Arabia's organizations in the private sector. In this research, organizations' management and policymakers are provided with several possible explanations. They may benefit from these results to maximize their efforts by focusing on mitigating the risks of artificial intelligence in the Saudi Arabia's private organizations.

4.7 Research Limitations

The first limitation is the time constraints, the current research has a much smaller sample size (84 respondents) than other studies, which can affect the reliability of this research. Secondly, with the online distribution of the questionnaires, respondents may choose random answers or the first answers that can also affect the accuracy of the research's results. Third, there are other factors that may impact risk management that are not considered in this research such as forecasting and planning diversity management, and other demographic patterns. Fourth, the data used for this study were extracted from private organizations in Saudi Arabia, but it is necessary to expand other sectors and consider different types of companies, such as public sector or banks.

4.8 Research Contributions

First, it contributed to the research by providing new quantitative knowledge about the impact of the artificial intelligence on the risk management of the organizations at the private sector in Saudi Arabia. Second, this research has been tested the conceptual framework in a new context in Saudi Arabia. Additionally, the research findings offer managers and organizations

an understanding of the relationship between research variables. Also, the results of this research are relevant for employees and managers at private sector organizations in Saudi Arabia. It can help them to better understand the important factors that affect the organization's risk management.

4.9 Conclusions

This chapter contains an analysis of the research results. Moreover, the research also described the implications and limitations, as well as recommendations for future research. Even though this study has limitations, it still contributes significantly to the literature by examining how the artificial intelligence effect the risk management of the organizations at the private sector in Saudi Arabia. As well as, the research variables are correlated, in addition to the relationships between them are approved.

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Appendix

Questionnaire

Thank you for taking the time to participate in our study. Your input is invaluable to our research efforts. This survey is a crucial component of our research, intended to collect data on the impact of AI applying in risk management. The questionnaire has been published through WhatsApp and designed using Google Forms for ease of access and data collection. And your answers will enable us to derive important understandings of the subject. This survey consists of 4 sections, these sections have been translated into Arabic “responses will take only 5 mins from your time.”

Q.1 Are you an employee at any private sector in Saudi Arabia?

هل انت موظف في القطاع الخاص في السعودية ؟

- Yes
- No

Section 1: Demographic Information:

2. Age:

- Under 18
- 18-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65 or older

3. Gender:

- Male
- Female

4. Education level:

- High school
- Diploma

- Bachelor's degree
- Master's degree
- Doctorate degree

5. Employment status:

- Employed full-time
- Employed part-time
- Unemployed
- Student
- Retired
- Other (please specify)

6. Industry/Field of work (if applicable):

- Finance/Banking
- Technology
- Healthcare
- Retail
- Manufacturing
- Education
- Government
- Other (please specify)

Section 2 : Artificial Intelligence Has Positive Impact On Credit Risk Management.

	Statement	SD	D	NS	A	SA
7	you use credit scoring models. يمكنك استخدام نماذج تسجيل الائتمان. لديك نموذج تصنيف ائتماني راسخ للتعليق بمخاطر الائتمان وتحديدتها بين العملاء من الشركات.					
8	your credit scoring models based on AI and Machine learning solutions. نماذج تسجيل الائتمان الخاصة بك بناءً على حلول الذكاء الاصطناعي والتعلم الآلي.					
9	you use AI and Machine Learning solutions to a higher degree today than 5 years ago when it comes to corporate credit risks. إنك تستخدم حلول الذكاء الاصطناعي والتعلم الآلي بدرجة أعلى اليوم مما كانت عليه قبل 5 سنوات عندما يتعلق الأمر بمخاطر ائتمان الشركات.					
10	AI and machine learning solutions helped you mitigate errors and faultiness when it comes to corporate credit risks.					

	ساعدتك حلول الذكاء الاصطناعي والتعلم الآلي على تخفيف الأخطاء والأخطاء عندما يتعلق الأمر بمخاطر ائتمان الشركات					
11	you base your strategic decisions on machine learning analytics. أنت تبني قراراتك الإستراتيجية على تحليلات التعلم الآلي.					
12	AI and ML driven solutions complement your risk management process. تكمل الحلول المعتمدة على الذكاء الاصطناعي والتعلم الآلي عملية إدارة المخاطر لديك					
13	you have an established credit scoring model for predicting and identifying credit risks among corporate clients. لديك نموذج تصنيف ائتماني راسخ للتنبؤ بمخاطر الائتمان وتحديدتها بين العملاء من الشركات.					
14	you are able to make predictions regarding potential bankruptcies (corporate) with the help of AI and ML driven solutions. أنت قادر على عمل تنبؤات بشأن حالات الإفلاس المحتملة (للشركات) بمساعدة الحلول التي تعتمد على الذكاء الاصطناعي والتعلم الآلي.					
15	it is a goal for your organization to further develop your AI and ML solutions within risk management. إن هدف مؤسستك هو مواصلة تطوير حلول الذكاء الاصطناعي والتعلم الآلي ضمن إدارة المخاطر.					

NOTE: SD (strongly agree), D (disagree), NS (not sure), A (agree), SA (strongly agree).

Source: (Mesihovic & Nordström, 2021).

Section 2: Artificial Intelligence Has Positive Impact on Business Risk Management.

	Statement	SD	D	NS	A	SA
16	AI integration in incident response planning has significantly reduced business disruptions. أدى تكامل الذكاء الاصطناعي في تخطيط الاستجابة للحوادث إلى تقليل اضطرابات الأعمال بشكل كبير.					
17	The use of AI in incident response contributes to quicker recovery from unexpected incidents. يساهم استخدام الذكاء الاصطناعي في الاستجابة للحوادث في التعافي بشكل أسرع من الحوادث غير المتوقعة.					

18	AI tools aid in accurately predicting the impact of potential incidents on business operations. تساعد أدوات الذكاء الاصطناعي في التنبؤ بدقة بتأثير الحوادث المحتملة على العمليات التجارية.					
19	The integration of AI has improved the coordination and management of incident responses. لقد أدى تكامل الذكاء الاصطناعي إلى تحسين تنسيق وإدارة الاستجابات للحوادث.					
20	AI-enhanced incident response plans are more comprehensive and effective than traditional plans. تعد خطط الاستجابة للحوادث المعززة بالذكاء الاصطناعي أكثر شمولاً وفعالية من الخطط التقليدية.					
21	The use of AI in incident response planning has increased the resilience of our business. لقد أدى استخدام الذكاء الاصطناعي في التخطيط للاستجابة للحوادث إلى زيادة مرونة أعمالنا.					
22	I am confident in the ability of AI-integrated plans to handle future business disruptions effectively. أنا واثق من قدرة الخطط المتكاملة للذكاء الاصطناعي على التعامل مع اضطرابات الأعمال المستقبلية بفعالية.					

NOTE: SD (strongly agree), D (disagree), NS (not sure), A (agree), SA (strongly agree).

Source: (Kalogiannidis et al., 2024)

Section 3: Artificial Intelligence Has Positive Impact on Operational Risk Management.

	Statement	SD	D	NS	A	SA
23	AI-driven predictive maintenance has noticeably reduced the frequency of operational downtime. أدت الصيانة التنبؤية المعتمدة على الذكاء الاصطناعي إلى تقليل وتيرة التوقف التشغيلي بشكل ملحوظ.					
24	The predictive alerts provided by AI systems are accurate and timely. التنبيهات التنبؤية التي تقدمها أنظمة الذكاء الاصطناعي دقيقة وفي الوقت المناسب.					
25	The use of AI for maintenance has led to cost savings in equipment repair and replacement.					

	أدى استخدام الذكاء الاصطناعي في الصيانة إلى توفير التكاليف في إصلاح المعدات واستبدالها.					
26	Predictive maintenance using AI is more efficient than traditional maintenance approaches. تعد الصيانة التنبؤية باستخدام الذكاء الاصطناعي أكثر كفاءة من أساليب الصيانة التقليدية.					
27	The implementation of AI in maintenance has improved overall operational efficiency أدى استخدام الذكاء الاصطناعي في الصيانة إلى تحسين الكفاءة التشغيلية الشاملة					
28	I am satisfied with the role of AI in predictive maintenance within our organization. أنا راضٍ عن دور الذكاء الاصطناعي في الصيانة التنبؤية داخل مؤسستنا.					

NOTE: SD (strongly agree), D (disagree), NS (not sure), A (agree), SA (strongly agree).

Source: (Kalogiannidis et al., 2024)

Questionnaire's References

Kalogiannidis, S., Kalfas, D., Papaevangelou, O., Giannarakis, G., & Chatzitheodoridis, F. (2024). The role of Artificial Intelligence Technology in predictive risk assessment for business continuity: A case study of greece. *Risks*, 12(2), 19. <https://doi.org/10.3390/risks12020019>

Mesihovic, A. E., & Nordström, H. (2021). Artificial Intelligence and Machine Learning usage in credit risk management. University of Gothenburg, School of Business, Economics and Law.