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The Effect of Artificial Intelligence Implementation on Risk Management - A Study of the UAE Private Retail Sector

By:

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Abstract

Background: This thesis examines how artificial intelligence (AI) reshapes risk management in the UAE private sector, with emphasis on project-risk decisions that depend on rapid, data-grounded analysis.

Methodology: An in-depth qualitative multiple-case study of two leading companies, using 30 semi-structured interviews with mid-level managers; data were analysed using Thematic Framework Analysis.

Findings: AI improves the timeliness and accuracy of risk work by (i) engineering cleaner, unified data and real-time exception signals; (ii) automating frontline controls (e.g., computer vision and robotics); (iii) formalising resilience through ERP/DR, reliability runbooks and incident drills; and (iv) building human capability via education partnerships and governance routines. The national AI/4IR agenda acts as a catalyst, while sector-specific tailoring and skills determine translation into practice.

Theoretical contribution: The study extends Diffusion of Innovation (DOI) and Technology–Organisation–Environment (TOE) perspectives to project risk management by identifying policy signalling and organisational reliability as adoption mechanisms, and by specifying sector-fit and talent pipelines as boundary conditions shaping outcomes.

Practical contribution: It offers a five-lever playbook—data plumbing, analytics automation, resilience stack (ERP/DR), skills pipelines, and ethics/privacy governance—that organisations can adapt to strengthen project risk management under uncertainty.

Overall, the research clarifies how AI can shift risk management from retrospective reporting to proactive, decision-ready insight in the UAE private sector.

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1.0 CHAPTER ONE: INTRODUCTION

The adoption of Artificial Intelligence, referred to in this thesis as AI, has been understood as one of the most exciting realms of invention in the field of technology. Many are excited about developing technologies that blur the boundaries between human intelligence and machine operations. Indeed, the field of AI provided technical innovation communities with the opportunity to be co-creators, having the ability to impact human intelligence in machines that would be produced in laboratories and factories and use this intelligence to solve real-world problems. However, the excitement surrounding AI is only valuable if it addresses real-world challenges that are beneficial to humanity.

More important to note are the changes that have been experienced in the field of AI inventions. For many decades prior to the development of this research thesis, the concept of using computer technology and machine intelligence to replace human intelligence was fathomable. Indeed, the historical founders of technology, who are largely recognised as pillars of technological inventions in the era of mainframe computers and supercomputers, may not have been able to clearly fathom this concept during their time. Many programs have been made since the invention of the first computers to develop more efficient technologies that have culminated in the development of intelligent machines, which contribute to improving human life on the planet. However, despite the significant improvement in the field of AI technologies, it is important to note that a lot still needs to be done in this field.

According to recent scientific studies on AI, including the study by Cheatham *et al*. (2019), the current modern societies have largely embraced the adoption of AI both in professional and social circles. The use of AI has been implemented in various transformation levels, with applications in different business organisations, and mostly when relating to the concept of cognitive computing. Cognitive computing has developed a key element of AI as it supports the process of machine learning, which forms the basis for the development of AI programs (Cheatham *et al*., 2019). For example, the use of AI in private business premises has been largely utilised to engage in enormous data processing processes, which present business organisations with superb decision-making processes for their business. The use of AI makes the process of data processing much easier and verifiable since such systems have the capacity to process large volumes of data processing, which in turn makes it easier for the company to build up a more creative and manageable service. They have also made it easier for organisations to develop more complex data storage systems that make it easier for organisations to keep long-term records and further accurately inform their decision-making process.

Aside from the private business sector, the use of AI is also making a huge impact in the public sector. The use of AI in the public sector has been largely adopted by governments, who also find numerous opportunities for the application of such key technologies in the management of their public service development. First on this list is the long range of public service provisions, which involve different sectors such as education, public health, transport, infrastructure and so on (Wu *et al*., 2014). Governments also find further applications of such products in policy making and enforcing developed policies. The government systems have a huge potential to transform their development and enforcement of public policies by adopting the features provided by AI technologies. For example, AI can be applied to improve the quality of public services. It is evident that using AI in such forms helps the public build more trust in the public service administration (Bussman *et al*., 2021). They enable the public to have confidence in the way policies are developed and enforced, and this builds more confidence in public institutions while at the same time reducing bureaucracies, which are the breeding ground for corruption and other forms of public service inconsistencies. Overall, the public would feel an increase in the efficiency and effectiveness of how the government administers services to them, and this builds up more trust in their government.

However, AI adoption in the public sector has been slower than in the private sector. This feature can be attributed to the changes in the types of challenges that are experienced with the adoption of AI, both in the public and private sectors. The use of AI in the public sector can both increase and reduce public trust. For example, as public trust is increased through the increase of transparency in providing services, there is a decrease in trust that results from the handling of personal data and information (Stone *et al*., 2020). AI systems may act as backboxes that collect personal information that individuals do not understand and how such information is utilised in their absence. This has contributed largely to the slow pace of the adoption of AI technologies in the public sector. However, when it comes to the private sector, the technology stakeholders have a full description of how they collect information, and there is little collection of personal information from the public. This makes it easier for the private sector to adopt the use of AI.

Risk Management is one of the key areas of interest for applying AI in the private business world. Risk management is a crucial field that requires top organisation managers to adopt innovative technologies and problem-solving solutions that help them develop effective risk management strategies (Sun *et al*., 2019). Therefore, the key technological developments that are presented with the use of AI cannot be ignored when it comes to risk management. Effective risk management relies on managers using data to identify potential hazards affecting organisational operations. Therefore, as AI presents a huge opportunity for data collection, analysis and utilisation, it becomes a significant player in the risk management process. The use of AI presents managers with machines and computer technology, which has the ability to perform tasks which require human intelligence at faster rates and with greater accuracy than human abilities. Therefore, this has become the rationale for the argument that technology can form the basis for replacing human intelligence in the future.

AI technology enables computers and machines to learn processes, interact with other machine components, and make judgments like humans. This means that they can operate and act in situations which previously only required the use of human intelligence. For example, they contribute to the decision-making process in relation to risk management. Decision-making is important in risk management since it depends on the ability to properly analyse a range of varying data elements and make decisions that perfectly fit the situations faced by the company (Bartam *et al*., 2020). Due to the increased uncertainty and competition in the modern business world, organisations and their managers need to use the available technologies to find ways to improve their organisations' performance. Effective use of technologies can help the company develop a certain competitive advantage in the market. While there is a lot of discussion on the exact potential that AI technologies have to build up the capacity of private organisations in strategic management and risk management, there is still a need for more scholarly material that discusses the impact of AI on the fuel of risk management. Therefore, this study will present the effect of AI on risk management.

1.1 Background of the Research

The increasing significance of this topic is linked to the increase in the importance of risk management within the business world. The increasing dynamics in business have led to unprecedented uncertainty that must be dealt with in the public business domain. This uncertainty stems from rapidly changing market conditions, intensified by globalisation. This has therefore led to a significant threat to the performance and sustainability of business organisations (Barta, and Görcsi, 2021). The various risks that emanate from businesses operating within the highly dynamic market structures expose the business to high risks in sustainability and performance. Business performance relates to the ability of the business to reach the market with its products, develop products that are effective in the market, and make sure it markets such products to the relevant consumers. With changing market conditions, consumers keep shifting their expectations, which means that consumer satisfaction has become a constantly moving target, making it even more challenging to meet. On the other hand, measures of sustainability are related to the business's ability to develop products that can be used over a more extended period of time or that ensure that the environment is protected. Sustainability can also include financial unsustainability, which results from being able to generate revenue and make a profit that ensures the company continues to meet its organisational objectives.

Therefore, to protect the business from the risks outlined above, business managers are obligated to implement effective risk management technologies. The risk management process is defined in the academic scholarly journals by Bartram *et al*., (2020) as the process through which the management of an organisation can identify, categorise and control the various threats that face the business and present a threat to their performance and sustainability, through the implementation of proper and specifically defined initiatives and decisions. This means that risk management is goal-oriented and deliberate. Measures that appear beneficial but result from sheer confidence cannot be categorised as risk management strategies.

the number of risks managers are concerned with varies widely in terms of the nature of risk and the severity they present to the business. When putting up risk management practices, the business needs to consider various sources of risks, which include natural disasters, financial crises, management risks, technology-based risks, legal risks, and operational risks (Barta and Görcsi, 2021). Therefore, with increasing challenges and risks in modern-day society, business organisations have to develop even more complete risk management strategies that will meet the challenges presented by the market conditions (Bussmann *et al*., 2021). For example, the COVID-19 pandemic has been the recent highlight in the business context, which has seen multiple organisations being exposed to multiple risks that have made it difficult for them to continue developing and operating sustainable business models. The COVID-19 pandemic is a perfect example of business risk because it presented a risk that spanned several fronts of business operations. The pandemic threatened to extinguish the operability, profitability and sustainability of the business institutions (Barta, and Görcsi, 2021). For example, it was first difficult for businesses that operated within the line of human interactions, such as grocery stores and warehouses, to find employees who would continue to provide vital services to the public. In addition, the pandemic also threatened the sustainability of businesses by disrupting the global supply chains, which ensured that goods and raw materials were made available on a global scale to manufacturers, producers and consumers. This arose from the subsequent border closures, which were put in place by governments to orchestrate the proper containment of the virus, which was determined to be transmitted through physical contact. All these presented unprecedented challenges and risks to the business and organisations that needed to be adapted sufficiently.

Over the years, businesses have effectively evolved their traditional risk management practices to suit the changing nature of risks experienced within the business realm. Therefore, the risk management practices have effectively evolved from traditional risk management, which essentially understood risks as a separate aspect of the organisational strategy, into the more recent Enterprise Risk Management (Hofmann *et al*., 2020). Enterprise Risk Management, as the more contemporary perception of organisational risk, upholds that risk management is a collaborative, cross-functional responsibility for the organisations, which needs to be given full effort and attention by the top management officers.

Another point of concern that forms important background information for this study is the previous trends of major business organisations, as well as small business organisations, to create and make available large volumes of data. Over the years, it has been evident that both small, large, and medium-sized business organisations have been producing large volumes of data that relate to the various areas of operation in their key areas of expertise. The provision and availability of large volumes of data are fundamentally meant to make decision-making within the business world easier and more efficient (Butcher and Himenez, 2019). In the wake of technology used to collect large volumes of data, business organisations have found themselves in possession of huge volumes of data. This data is made available through various technology-based platforms that interact with customers, some of whom provide their preferences in relation to products, the nature of market behaviours, changing demand and supply patterns, and so on. Therefore, an organisation can use these data to predict the occurrence of risks and evaluate risk mitigation techniques that they can employ on the face of each of the respective risks they might face. However, as businesses continue to gain larger volumes of data, they also face the challenge of obtaining methods to properly analyse and present such data in a way that will benefit the decision-making processes. Without a proper system that can be used to analyse and make meaning of such data, it is impossible to use the data in a meaningful and valuable manner. Therefore, with the development of modern technology, it is possible to develop more structured techniques that can be used in analysing the data and aid the decision-making process. This data can also be used to develop a risk mitigation process since it provides information about the various risks that contemporary business organisations face. This has undoubtedly created a unique opportunity to implement AI within the data processing, analysis and transmission systems.

Another key area of operation for modern-day organisations, in which the process of risk management, data processing and identification is applied, is within the project management process. The role of project management is the occupational process through which companies and other professionals organise and allocate their resources in a unified manner towards the accomplishment of specific organisational goals. Proper use of project management ensures that certain goals that organisations set out to accomplish, which make up part of their greater organisational success portfolio, are achieved. For example, through the use of project management, the organisation can consolidate its human resources, which will be used to accomplish specific tasks required to complete a certain project, as well as consolidate its financial resources, and plan their time for when their project needs to be completed (Butcher and Himenez, 2019). As a result, project management is one of the areas in which risk management needs to be vehemently and diligently implemented. Project managers often pay attention to the volume of resources needed to complete a certain project, as well as the time required to complete the project. The existence of risk within the project management process poses a considerable threat to both the cost of completing the project as well as the timelines for the completion of the project (Khatib *et al*., 2021). Threats in risk management could first make it more expensive to get certain crucial elements of the program completed, or they could also significantly delay the progress in a manner that makes it hard for the whole project to be completed in time. In both cases, the involved organisation has a lot to lose regarding their organisational goals, performance and success. This shows the significance of proper risk management within the project management scope and how it relates to the significance of organisational concerns and goodwill.

The use of AI in risk management related to project management activities is supported by the technological capabilities which AI presents to this field. The use of AI allows project managers to have certain capabilities, including tracking project features, efficient digital management of resources, tracking quality metrics, and enforcing quality assurance requirements within the project management scope (Hofmann *et al*., 2020). These are all the combinations of the many features AI brings to the project management scope and provide more specific solutions that can contribute to the vindication of efficient project management activities. It also potentially validates the use of AI as a risk management tool within the scope of project management as a valid topic of interest worth scholarly attention.

The preamble to this study, as outlined so far in this background scrutiny of this research topic, shows the huge potential of AI technology as a risk management tool in business. There is no doubt as to the huge potential that business owners and organisations can tap into when they fully implement the use of AI technologies in risk management, especially for the private sector business, as per the focus of this study (Butcher and Himenez, 2019). However, despite this distinct deliberation, it still holds that adopting AI in both the public and the private sectors within business organisations has been slow and inconsistent. The application and implementation of AI processes have been underachieved within most institutions. This slow pace would be influenced by a range of factors. Still, one of the most pertinent reasons falls under the lack of proper understanding of the potential that such adoption of technologies might have on the implementation process. The majority of business organisations lack a proper understanding of how the use of AI can help them improve their overall risk management process (Bussman *et al*., 2021). In addition, there is little understanding of how AI can be applied in the various sectors of business organisation development for both the public and the private sectors. This argument leads to the need to conduct a study that would be used to study and understand the implementation of AI within the public and private sectors as a risk management technique.

1.2 The Problem Statement

The private sector has largely been on the front foot when it comes to the implementation of modern technological inventions to improve the efficiency of business operations. Compared to the public sector, the private sector has made significant progress that outlines them as a leader in this aspect. In addition, there is a progressive improvement that has been witnessed within the risk management programs employed by organisations within different operational settings. This includes the adoption of modern Enterprise risk management practices (Wu *et al*., 2014). The United Arab Emirates (UAE), for example, has seen tremendous adoption of technology-based programs, both within the public and private sectors. In essence, the UAE has been considered one of the pioneer countries that have given a forefront to the adoption of AI both in the public and the private sectors (Khatib *et al*., 2021). This, therefore, means that the case studies available within the UAE, in both the private and the public sectors, can be used to provide crucial learning points for this process that can be emulated with other countries and institutions that are soon to follow in this path. The adoption of AI within the UAE has been based on data-driven decision-making technologies, which aim to increase the competitiveness of firms and organisations employing these methodologies.

The UAE has the National Strategy for Artificial Intelligence 2031, which was developed to act as the blueprint for the country's adoption programs for AI. Under the leadership of Sheikh Mohammed bin Rashid Al Maktoum, who was the vice president and the prime minister of the regions, the cabinet adopted this strategy with the sole purpose of strategically positioning the UAE as a global leader in the adoption of AI by the year 2031, and at the same time to come up with an AI-based integrated system, which would foster the delivery of services to the public in the regions. There is no doubt that this goodwill from the government and the public, in general, has largely contributed to the inclination of AI adoption within the regions. This is also expected to make it easier for private sector practitioners within the region to adopt AI and make it even more effective with the support of the public and government institutions. However, several challenges remain, even within the UAE public sector, concerning the adoption of AI programs.

Several UAE private sector industries within the UAE are adopting AI to enhance operational efficiency. This has been witnessed mainly within financial institutions, health institutions, and education systems. This shows that such business operatives recognize that they can use AI abilities to make their business more effective and productive. According to Aziz and Dowling (2019), further use of AI in risk management has been argued to be synonymous with improving productivity and efficiency and, at the same time, helping firms reduce operational risks. However, it is important to note that despite this goodwill, there is still a lack of proper evidence that shows the success obtained with using this technology for risk management in institutions (Khatib *et al*., 2021). Therefore, this study aims to fill this gap in research by providing a scholarly examination of the implementation of AI for the purposes of risk management. To do this, it is vital to narrow down the area of study to private business, since it has already been established that both private and public institutions have different demands when it comes to implementing AI. This study will focus on implementing AI within the private sector, mainly business firms, which have attempted to go down this path.

1.3 Justification of the Study

The study by Barta and Görcsi (2021) provided a background understanding that can be used to evaluate the amount of knowledge made available within this field of study. In this research article, it is evident that there is a lack of sufficient scholarly knowledge concerning the implementation of AI as a risk management strategy. The research article also focused on the behaviour of private business organisations' approach to risk management (Khatib *et al*., 2021). It is evident that despite the availability of clean and promising alternatives to this topic, most practitioners have still maintained their lack of commitment to adopting new and technology-based techniques for risk management. Most private organisations still stick to the old traditional methods of risk management. The use of AI as a modern solution to risk management challenges is still not fully adopted. According to the study by Baryannis *et al*. (2019), this status quo cannot continue to exist, as the complex nature of real-world problems continues to show up. There has to be a breakthrough that will enable business leaders to take up the challenge of making a program for implementing and using AI within their business cycles.

Biryanis *et al*., (2019) also discuss the importance of this transition to the decision-making process. They argue that such cohesion would be a critical component in enhancing the pre-existing decision-making and support systems that relate to the risk management process.

Already, a number of businesses have taken up the exciting challenge of enforcing the use of AI within their company operations. These companies have primarily adopted AI for supply chain management and financial risk mitigation. According to Schwarz and Sánchez (2015), most businesses have already expressed concerns over risks that are associated with the use of AI in the protection of the public. They also expressed concerns about the significant lack of understanding of how the available AI technology can best be used to aid their risk management strategies. Conducting a study into these issues will help future business organisations fully understand this topic and develop meaningful suggestions on how to properly implement AI within organisational decision-making.

Private sector firms stand to benefit significantly from this study. The study focuses on the challenges, opportunities, and solutions that are unique to private sector organisations. There is a continuous demand for new and improved solutions to the modern challenges that threaten the performance and sustainability of current business organisations. This, therefore, justifies the need to integrate the abilities that technologies present to help solve modern-day challenges. For the researcher, this study provides an opportunity to explore an under-researched area of scholarly interest. It also led to a significant contribution to the field of research by filling a knowledge gap in the use of AI for the purpose of risk management for private organisations.

1.4 Research Goals and Objectives

1.4.1 General Objectives

This study aims to examine AI's impact on risk management in private retail project management. To meet this aim, the following specific research objectives were used to guide the research.

1.4.2 Specific Objectives

1. To examine how the UAE National Strategy for AI 2031 has affected the project management efforts in the private retail sector.

2. To analyse the strategic approaches adopted by private retail sector business organisations in the UAE to enhance their risk management efforts.

3. To explore the future of AI applications in risk management on project management activities, applications, and the potential for application in the future.

1.5 Thesis Structure

This thesis report is divided into seven chapters. The first chapter is an introduction that provides the background of the study, introduces the research questions, and sets the foundation for the next sections of the study. Chapter Two contains the background to the research, which mainly focuses on the background of AI use within the UAE and in the retail sector. Chapter three is the literature review, where the researcher focuses on looking at the existing theoretical information that relates to the topic of study, to establish how this research study will fit into the existing body of scholarly materials. In chapter four, the methodology is presented, which includes the data collection and analysis method, as well as a justification for using these methods presented through the research design and philosophy. The results collected are then presented in Chapter Five. Chapter six then contains the analysis of results, which provides a detailed scrutiny of the results obtained to determine the patterns and knowledge that can be derived from the study. This is combined with a discussion of results, showing a connection between the results obtained and the research questions. Finally, chapter seven contains the conclusions and recommendations made from the study.

2.0 CHAPTER TWO: BACKGROUND TO RESEARCH

This chapter provides the contextual foundation for the research by outlining the broader developments that shape the study of artificial intelligence (AI) in the United Arab Emirates. It highlights the national strategies and policies that have positioned AI as a driver of innovation, the historical evolution of technology and industrial revolutions, and the specific dynamics of the UAE retail sector where this study is situated. The discussion is descriptive in nature, focusing on how government vision, technological change, and public perception have created the environment in which AI adoption occurs. To ensure this background is well grounded, the literature informing this chapter was identified through targeted searches in academic databases such as Scopus and Web of Science, using keywords related to AI, risk management, and retail in the UAE. This provides a strong basis for understanding the context before engaging in critical evaluation in the next chapter.

2.1 The Adoption of AI in the UAE

The adoption of AI in the UAE has been largely influenced by the adoption of AI in the public sector, which the administration and the rulership of the region have fostered. There is no doubt that the adoption of AI in the public sector shows great potential to transform the service of public delivery, as argued by the OECD (2020). This gave a significant reason for the UAE prime minister and vice president to seek out the implementation of AI within the region's public sector. According to Wirtz *et al*., (2019), the overall rate of AI productivity is expected to continue increasing steadily with a 2% increase for the next 15 years. Some of the key areas expected to benefit even more from adopting AI include the resource allocation system, the automation of repetitive tasks, reducing the dependency of human decision making, which significantly slows down processes, and addressing further limitations within the e-government services. Therefore, it is no surprise that Sheikh Mohammed, the president of the UAE, prioritised the public sectors, such as healthcare and education, when it comes to implementing AI in the region.

AI within the UAE has also greatly reduced the overall burden on administrative tasks that need to be performed within both public and private institutions. One example is the time taken to process immigration (Hamilton Skurak *et al*., 2021). While most individuals have to submit documents which need to undergo verification and counter-checking within multiple databases, such as criminal databases and medical records, it is obviously very difficult to have such a process conducted by human action. The use of AI, however, presents a huge potential that can be harnessed through robotic process verification (Butcher and Himenez, 2019). Automated document verification and records checking can help reduce the verification process and overall immigration by a large margin. In addition, with an integrated system, it is possible to have individuals receive services by making only a single application. This, therefore, significantly improves the process's efficiency and reduces the overall cost required for the applications. The same argument can also be applied to healthcare institutions, which are known to be a significant part of all the government spending that most governments engage with.

According to Pappass *et al*. (2018), the AI field has significantly grown and diffused from an area of academic research into a fully functioning area that focuses on the development of organisations and building competitive advantage. According to the International Data Corporation, the global spending on AI by 2023 is expected to increase to around $89 billion, which will double as much as what was spent globally in 2019. The World Economic Forum of 2018 also reported that by the year 2025, AI will also form a quarter of the world's GDP. This shows a significant prospect for using AI within the commercial world and stresses the importance of the file in the modern era.

While anticipating significant developments and social and economic changes to be brought about by the use of AI platforms, most governments have put in place digital transformation systems that aim to streamline their communities' adoption of AI (Butcher and Himenez, 2019). Countries such as Singapore, New Zealand, Germany, China and the UK have all made some significant progress in the adoption of AI, especially through revamping their use of digital systems, which are more AI-friendly (Hamilton Skurak *et al*., 2021). For example, in China, over $1.2 billion was spent in 2021 on the development of AI-related infrastructures. The region around Europe has seen an investment of over 700 pounds spent in building private and public partnerships, which aim at laying the foundation for the use of AI systems (Writs *et al*., 2019). These investments speak to the AI assimilation process into the public and private sectors.

Having compared the extent of AI adoption in the UAE with that of Singapore and China, it is quite clear that while the UAE has made substantial progress, mainly in government-driven AI projects, the private sector AI remains an issue of concern. Singapore provides a comprehensive approach to data governance frameworks. At the same time, China invests in large-scale infrastructure for the nation that could efficiently manage risk in the use of AI systems, which the UAE could emulate (Haddad et al., 2020). On the other hand, UAE retail lacks the strong AI foundation like China or the rigid regulatory framework as seen in Singapore. This raises questions about the UAE retail sector's readiness to handle AI risks within its operating area, such as data protection and continuity.

The process of assimilation is defined as an organisational press, which is set in motion with the organisational members have a hint about an innovation or a program, which can lead to them acquiring the new piece of innovation or technology and finally leads to the fruition with the complete acquisition of the said technology (Hamilton Skurak *et al*., 2021). Based on this definition, two things come out clearly. The successful assimilation of any technology first depends on the practical and working integration of the innovation with the existing innovations (Haddad et al., 2020). In the case of AI, assimilation of AI depends first on the ability of the organisation to include the new technology with the old way of the organisation's practices. What this merging process highlights is that the merging of the latest and the old system structures and boundaries is a process that requires complex skills and resources that might well go beyond the ability of specific organisations to avail (Butcher and Beridze 2019).

In their study, Lium and Kim (2018) clearly state that despite several pieces of literature discussing the adoption of AI in the public and private sectors, there is still a need for more literature that extensively covers the assimilation challenges. The more concerning piece of information that would make a significant difference within this field of practice is the availability of empirical evidence and studies, which can be used to develop a stronger basis on which to make generalisations concerning the challenges facing the assimilation forces of AI systems (Butcher and Himenez, 2019). Further on, it is essential to note that AI technology represents a section of ideal technology that is meant to be applied within the public and private sector institutions, where plenty of changing variables make it impossible to do pre-programming for the assimilation phase. This means that more advanced knowledge on the evidence-based experience that institutions and individuals have had with their past AI assimilation can help others make informed decisions when going down the same roads and when building on AI programs.

It is worth noticing that the UAE government has actively promoted the adoption of AI, which plays a noticeable role in the adaptation process of the private sector. However, as for its direct impact on the effectiveness of risk management, AI seems to have vast potential, but its implications are still not very specific. For instance, in the UAE's retail industry, AI serves as a tool that can streamline operations, minimize errors, and improve decision-making (Smith and Smith, 2021). However, this technological change also introduces another level of risks, such as the threat posed by hackers or the danger of being stuck with inert AI systems. While the government's efforts to support AI are positive, they may obscure issues affecting private companies integrating these solutions, including risk management.

2.2 The UAE Government Plan and Vision

A lot of the discussion around the UAE in modern-day society has been spurred by the goodwill supported by the government in the AI implementation. As much as this study will focus on the implementation of AI in the private sector, it is impossible to completely do away with the role played by the government in these elements (Khatib *et al*., 2021). The intention of the UAE government to push for increased adoption of AI within the UAE has been a major force in the adoption of AI by the private sector, which has closely intertwined the two sectors. This is the reason why this literature review focuses a bit on the perspective of the UAE government on AI.

From a background point of view, the UAE government was established in 1971. Ever since its inception, the UAE government has been on the front foot when it comes to delivering services to its people, mainly to provide world-class services that would appeal to citizens, expatriates and visitors (Almarzooqi, 2019). Therefore, with this interest in mind, the UAE government has not been historically naïve when it comes to adopting technology as a source of competitive advantage regarding service delivery. For example, they launched the strategic e-Government platform, which was aimed at facilitating the use of ICT to deliver government services (Khatib *et al*., 2021). In 2010, the government announced its vision for 2021, which mainly focused on improving the quality of service offered in different arms and sectors of government. This included the development of a government platform access stage, known as the m-government, which would enable people around the clock to access government services.

Aside from these past historical developments, the UAE government has also had the UAE centennial plan for 2072. The centennial plan was announced in 2017, and this was a vision that was meant to guide the country over a span of five decades through certain prosperity-based goals and visions (Almarzooqi, 2019). Four main aspects of the government were included in this plan: government, economy, education, and the community. The country would set forward to obtain a good functional government, the best education, a strong economy and a happy community (Chand 2017). In other words, this vision would help them to be the best country to live in by the year 2071. Therefore, the government embarked on a strategy to focus on the adoption of cutting-edge technology, including AI, to help them achieve these ambitious visions. This would also include embarking on a public program that targets equipping the youth and the working population with skills to be effective in the new digital world.

The UAE government also has a concurrent strategy for the year 2031. In 2017, the government launched the AI strategy, which was meant to be a key milestone in the transition to the technology revolution and put the country in a strategic position. This strategy was also key to the overall centennial plan developed for the year 2071. The story targeted the adoption of various AI power systems, which would help boost the overall government performance, provide efficient solutions to real-life challenges, and strategically position the UAE as the Silicon Valley of AI (Khatib *et al*., 2021). During this strategy development, nine key areas were identified as ones that were most likely to benefit from the adoption of AI. These included traffic control systems to reduce accidents and congestion, environmental adaptability and protection, education, technology, water conservation, renewable energy, space exploration, healthcare and transport.

Therefore, as part of the strategies to meet these ambitious objectives, the government established the Ministry for Artificial Intelligence and appointed a minister in charge of this ministry, whose only target was to ensure the adoption strategies of AI were implemented (Almarzooqi, 2019). They also formed an intergovernmental council, whose main aim was to ensure they iron out arising matters that may be experienced in different government sectors and may have hindered the implementation strategy in some way (Halaweh, 2018). The ten council members work closely with the ministry for AI to ensure they address the various challenges experienced during the implementation process. Since this period, the government has engaged in multiple workshops to provide the public with the needed manpower and resources to help them integrate AI systems smoothly without having a skills issue.

The leadership and influence of Sheikh Mohammed bin Rashid al Maktoum, vice president and prime minister of the UAE, were also significant to these developments. In 2008, he established the need to set up a government leadership program, which has been instrumental in pushing the country's agenda for AI development (Halaweh, 2018). The government has also strongly invested in leadership development to achieve an effective AI-based development program. This has also increased the desire of the government to bring up new leaders who will see the country in its development and embrace AI in the future (Khatib *et al*., 2021). The government has a leadership program that uses different methods and strategies to help nurture and develop public leaders equipped with modern-day leadership competencies. This program also targets the current government officials to ensure they are equipped with the necessary leadership skills to sustain the program.

2.2.1 Development of Research Infrastructures

As part of their AI strategy, the UAE government understood the importance of building a robust research-based community. The UAE government has set out key endeavours to develop a robust research infrastructure. This was further validated by the AI Hardware Infrastructure Report, which was published in November 2020 and claimed that the UAE owns the 36th most powerful and high-performance computer globally. This is significant because it provides the computational capacity of the hardware resources that are important for the overall development of AI technologies (Barta, and Görcsi, 2021). It also shows the government's high commitment to ensuring that it achieves its goals as a modern-day AI leader. A considerable percentage of the total hardware processing power that is contained in the UAE is held by the private sector. This is considered to be around 89% of the total processing power the USA contains. However, the key to the research and development includes the academic institutions, such as colleges and universities. Such institutions are also key to having large volumes of processing power that help them push for their research agendas and lead to the development and creation of new knowledge regarding the assimilation of AI. An example includes the New York University, Abu Dhabi, which takes the lead in increasing computer vision, natural language processing, health informatics, and climate modelling among other key areas of interest (Smith and Smith, 2021). The UAE University also takes the lead using three HPCS that help them in their various research projects directed towards high-performance AI systems. The robust research activities within the UAE are expected to increase the country's potential to ascertain its position as a world leader in AI.

2.2.2 Talent Building and Capacity

Talent Building (TB) is key as the development of AI and its assimilation into the traditional problem-solving process is a process that requires a lot of talent and human resources. While the use of AI is thought to be a simplified process that largely depends on the user-friendliness of AI systems, a lot of technical expertise is required to develop such systems (Barta and Görcsi, 2021). This means that technocrats, who include both a mixture of computer software and hardware engineers, along with a range of other professionals, are needed to build this industry. This necessitated the development of training programs, which aim to ensure the availability of the needed skilled manpower within the UAE (Sanchez *et al*., 2020). For example, in partnership with Kellogg College, the government built an executive-level coursework program, which would then train the UAE nationals on the key elements they would need to push for their national growth strategy. The government also engaged in multiple summer camps, which brought together high school and university students to help integrate the knowledge-sharing process and access the various institutions within the country. The Mohamed Bin Zayed University of Artificial Intelligence is also one of the key universities that have come forward as a result of human resource development to cover the need for AI-based talents within the region.

The healthcare system in the UAE has been especially illustrated in the practice of adopting AI and using it as a symbol of national significance. One of the healthcare stresses included the launch of Medopad, a smart application that can consistently monitor lifethreatening medical conditions and allow patients to proactively implement medical interventions (Shamout and Ali, 2021). The key to establishing AI in healthcare is mainly concerned with data gathering and analysis, which helps to make informed interventions for the overall wellness of the population. The Dubai Health Authority, for example, partners with Agfa Healthcare specifically to utilise the AI-based workflow, which facilitates the medical imaging process in treating TB.

2.3 Historical Technology Development and the Industrial Revolutions

Technology has always shaped the course of human development, influencing how societies grow and how economies are organised. The history of the industrial revolutions is a clear demonstration of this: each major technological shift did not just bring about new machines or inventions, it transformed the way people worked, lived, and interacted with one another. The First Industrial Revolution, which took place in Britain between the mid-18th and mid-19th centuries, is often remembered for its groundbreaking use of steam power. Railways, steam engines, and mechanised factories suddenly made it possible to produce goods on a much larger scale and at greater speed than before (Halaweh, 2018). This shift created enormous opportunities for trade and manufacturing, but it also sparked rapid urbanisation and changed traditional patterns of labour.

The Second Industrial Revolution, beginning in the late 19th century and extending into the early 20th century, took industrial growth to another level. The arrival of electricity transformed production lines, with assembly systems enabling mass production in ways that were unimaginable a few decades earlier (Philbeck & Davis, 2018). New materials like steel and new communication tools such as the telephone and telegraph allowed industries to grow rapidly and connected markets across countries. This period laid the foundations for the global economy as it is recognised today. The Third Industrial Revolution, sometimes called the Digital Revolution, emerged in the mid-20th century with the invention of computers and digital communication technologies (Philbeck & Davis, 2018). The rise of the internet in the 1960s and 1970s, along with personal computers and affordable electronics, accelerated globalisation. Information could now travel across the world instantly, making it easier for businesses to connect with consumers and partners far beyond their borders. Automation became more common in industries, and several traditional jobs—such as telephone operators and bookkeepers—began to disappear as digital systems took over routine tasks (Shamout & Ali, 2021).

The current stage is commonly referred to as the Fourth Industrial Revolution. Unlike previous revolutions that focused on mechanisation or digitisation, this one is marked by the merging of physical, digital, and even biological systems. Emerging technologies such as artificial intelligence (AI), robotics, blockchain, 3D printing, and the Internet of Things (IoT) are advancing rapidly, reshaping both industries and daily life (Halaweh, 2018). What sets this revolution apart is not only the speed of change but also the breadth of its impact. AI systems are not just performing simple tasks; they are taking on roles that involve reasoning, prediction, and creativity, which were once considered exclusively human capabilities (Philbeck & Davis, 2018).

Each of these revolutions has had profound effects on the global workforce. Entire sectors have disappeared, while new professions and industries have been created. For instance, in the United States, the share of the workforce employed in agriculture fell from 41% in 1900 to just 2% by the year 2000 due to advances in agricultural machinery and farming techniques (Philbeck & Davis, 2018). Similarly, the invention of ATMs revolutionised banking, enabling financial institutions to serve more customers with fewer staff. Other jobs, like cashiers and clerks, have steadily been phased out by automation (Shamout & Ali, 2021).

The Fourth Industrial Revolution goes even further. AI, robotics, and IoT are not only changing what people do, but also redefining the very structure of organisations and industries. Intelligent machines analyse data, predict trends, and support decision-making in ways that are faster and more accurate than human capability alone. Nanotechnology and biotechnology are advancing medicine and materials science, creating opportunities that were science fiction only a generation ago (Halaweh, 2018). For the UAE, this context has special importance. As part of its long-term strategy to reduce dependence on oil revenues, the country has embraced AI as a key driver of economic growth and diversification. National initiatives such as Vision 2021 and the Centennial 2071 Plan explicitly place AI and advanced technology at the centre of development. The government recognises that in the global race to harness the Fourth Industrial Revolution, countries that integrate AI into their industries and services will lead in innovation and competitiveness.

Looking back at the earlier industrial revolutions helps to make sense of where the UAE stands today. Each revolution marked a period of massive social and economic restructuring, and AI represents the latest chapter in that history. Understanding this trajectory is essential because it shows that the UAE's adoption of AI is not an isolated development but part of a broader, ongoing story of technological transformation.

2.4 Historical Evolution of Artificial Intelligence

Artificial intelligence is not a sudden innovation; it is the result of decades of work, experimentation, and ambition. The history of AI shows how ideas that once belonged in philosophy or science fiction gradually became practical technologies that now shape industries and everyday life. The story begins with Alan Turing in the early 1950s. Turing posed the fundamental question: can machines think like humans? His famous "imitation game," later known as the Turing Test, was designed to assess whether a machine could convincingly mimic human responses (Shahroom & Hussin, 2018). This idea opened the door to treating machine intelligence as something that could be studied and developed systematically.

Not long after, John McCarthy and a group of computer scientists formally coined the term "Artificial Intelligence" in the mid-1950s (Barta & Görcsi, 2021). By framing AI as its own field of research, they laid the groundwork for decades of exploration into how machines could perform tasks that normally required human intelligence. From the start, the ambition was to build systems that could reason, learn, and adapt. Progress in AI was uneven at first, with periods of great excitement followed by moments of disillusionment. In the 1970s and 1980s, "expert systems" became one of the first widely used forms of AI. These systems could replicate the decision-making of specialists in narrow fields, such as medicine or engineering, by following programmed rules. They demonstrated that computers could indeed solve complex problems, but their limitations soon became clear. Without the ability to learn, they could not adapt to new problems outside their scope (Philbeck & Davis, 2018).

A landmark moment came in 1997 when IBM's Deep Blue defeated world chess champion Garry Kasparov. This victory highlighted the potential of machines to surpass humans in specific domains that required strategic thinking and calculation (Philbeck & Davis, 2018). From that point on, the public and researchers alike began to see AI not as a theoretical concept but as a tangible force capable of reshaping competitive environments.

The 21st century brought a turning point with the rise of big data and cloud computing. Vast amounts of digital information, combined with cheaper and more powerful processors, allowed for the training of advanced machine learning models. AI was no longer limited to rule-based systems; it could now "learn" from data and improve over time. This shift led to applications across a wide range of fields, including natural language processing, facial recognition, predictive analytics, and fraud detection (Halaweh, 2018). In the UAE, the evolution of AI has been strongly linked to national ambitions for innovation. The establishment of the Ministry of Artificial Intelligence in 2017 and the creation of the Mohamed bin Zayed University of Artificial Intelligence signalled a long-term commitment to leading in this area (Smith & Smith, 2021). These moves reflected the recognition that AI is not just another technology but a cornerstone of future competitiveness and development.

The history of AI therefore shows how the field has progressed from a philosophical question to a core component of modern economies. For the UAE, understanding this evolution is important because it illustrates why AI adoption has become such a central priority. The tools being used in the country's retail sector today—whether predictive analytics, machine learning, or computer vision—are built on decades of breakthroughs. This long trajectory provides the foundation for how AI is now expected to reshape risk management and business operations.

2.5 Artificial Intelligence and Organisational Change

Every major technological shift has forced organisations to adapt, and AI is no exception. The integration of AI into business processes has changed not only how organisations operate but also how they view their workforce, strategies, and even their role in the economy. Organisational change can be triggered by internal factors, such as management decisions or workforce issues, or by external ones, such as market shifts, regulations, or new technologies (Desai & Shah, 2018). In the case of AI, the most powerful driver of change is the pace of technological advancement itself. Businesses are under pressure to adopt AI tools not just to improve efficiency but also to remain competitive in industries where customer expectations and global benchmarks are rising.

Traditionally, economic growth was measured through labour and capital, but AI adds a new dimension. Intelligent machines now act as a kind of "virtual workforce," performing tasks once reserved for humans. They can automate routine activities, augment human work, and create entirely new ways of delivering products and services (Purdy & Daughtry, 2017; Desai & Shah, 2018). This has significantly changed productivity patterns, pushing organisations to rethink how they structure jobs and deploy resources. Employment has been deeply affected. Earlier revolutions reduced routine manual work, while also creating new industries that demanded different skills. The Fourth Industrial Revolution goes further by targeting non-routine work as well. AI systems are increasingly capable of analysing data, managing logistics, and even handling customer interactions (Schwab, 2016). As a result, organisations are not just automating repetitive tasks but also reshaping higher-level roles that involve decision-making (Natasia et al., 2022).

This shift has made reskilling and upskilling essential. Workers need not only creativity and problem-solving skills but also digital literacy to work effectively with intelligent systems. Many organisations are investing in training programs to prepare employees for hybrid roles where humans and AI collaborate (Shahroom & Hussin, 2018). At a strategic level, AI enables companies to be more agile. With real-time analytics and predictive modelling, organisations can adjust quickly to changes in consumer demand, supply chain disruptions, or competitive pressures (Halaweh, 2018). In sectors like retail, this agility is especially critical, as businesses are able to personalise services, anticipate risks, and streamline operations through AI-driven insights. However, the integration of AI is not without challenges. Concerns about algorithmic bias, data security, and ethical use remain pressing. These issues are particularly relevant in the UAE, where the rapid adoption of AI is accompanied by a need for strong regulatory frameworks that protect both businesses and consumers (Natasia et al., 2022).

In the UAE's retail industry, these dynamics are especially visible. Large companies are implementing AI-driven predictive analytics and computer vision systems, while smaller businesses often struggle with the costs and complexity of such technologies (Abouelmehdi et al., 2018). This uneven adoption reflects the varying capacities of organisations to handle technological change and highlights the importance of resources and organisational readiness. In short, AI has become a central driver of organisational change. It offers unprecedented opportunities for efficiency and competitiveness, but it also requires significant adjustments in skills, culture, and governance. For the UAE, these changes are part of a broader effort to position itself as a global hub of innovation, showing how closely organisational transformation is tied to national development goals.

2.6 The AI Revolution

Artificial intelligence (AI) has become one of the most talked-about forces of change in recent decades, often described as the hallmark of the Fourth Industrial Revolution. Where earlier revolutions were driven by steam, electricity, and digital communication, this new era is being shaped by systems that can "think" and learn in ways that echo human intelligence. AI combines data-processing power, algorithms, and machine learning to analyse huge amounts of information and make decisions that once required human judgement. This ability has placed AI at the centre of global debates about innovation, growth, and the future of work (Barta & Görcsi, 2021).

At its simplest, AI is about simulating human-like reasoning, learning, and problem-solving. Machines can now sift through massive datasets, detect patterns, and generate insights that allow organisations to work faster and with fewer errors. In countries like the UAE, this potential has been quickly recognised. Businesses and government institutions alike see AI as a way to improve efficiency, personalise services, and tackle complex challenges in real time (Mikalef Boura et al., 2019). In retail, AI supports everything from predicting demand and managing inventories to enhancing customer experiences, while in healthcare it is used for diagnosis and treatment planning (Allen, 2019).

The Global Picture

Around the world, the adoption of AI has picked up speed, cutting across industries and reshaping the way societies function. Governments and businesses are weaving AI into their daily operations, with applications ranging from education and finance to manufacturing and logistics. Customer service is one of the most visible areas, with chatbots and digital assistants now a familiar presence. These tools make information accessible at any time, reduce waiting times, and allow organisations to serve thousands of customers simultaneously (Abouelmehdi et al., 2018).

Other uses are less visible but no less transformative. Fraud detection systems scan millions of financial transactions in real time, spotting unusual activity and protecting both businesses and consumers (Barta & Görcsi, 2021). Predictive maintenance in industries such as aviation and energy is another example. By using AI to anticipate faults before they happen, companies save money and avoid costly disruptions. In the transport sector, AI forms the backbone of research into autonomous vehicles, powering navigation and safety systems that could redefine mobility in the years to come.

Despite these successes, AI has also stirred debate. Concerns about job losses, ethical issues, and cybersecurity risks have become part of the global conversation. Some worry that increased reliance on intelligent systems could displace workers, while others highlight risks of bias or privacy violations. Countries such as the United States, China, Germany, and Japan have responded by creating strategies and regulations designed to manage AI adoption responsibly (Hamilton Skurak et al., 2021).

The UAE's Approach

The UAE has embraced AI with unusual speed and ambition. The government has identified AI as central to its future, weaving it into long-term development strategies that aim to reduce reliance on oil and position the country as a global technology hub. Plans such as Vision 2021, the AI Strategy 2031, and the UAE Centennial 2071 all emphasise the role of intelligent technologies in driving economic and social transformation (Al Batayneh et al., 2021).

In retail, AI is increasingly visible in day-to-day operations. Retailers are using it to forecast customer demand, track buying trends, optimise supply chains, and provide personalised marketing. AI-powered assistants and chatbots now interact directly with customers, helping them find products or resolve queries quickly and conveniently (Akram et al., 2021). Beyond retail, AI is being applied in healthcare, where imaging systems support diagnosis; in logistics, where algorithms map the most efficient delivery routes; and in banking, where fraud detection and compliance monitoring have become routine (Smith & Smith, 2021). This wide-ranging use reflects the UAE's belief that AI is not just a tool but a driver of national competitiveness. However, adoption has not been without challenges.

Challenges in Adoption

One of the biggest hurdles to AI integration in the UAE is public trust. Many people remain cautious about automation, particularly when it involves personal or sensitive data. Cybersecurity risks are another concern, as reliance on connected systems creates new vulnerabilities that can be exploited by malicious actors (Hamilton Skurak et al., 2021).

There are also organisational issues. Not all companies are equally prepared to adopt AI. Some lack the resources, while others face resistance from entrenched ways of working. Collaboration between the public and private sectors is not always smooth, and smaller firms often struggle to keep up with the rapid pace of change (Barta & Görcsi, 2021). Another key challenge is the skills gap. AI requires specialists who can build, manage, and update these systems, but demand for such talent far outstrips supply. Although the UAE has established initiatives like the Mohamed bin Zayed University of Artificial Intelligence, the need for skilled professionals remains high (Shamout & Ali, 2021).

Workforce and Social Impact

AI's spread raises important questions about employee well-being. On one hand, automation reduces repetitive tasks and gives workers space to focus on higher-value activities. On the other, it introduces uncertainty and anxiety about job security. Research by Gorgenyi-Hegyes et al. (2021) and Krekel et al. (2019) suggests that employee well-being should be considered across physical, social, emotional, psychological, and intellectual dimensions, all of which can be affected by rapid technological change.

For the UAE, where human capital is central to future growth, this balance is critical. National strategies highlight the importance of training and reskilling, ensuring that citizens and residents alike are equipped to adapt to AI-driven changes. Initiatives in education, leadership development, and capacity-building all reflect this effort to prepare the workforce for new realities (Al Suwaidi et al., 2020).

Ethics and Governance

No discussion of AI would be complete without addressing its ethical and governance dimensions. Issues of fairness, accountability, and transparency are becoming central as AI systems increasingly influence decisions that affect people's lives. Questions about data privacy, bias in algorithms, and lack of oversight have been raised in areas from recruitment to consumer profiling (Al Batayneh et al., 2021). The UAE is still in the process of building a robust governance framework for AI. Compared with countries like Germany or Japan, where regulatory structures are more mature, the UAE is at an earlier stage. However, the government has signalled its intent to strengthen these frameworks, drawing on global partnerships and international standards. Maintaining public trust will depend on ensuring that AI is not only effective but also ethical and transparent.

The AI revolution is reshaping industries, economies, and societies at a global level, and the UAE is very much part of this story. Globally, AI has already shown its power in areas like fraud detection, predictive maintenance, and customer service. In the UAE, its role is even more striking, tied to ambitious national strategies and visible in everyday sectors such as retail, healthcare, and logistics. At the same time, challenges remain: cybersecurity risks, organisational readiness, workforce skills, and ethical concerns all demand ongoing attention. The UAE's ability to navigate these challenges while capitalising on AI's potential will determine how successful the country is in positioning itself as a true leader in this field. For now, what is clear is that AI has moved from being a futuristic concept to an everyday reality—one that is steadily shaping the way the UAE's economy and society function.

2.7 Focus on the Private Sector

Within the UAE, several private organisations have taken the mantle to adopt the use of AI within their daily operations in the interest of boosting their customer service and increasing profitability, and for others, they have become merchants of AI technologies. An example of technology merchants is the companies that develop and maintain AI-based technologies for the public or other companies. As a result, this continues to be a more formidable business within the region, even as more and more technologies are deployed in line with AI technology. The UAE retail sector is used as a case study to properly investigate the issue of AI adoption in the private sector.

2.7.1 Unique Features of the Retail Sector

The retail sector is one of the most vibrant segments of business operations, and it involves direct interaction with consumers, selling a vast range of products, and managing elaborate supply chains. It is important to know some of the specific characteristics of this sector first to fully grasp how artificial intelligence (AI) can recreate society. Another great characteristic of the retail industry is that it elaborates customer-centred strategies extensively (Mostaghel et al., 2022). Retailers compete in a very stiff market, and therefore, the power of conquest is very crucial. This customer orientation leads to the continuous search for more individualised customer experiences where businesses seek to know and meet individual customer needs and demands (Hänninen et al., 2018). E-commerce enhances this focus by allowing retailers to track and collect customer data on interactions, preferences, and purchases.

Customisation or personalisation is no longer a fad but rather a necessity in the new generation of retail stores. Today's consumers want more personalised messages that address their specific requirements and wants. Such expectations have been realized in loyalty programs, targeted marketing, and tailored products and services (Akram et al., 2021). Retailers deploy this analysis to identify customer needs to segment the market to arrive at an agreed-upon strategy that would increase customer satisfaction. Sophisticated customer targeting is especially valuable in highly competitive environments since it often creates a competitive advantage on the demand side by affecting customer loyalty and willingness to return to the seller (Malenkov et al., 2021).

The retail business also has another robust, unpredictable and complex logistics model in the form of its supply chain management and inventory system. Retail supply chains are complex since they involve key players, including manufacturers, suppliers, distributors, and logistics service providers. The products are too many and varied, the demand patterns are also unique, and there is constant pressure to achieve and maintain the right inventory levels. Retailers struggle to balance stocking enough products to meet demand while avoiding excess inventory that ties up capital and increases storage (Gavrila and de Lucas Ancillo, 2021). Supply chain management is important in order to improve product supply, supply lead times, and eliminate stockouts. This is especially true in industries such as fashion retailing, where fads come and go within short durations of time and quick adjustments in response to market needs are imperative.

However, it is also important to note that the retail industry experiences the following problems which are seasonal fluctuation and promotional activities. Seasonal fluctuations are some of the common places where fluctuating customer traffic can be observed by retailers, for example, during end-of-the-year holidays, the beginning of a new school year, and black Friday weekends. To address these fluctuations, accurate demand forecasting and flexible supply chain management must be applied (Alexandrova and Kochieva, 2021). They must be able to recognize periods of high demand, stock in sufficient quantities to meet the anticipated demand and effectively manage the promotional campaigns during such periods in order to exploit such opportunities. Failing to do so leads to loss of sales, dissatisfied customers, and overall, reduced sales revenue.

The retail industry also faces the issue of multichannel management, in which there is unified communication, sales, and service to the client. The advent of the Omni channel retail store, where customers engage the brand on physical and digital platforms, has made retailing a complex affair (Har et al., 2022). For multi-channel inventory management, retailers should ensure that there is compatibility in the inventory at any given channel a customer chooses, which means they should have the option of a similar shopping experience (Galera-Zarco et al., 2020). This entails effective stock control procedures and up-to-date sharing of data on inventory, as well as adequate means to satisfy customer demands through quick and correct shipments.

Over the last few years, the retail environment has been greatly impacted by technology, which, most certainly, has been driven by technology in all its forms. The shift towards the use of electronic commerce and the increased deployment of portable electronic gadgets have impacted the way consumers engage and do business with merchants. Internet sellers guarantee comfort, selection of goods, price comparison, and reviews, which form the current consumer expectations. This implies that retailers are forced to adapt to the market forces by coming up with new ideas frequently and applying technology options where possible. This consists of effective e-commerce platforms, mobile applications, and convenient payment systems that help to improve the shopping experience (Korchagina et al., 2020). In addition, Advanced technologies like Augmented Reality (AR) and Virtual Reality (VR) are at the junction of changing the retail industry. AR and VR technologies can be used in the creation of engaging and interactive retail experiences that unify the virtual and physical worlds of online shopping. For instance, AR applications help customers see how furniture would look in their house or how a particular type of clothing would fit them. This enriches the shopping experience compared to other options like browsing through catalogues (Ramazanov et al., 2021). Not only do these technologies serve the purpose of customer engagement, but they can also minimise the rate of return because customers make more informed decisions.

There is growing pressure in the retail sector today with regard to the question of sustainability. Consumers are gradually waking up to the fact that some of the products they consume affect the environment negatively, and they are looking forward to buying from environmentally responsible firms. In turn, retailers adopt measures that aim to minimise the negative impact of sales promotion, including initiatives like minimisation of the use of packaging materials, the use of environmentally friendly materials, and the promotion of recycling, among others, as pointed out by Ziaie et al. (2021). Further, there is increasing recognition of such ideas as the circular economy, which implies using extended-life solutions for products that will undergo remanufacturing or recycling (Korchagina et al., 2020). It has also been adamant that the companies that adopt sustainability not only meet customer expectations but also stand out in a world where shoppers are sensitive to the environment. When it comes to global retail, the sector is likely to face various regulatory and compliance issues. Companies that have stores in several countries have the probability of dealing with numerous laws on consumer rights, data privacy, product quality, and labour rights (Ramazanov et al., 2021). It is imperative to adhere to these regulations to avert legal consequences and sustain the consumer's trust. Retailers need to make significant investments in strong compliance programs and need to track relevant legal requirements across all the geographies in which they operate.

Last but not least, domestic retail is known for its dynamism and constant evolution. They note that consumer preferences, technology, and markets change rapidly, meaning that retailers have to be equally responsive. To succeed under these circumstances, retailers should be ready to adapt to new patterns quickly, make use of innovations, and continuously transform the approaches used in their businesses (Korchagina et al., 2020). This constant change requires a proactive strategy so that the retailers can read market trends and equip themselves for the future. Hence, the outlined peculiarities of the retail sector such as its customer-oriented nature, venting and inventory issues, concentrating on the Omni channel selling approach, digitalisation potential, incorporation of emergent technologies, concerns about sustainability and compliance with the regulation, and high activity rate make the environment striking and turbulent (Galera-Zarco et al., 2020). These features define the environment within which retailers' fashion and design strategies for competition and diversification. Knowledge of these characteristics is crucial to comprehending the role of AI in developing the sector and solving its current issues to enable finding new paths to create value.

2.7.2 Integration of Artificial Intelligence in the Retail Sector

Implementation of Artificial Intelligence in the retail sector has been a revolutionary process that has revolutionised the approach that retailers have adopted in their operations, customer relations, and supply chain management. In the past, the retail industry has been at the forefront when it comes to the integration of different technologies to unlock competitive advantages, and this includes the application of AI. AI in the retail context was initiated in the early 1980s with the first use of automated inventory tracking systems and customer relationship management systems (Ramazanov et al., 2021). Yet, the true surge in the widespread implementation of AI has happened in the last decade, fuelled by developments in ML, BDA, and CC.

Another reason why companies in the retail industry have had to embrace AI is the desire to transform the shopping experience. A few examples of AI applications are machine learning and natural language processing, which have helped retailers bring personalisation to a mass scale. Based on buyers' data, there are advanced machine learning algorithms that skim through the data collected from buyers to determine what kind of products this particular buyer would be interested in or more likely to purchase (Ziaie et al., 2021). Extending beyond conventional targeted product suggestions, this form of personalisation goes as far as targeting marketing strategies, product prices, customer services, etc., (Alexandrova and Kochieva, 2021). For instance, natural language processing-based chat-bots can respond to customer inquiries in real time, which not only saves time but also reduces the volume of work from human agents.
AI has also been used actively in the supply chain and inventory management to find excellent ways of working. Retailers have continued to experience problems in managing inventory, demand forecasting, and disruption of supplies (Galera-Zarco et al., 2020). These techniques

have undergone a significant change due to AI-driven predictive analytics, where organisations can predict the demand magnitude, develop appropriate stock magnitude, and assess supply chain threats before they worsen. For example, AI algorithms can use historical sales records, market trends, weather conditions and other external factors to forecast future demand with a high degree of accuracy (Korchagina et al., 2020). This ensures that the retailers are able to stock the appropriate product mix in the correct quantities and at the correct time thus eliminating cases of stock out and stock accumulation.

Another area of great adoption of AI in retail is the integration of computer vision technology. It has the benefits of increasingly enriching in-store experiences and optimizing store operations for retailers (Galera-Zarco et al., 2020). For instance, AI can be used in cameras and sensors, and it becomes easier to detect when stores or shelves are low in stock or some stocked items are out of stock. This technology not only helps retailers define how the shelves should be stocked and arranged but also helps them gain insights into the customer traffic pattern and which products draw attention (Ramazanov et al., 2021). Also, computer vision helps prevent loss because it reduces theft by detecting suspicious activities.

To say the least, AI assists in improving the e-commerce experience in every possible way. As more consumers have started shopping online, retailers have used artificial intelligence on various fronts in their online stores. Collecting data on customers, their browsing and purchasing behaviour, as well as their social media interactions, AI algorithms suggest products and offer advertisements that are most relevant to the customers (Ziaie et al., 2021). Additionally, the availability of self-service through AI-based chat-bots and virtual assistants enables customers to be aided throughout the online shopping process and even search for products easily. AI has also been incorporated in SEO and other marketing techniques that have made it easy for retailers to attract and maintain the customer base they have.

AI, when applied in retail, is not without its fair share of problems. One challenge is the high cost of adopting AI applications and solutions in a business or an organisation. Assuming that all retailers can leverage AI, they have to use high-quality software and hardware and employ experienced professionals in AI (Alexandrova and Kochieva, 2021). Also, with AI, existing systems may need to be redesigned and integrated into the new system, which may prove to be tedious and time-consuming (Sy, 2019). Privacy and security also remain factors that may lead to challenges due to customer data risks amid laws like GDPR. Nonetheless, there are numerous advantages of investing in artificial intelligence within this sector. Organisations that adopt AI technologies in their retail business are in a position to realise enhanced efficiency, customer satisfaction, and revenue (Har et al., 2022). These intelligent solutions help retailers to analyse trends and make decisions in supply networks while creating relevant customer experiences. In addition, using AI allows retailers to respond quickly to the increasing dynamics and constantly changing market, thus being more effective in responding to changes in trends and consumers' preferences.

Some examples of successful AI implementation in retail are presented below. For instance, Amazon.com, being at the forefront of the use of AI in retailing, relies on Artificial Neural Networks in processing data to feed into its recommendation system, which contributes largely to its sales. Thus, Amazon's AI is not limited to customer interactions but also follows through to its supply chain, where it uses predictive analytics to optimise delivery routes and warehouse placement (Har et al., 2022). Another prominent example is Walmart, which uses AI technologies for demand forecasting, inventory control, and the services it provides to its customers. Another use case enjoys millions of customers annually; Walmart's conversational AI-powered chat-bots attend to their customer service enquiries promptly and accurately.

Within the fashion retail industry, it is worth mentioning that nowadays many companies utilising AI technologies to enhance their products and services, such as Zara and H&M; in particular, such companies use AI algorithms to identify the main trends in fashion and the specific customer preferences, thus providing the corresponding clothes and accessories, produced to meet the current demand (Ramazanov et al., 2021). AI solutions also help these retailers in managing supply chain operations and the stock they need to maintain. Thus, by the integration of AI in the sphere of visual search technology, customers can find related products by uploading images, which can make online shopping more engaging for them (Alexandrova and Kochieva, 2021). It is worth emphasising that the current trends in artificial intelligence adoption in the retail industry are dynamic and developing further. Retailers are continually seeking innovative options for AI implementation, including smart shopping assistants that use voice control, delivery robots that operate autonomously, and intelligent fitting rooms (Ziaie et al., 2021). The above innovations are set to strengthen customer experiences, optimize processes, and unlock opportunities for growth in the retail industry. AI is still advancing, and with this pace, its use is expected to grow in retail, allowing for even more applications to be implemented.

Although AI has disrupted specific domains, such as customer relations and supply chains in the retail industry, it is essential to understand that its ability to prevent risks is not 100% effective (Al-Ayed, 2019). Automated tools, for instance, advanced predictive analytics tools, can help estimate the demand in the concerned market to minimise the associated risks involved in stock management. Still, at the same time, their potential is limited to historical data and can be easily affected by a dynamic change (Alexandrova and Kochieva, 2021). Furthermore, the use of Artificial Intelligence to automate the detection of fraud improves security, but these systems can also be hacked by experienced cyber criminals, implying the introduction of more risks. Hence, while AI brings new approaches to addressing some risks, it also pushes the retail sector to implement effective protection against cyber threats and monitoring to address the risks that come with these technologies.

To sum up, using AI in the retail industry has significantly improved retailers' work, customer relations, and supply chain management. From one-on-one customer interactions and efficient inventory replenishment to advanced e-commerce and smart store solutions, AI has become a standard for retail businesses (Har et al., 2022). However, as will be shown in this article, the need for and the potential advantages achievable only through the integration of AI in the retail process far outweigh the concerns stemming from its implementation (Alexandrova and Kochieva, 2021). AI is a promising technology that is still in its nascent stage, and its continued development means that the technology will become increasingly important to the retail industry in the future.

2.7.3 Benefits of AI for the Retail Sector

The implementation of AI has been revitalizing for the retail sector as it introduces numerous opportunities for different forms of change across all aspects of retailers and consumption. By applying AI technologies, retailers can improve customer experiences, manage supply chains, leverage data, and provide security, providing a strong competitive edge within a constantly progressing market (Ramazanov et al., 2021). In this respect, the key advantages go far beyond the aspects of marketing and customer relations targeting; they also pertain to inventory and other peculiarities of retail operations, such as, for instance, fraud risks. Customer experience is among the most significant areas that benefit from the integration of AI in the retail industry. Technologies like machine learning, natural language processing, and computer vision infuse new ways of engaging customers in retail operations (Korchagina et al., 2020).

Recommendations on the basis of artificial intelligence study the patterns of browsing history, purchasing habits, and even social media profiles to recommend products that might suit the consumer. It provides a more pleasing experience for the customers while shopping and makes them return for more and or purchase more, thus enhancing the conversion rates (Ziaie et al., 2021). Furthermore, AI-enabled chat-bots and virtual helpers ensure customers receive immediate assistance and assist customers with product queries or searches and navigation throughout the shopping experience. Notably, the above-stated AI tools can respond to more than one question at a time, making the service fast and efficient for the customers.

Another important application of AI is in enhancing the functionality of the supply chain and inventory systems. Traditional demand management for retailers revolves around the need to hold inventory at the optimum level, which means a balance between actually satisfying customer needs while at the same time avoiding the overstocking of products, as this takes up capital and attracts other costs such as storage (Alexandrova and Kochieva, 2021). AI-based decision support systems use historical sales data, market trends, and factors that influence demand, like weather, to make highly accurate predictions (Ziaie et al., 2021). This leads to better management of inventory by retailers, whereby they can avoid situations where there is no stock at all or situations where there is excess stock. Also, certain algorithms in the field of AI can minimise the problems connected with supply chain management, including the analysis of the simplest yet time-consuming problem of determining the most efficient way of shipping and product delivery schedule (Alexandrova and Kochieva, 2021). This results in quicker and more accurate order deliveries, which in turn improves customer satisfaction as well as increases process efficiency.

Another advantage of AI for the retail sector is that it can help organisations make data-driven decisions. Supermarkets and other retail stores generate a huge amount of data from different sources, such as POS systems, e-commerce websites, social media, and customer feedback. AI technologies can analyse these types of data and make relevant conclusions that can impact strategic decisions (Korchagina et al., 2020). For example, it becomes easier for retailers to understand patterns and trends considering numerous customers in order to improve their methods of marketing and goods offerings. By means of predictive analytics, retailers can also predict which change is imminent in the market and what course of action needs to be taken. Therefore, with the help of AI, retailers can make the right decisions that will improve competitiveness and growth.

Notably, AI benefits the retail industry in terms of satisfying clients and increasing organisational efficiency, safety, and methods of combating fraud. Many retailers have adopted Artificial Intelligence (AI) technologies, including machine learning and computer vision, in identifying fraudulent activities (Har et al., 2022). The real-time data of transactions can further be analysed by the AI algorithms, and it can independently detect suspicious patterns and alert for possible fraudulent transactions (Ramazanov et al., 2021). This reduces the risks of financial loss and ensures the customers' data is safe from misuse by hackers. Computer vision technology is also employed to block losses in actual shops through surveillance of activities and detection of dubious actions. These automated security initiatives contribute to an extra barrier and shield customers when they are in the course of shopping.

The next area that is beneficial to retailers is the high capability of AI in marketing personalisation. Part four shows how the application of loyalist marketing in traditional marketing methods transforms them to be more effective as opposed to the traditional methods that only use demographic data. Conversely, AI can help retailers develop more specific and relevant promotional messages to their customers (Ziaie et al., 2021). AI algorithms reveal customers' needs and behaviours by analysing the data collected and dividing it into specific categories. This enables the retailers to create unique promotional messages for the specific customer, making them more likely to respond positively (Galera-Zarco et al., 2020). The concept of personalised marketing not only helps enhance the efficacy of promotional campaigns but also assists in providing a better experience to customers by providing them with better and more targeted content.

Another emerging application of AI in retail is the augmentation of the shopping experience inside the store. The application of AR & VR has also been adopted and incorporated within retailing environments to enhance interactivity (Ziaie et al., 2021). For instance, the use of AR in the applications lets customers see how the products will blend in their homes or how particular clothes will fit them, which in turn makes the shop much more exciting (Har et al., 2022). Some of the applications of VR that may be implemented in the sale of goods include the use of virtual space where customers may physically walk through showrooms. In addition to serving as tools promoting customer interaction, these technologies are beneficial as they minimise the risk of the customers returning the product they have bought due to dissatisfaction.

AI also helps in the effective management of customer relationship management (CRM). The use of AI can even integrate and analyse customer data to moderate the nature and tone of future communications (Ramazanov et al., 2021). This helps the retailers in being in a position to handle other complaints from the customers in a timely manner and also serves as a way of enhancing the standard of services so as to enhance their relationship with their customers. It also enables CRM to be less dependent on human labour for simpler activities such as follow-up email communication and the monitoring of consumer interactions (Galera-Zarco et al., 2020). Ultimately, with advancements in overall CRM abilities, AI makes it easier for retailers to retain consumers' entertainment and boost their overall satisfaction. Workforce management is another area where AI can be of great value to the retail industry (Ziaie et al., 2021). Sophisticated applications of artificial intelligence can be effectively used to manage staff working in various schedules in order to address the traffic and sales of the store at different times. This enhances operational effectiveness and lowers expenses for human resources (Korchagina et al., 2020). Training and development can also be helped by AI, which can analyse employees' needs and suggest specific courses for them. This assists retailers in increasing the efficiency and effectiveness of employees, thus improving morale and customer satisfaction as well as operational efficiency.

In conclusion, integrating AI in the retail industry brings numerous advantages that revolve around enhancing some of the business operations. Some of the benefits of AI include better customer satisfaction, efficiency in supply chain management, aid in the decision-making process, and security, among other factors, which help retailers to remain relevant in the market (Har et al., 2022). The flexibility in tailoring marketing messages, designing compelling store environments, and improving CRMs adds to the argument that AI may revolutionise retail. The role of AI remains dynamic as more technologies are developed, and it only enhances the retail function as it continues to look for new ways to become more efficient and profitable.

2.8 The Public Perception of AI in the UAE

The public perception of Artificial Intelligence in the United Arab Emirates (UAE) is a topic that has been well-studied by scholars and researchers. The general perception of AI in the UAE is varied and complex. While a substantial body of literature aims to explore AI's potential benefits, there are also many articles concerned with the risks and dangers of AI. The public perception of AI in the UAE is quite positive (Wirtz *et al*., 2019). However, some concerns about how AI will affect the workforce and what it means for the country's future. While some concerns have been raised, even those tend to focus more on the future of AI than on its present. AI has become a tool companies use when they need it, making it popular with consumers and the general public (Nadjawi, 2020). One example of this would be the use of AI by companies like Du, which uses it to help people with disabilities navigate their surroundings. The company's website states that it uses artificial intelligence to help people with disabilities navigate their surroundings. Another example would be how companies like Google use AI to analyse search history and present recommendations based on what an individual has been looking for. It helps users find whatever they are looking for faster than ever before and makes them feel more confident about their search results. These are just two examples of how AI can improve our everyday lives by making things easier or more convenient.

The UAE has a long history of AI research and development and was the first country in the Arab world to have a national AI strategy. However, despite the advancements made by local researchers, the public perception of AI in the country is still mixed. The UAE's first national AI strategy was developed in 2017 (Ziaie et al., 2021). The strategy outlined six significant areas of focus for the country's researchers and developers: smart cities, healthcare and medical research, the retail sector, transportation systems, manufacturing and logistics, and financial services. The strategy also emphasised that AI should be used to solve real societal problems rather than just being seen as a tool for improving productivity or profitability. According to a recent study by QED Insights on public perception of AI in the UAE, published in 2019, in general terms, there is widespread support among Emiratis for using AI technology to address problems they see in their everyday lives.

In the UAE, AI research is overseen by the Dubai Future Foundation, founded by Sheikh Mohammed bin Rashid Al Maktoum in 2008. The foundation's mission is to use technology to improve the quality of life in Dubai and beyond. To achieve this goal, it has allocated substantial funds toward domestic and international research projects related to Artificial Intelligence. One such project was conducted at Stanford University between 2015 and 2017. In the past, AI could be used only by a few specialised companies, with little hope of being adopted by anyone other than those companies (Nadjawa, 2020). However, that is no longer the case. As more and more people begin to use AI in their daily lives, they are starting to see it as something that anyone can use, and it is not just limited to businesses. Many people use AI in ways that were not even intended by the original developers (or at least were not intended by them when they first released the software).

In 2016, members of Dubai's government began experimenting with AI applications to improve traffic flow and reduce city congestion. The results were impressive: traffic decreased by 20% for six months, leading to an increase of about $500 million in revenue for Dubai's economy during that period (Wirtz *et al*., 2019). This use case shows what can be done with AI when it is deployed correctly—and how much better off organisations would be if all governments used similar models! There has been some recent controversy around this type of technology because many feel these programs violate their privacy.

The UAE's public perception of AI is relatively low. While there is growing recognition that AI can be an essential tool for business, there is still much scepticism about how it can be used and its benefits. The first thing to note about public perception of AI in the UAE is that it has been slow to develop (Wirtz *et al*., 2019). The country has only recently begun incorporating AI into its economy; it was recently reported that Dubai's government had created its own AI for Good group, which aims to engage with tech leaders and investigate how AI technology can benefit society (Halaweh, 2018). The lack of awareness among Emiratis may be partly due to a lack of educational opportunities regarding AI. Some surveys have shown that only 25% of students in Abu Dhabi have heard about AI. In contrast, another survey found that only 16% had heard of machine learning (Ziaie et al., 2021). These statistics suggest that while many Emirati students know about computers and internet access, they may not have received enough information about how these operate.

The country is one of the most technologically advanced in the world. Still, it has a relatively small population and a relatively small amount of data to work with—both of which are challenges when creating an AI system replicating human thought processes. One way UAE organisations overcome this challenge is by building systems that can perform simple tasks like identifying objects or making predictions (Ziaie et al., 2021). They are also working with traditional humans to interact with their computers in ways that feel natural to both parties, so that users do not feel like they are taking on more responsibility than they should be. However, there are still some misconceptions about what AI does for us. In particular, many people think it will take over all jobs, but this is not true: AI systems are designed to work alongside humans without replacing them.

The country's government has made significant investments in the field, including $1 billion in its first AI round. Vision 2031 plan and $2 billion more in subsequent rounds. This funding has led to significant progress in developing an increasing AI industry today (Almarzooqi, 2019). According to a report from the World Bank, the UAE has become one of the most competitive nations for AI research and development, ranking above countries like Japan or Korea but far behind countries like China or the U.S. The UAE has also become a leader in using machine learning to solve real-world problems such as traffic congestion and air pollution (Wirtz *et al*., 2019). In addition to financial support from government sources like the Road & Transport Authority (RTA), companies like the Ras Al Khaimah Development Authority (RAKDA) are also making significant investments in AI technology. For example, RAKDA recently announced plans to use AI to improve road traffic management through a project called Smart Roads (Shanti *et al*., 2021). The project will combine laser sensors with machine learning algorithms to identify traffic flow patterns so that they can be optimised as needed over time based on current conditions instead of relying solely on static rules.

One of the essential things that can be learned from this literature review is how the public's perception of AI has changed over time. For example, public opinion about Artificial Intelligence has shifted towards a more positive perspective in the past few years. The reason for this shift is not apparent; however, it does seem to be correlated with advances in Research and Development (R&D) as well as public awareness campaigns that highlight how advanced AI technologies could be used for positive purposes like improving healthcare or providing new forms of entertainment or education (Wirtz *et al*., 2019). The UAE has also been making significant investments in AI R&D in recent years, and these tend to be more secretive than those made by other countries whose governments are more open about their goals concerning AI development. This secrecy suggests that many parties are vested in keeping their goals hidden.

The prospect of AI in the UAE, according to Batayneh *et al*. (2021), covers much of the period during which users can see a significant change in public perception; they argue that the UAE's lack of laws and regulations regarding AI is causing problems for businesses and consumers alike. Still, they also note some positive aspects: The UAE is one of the few countries where AI research is focused on solving real-world problems rather than testing new technologies or creating new products (Butcher and Himenez, 2019). While this may seem bad at first glance, companies can develop products quickly and efficiently without waiting for government approval or approval from other organisations such as universities or scientific journals.

The country has been attempting to move away from dependence on oil for many years, and AI is one way for it to diversify its economy. The public perception of AI in the UAE has changed dramatically since it was first introduced. In the early days, people were sceptical about how it would affect society and businesses (Al-Sharieh, 2021). However, as time passes, people begin to see that AI can be used for good instead of evil. In 2011, when the first AI-powered robot was unveiled at Dubai's Future Orientation Exhibition, many people were sceptical about its use in society because they did not understand how it worked or what benefits it could provide (Butcher and Himenez, 2019). It could do tasks like cooking meals, cleaning the house, and making coffee using only natural language commands from users around it—no programming required! People were blown away by this new technology and asked, "Is this legal?" "Will this become self-aware?" Moreover, "How long before it goes rogue?"

In the UAE, there is much interest in AI. Companies are investing in it and even using it in their day-to-day operations. However, there is still a stigma around AI and its use. A negative attitude toward AI is caused by people thinking it will put them out of a job (Alhashmi et al., 2019). It is not entirely true; companies like Google and Facebook have used AI for years to find and prioritise data for their products. It makes sense because as technology advances, humans need to find new ways to work with it, or they will be left behind (Riaz *et al*., 2022). Some people still think that artificial intelligence will replace humans entirely and that they will be left to deal with robots who make all our decisions. It is not valid. Artificial intelligence will not take over the world or replace human jobs. Instead, it will help humans to make better decisions and do their jobs more efficiently. This can already be seen today: automated systems are used in many different industries, from finance to healthcare to retail to education (Alhashmi *et al*., 2019). There are also many benefits for society in the use of AI in these ways: for example, by using machine learning algorithms to predict stock market movements before an investment opportunity arises or by providing healthcare providers with more accurate diagnostic tools to improve patient care significantly (Alhashmi et al., 2019). However, there are some concerns about AI technology in general. For instance, some people worry that it could be used negatively by corporations or governments to control people's behaviour towards one another (such as through social media manipulation).

Many applications today use techniques such as computer vision and natural language processing, which are elementary to implement and do not require deep learning capabilities (Butcher and Himenez, 2019). This can be seen in chatbots: they are easy to build but cannot learn new things, improve themselves over time (or even respond appropriately when they are told something new). The future holds more opportunities than just chatbots! (Mohasses, 2019)

There are many areas where AI could be helpful in our lives, including healthcare and education, but there will also be some challenges along the way.

People in the UAE think it will be a disruptive technology that will change how people live and work (Mutawa and Rashid, 2020). It may be one of the most critical developments of the century, as it will allow humans to do what they have always dreamed of—to live lives of unimaginable luxury. However, this is a misconception (Alhashmi et al., 2019). It is true that AI has been developed in recent years and is being used by many companies across all industries; however, this does not mean that it will revolutionise everything about life for everyone everywhere, all at once. Instead, AI will help create new jobs for those currently unemployed or underemployed and improve the quality of life for those who already have jobs (Batayneh *et al*., 2021). What is more important than these changes is how humans can use AI to improve their lives and make them better than before. It means taking time to understand how AI works and learning how best to apply its potential benefits in daily life.

They see AI as something that will improve their lives or make them feel more efficient in how they use their time. It does not mean that people are not concerned about privacy concerns—they are! However, they also see how important it is for governments to protect privacy so that people can feel comfortable using technology without feeling like they are being watched or tracked by someone else. One of the most important factors is that there are no negative stereotypes about how AI can be used to eliminate jobs or increase unemployment. On the contrary, many believe that AI will create new jobs and positions for people who have been left out by globalisation and automation (Almarzooqi, 2019). Some think this process has already begun, with more jobs being created than lost as companies replace human workers with robots or computers (Khatib *et al*., 2021). Another reason people in the UAE feel comfortable discussing AI is that there are so few other countries with which they compare their experiences. While there are some examples from around the world where people's lives were negatively impacted by automation—like in China—this does not seem to be happening here as much, at least not yet, which means it makes sense for them to embrace it instead of rejecting it outright like others might have done before them (Al-Sharieh, 2021).

In the past few years, it has become increasingly common for people to see AI as something that can be used to make their lives easier. For example, many Emiratis use voice assistants like Siri or Alexa on their smartphones and are excited about them. Some believe this will lead to a more convenient way to communicate with others, while others think it will make their lives easier by allowing them to shop online without worrying about what they say when they ask for items (Khatib *et al*., 2021). This shift in perception is likely due to several factors. One is that people are starting to see the benefits of using AI technologies, in terms of convenience, efficiency, and productivity, which makes it more appealing than ever before. Another factor is that there are so many different types of AI technologies available now (so many ways to use them), which means that there is plenty of opportunity for people who want them but may not have known what they were looking for before now has more options than ever before (Almarzooqi, 2019). The government of Dubai has made significant investments in developing an autonomous vehicle program, but this project has faced many technical challenges and political obstacles (Alhashmi *et al*., 2019). The government also intends to use AI to improve its financial services sector by using machine learning algorithms to detect fraud more efficiently than human employees can do alone.

The UAE's leadership has made it clear that they believe AI will help them create a more technologically advanced economy, improve the quality of life for their citizens, and increase their national prestige (Halaweh, 2018). These three goals are interrelated and mutually reinforcing. If an economy enhances quality and productivity, the country can attract new businesses, increasing employment opportunities for Emiratis. It creates more tax revenue for the government, which allows it to spend more on education and infrastructure projects. The goal of increasing the quality of life for Emiratis is also related to their ability to compete with other countries in terms of technology (Khatib *et al*., 2021). They are looking at AI to solve problems like traffic congestion or pollution caused by vehicles or factories (which would make life easier for people near these things). Another way AI could help them is by improving healthcare delivery through better diagnosis and treatment options—this would reduce costs overall while increasing access for poorer people who need it most.

In general, the public is quite optimistic about the future of AI. They believe that AI will help them with their daily lives and help them achieve more than they would alone. Some think it will take over humanity's role as leaders and rulers, while others are more sceptical of this claim. When it comes to specific applications of AI, there is less consensus on how people feel about them. For example, some people believe that autonomous cars are inevitable soon, while others say they are not ready yet. Some believe that robots can perform all kinds of tasks better than humans now; others believe that robots will not be able to perform any task. Therefore, to understand the process and dynamics of the formation of such perceptions in the UAE with specific reference to the sector of retailing, it is pertinent to look into the relevance of Institutional Theory (Alhashmi et al., 2019). From the institutional theory perspective, organisations are bound by societal and legal rules; this means that adopting new technology, such as AI, is guided by societal, legal, and institutional requirements (Ali and Ahamat, 2020.). Thus, for instance, the UAE can serve as an example of government-led AI promotion, which topped the list of countries with positive attitudes towards AI, as many citizens believe that AI is one of the major drivers for their country's economy and innovation agenda.

Nonetheless, the same institutional pressures may also create resistance to AI use, particularly in sectors such as retail, due to issues like data privacy as well as job losses resulting from automation. Although the Prime Minister and his administration have been touting AI to enhance the performance of civil servants and public organisations, there is still a section of the population that harbours resistance to the positive effects that AI may have on the employment market (Alhashmi et al., 2019). This resistance is most notable in the retail industry, where the use of AI in automation may cause displacements of some employees in customer service occupations.

However, the public's perception of AI largely depends on how these organisations handle the aforementioned issues. The extent to which retailers are open about their use of AI and adhere to strict data protection laws will determine the level of acceptance from customers (Ali and Ahamat 2020.). This aligns with the concept of isomorphism in institutional theory, where organisations mimic other organisations' practices to attain legitimacy due to regulations and society. Thus, the UAE retailers who can manage public perception of AI and align the retail AI strategies with the government programs and public demands would be able to minimise risks associated with the public rejection of AI utilisation in retail business (Allan, 2020). Finally, the theory of institutionalization assists in understanding how the UAE's consumers' perception of AI may shift over time. Thus, as AI technologies are used pervasively in the nuts and bolts of the new retail experience—through targeted adverts, check-out-less stores, and robot concierges—the public will come to accept these technologies routinely (Almeida et al., 2022). There is, however, a danger involved in this process of institutionalisation, which is the management of risks related to AI, such as hacking or the inherent, racially biased algorithms. Retailers who do not mitigate these risks may suffer negative impacts on their reputation and thus contribute indirectly to heightened negativity about AI from the public (Al-Sharieh, 2021). Hence, despite positive perceptions of AI in the UAE, there are emerging issues of legitimacy, trust, and institutional pressure that need to be addressed for sustainable AI implementation in retail businesses.

3.0 CHAPTER THREE: LITERATURE REVIEW

3.1 Introduction

The purpose of this chapter is to provide a critical examination of the body of knowledge that informs the study of artificial intelligence (AI) in risk management within the retail sector. While research on AI has expanded rapidly in recent years, the majority of published work focuses either on the technological aspects of AI or on its application in broad business contexts, with relatively limited attention to its role in risk management and its adoption in specific regional settings such as the Gulf and wider Middle East. As a result, the review in this chapter is essential for situating this study in relation to existing scholarship, identifying where current knowledge is strong, and exposing the areas where significant gaps remain. These gaps will, in turn, serve as the foundation for the research questions that guide this thesis.

A literature review goes beyond describing what has been published; it seeks to evaluate, compare, and critique different perspectives. In the context of AI and risk management, the literature includes contributions from computer science, information systems, management, and sector-specific studies in retail and finance. Each of these bodies of work brings a slightly different lens to the topic, but taken together, they provide a more complete picture of both the potential benefits and the inherent challenges of adopting AI. However, as will be shown in this chapter, much of the scholarship has been fragmented, either focusing too heavily on technical possibilities without considering organisational realities, or else generalising findings from Western contexts without considering cultural, institutional, or regulatory differences in emerging markets such as the UAE. A critical review, therefore, enables this study to carve out a clearer space in the conversation.

This chapter is organised into several sections. The first major section explores how AI has been positioned within risk management more broadly. Here, the review examines literature that highlights AI's capacity to enhance decision-making, automate processes, and detect anomalies at scale, alongside more critical contributions that warn of algorithmic biases, cyber vulnerabilities, and governance challenges (Brynjolfsson and McAfee, 2017; Dwivedi et al., 2021). The discussion is not limited to the promises of AI but also considers the ongoing debates about its limitations, trade-offs, and implications for organisational resilience.

The second section turns to the retail sector specifically. Retail has been a fertile ground for AI applications, from demand forecasting and inventory optimisation to customer behaviour prediction and fraud detection (Huang and Rust, 2021). Yet, as the review will show, studies of AI in retail often prioritise consumer-facing innovations, such as personalised marketing or recommendation systems, while risk management tends to be treated as a secondary issue. Moreover, much of the research is situated in mature economies with highly digitised retail infrastructures. Less attention has been paid to contexts such as the UAE, where retail is a major contributor to the economy but where adoption of digital risk management tools is still developing. This imbalance in the literature justifies the need for closer examination of how AI is understood and implemented in a setting that has unique institutional, cultural, and regulatory characteristics.

The chapter then considers theoretical frameworks that can help to explain patterns of adoption and the challenges organisations face in integrating AI into risk management practices. The focus here will be on the Diffusion of Innovation (DOI) theory and the Technology–Organisation–Environment (TOE) framework, which together provide complementary insights into how innovations spread and what factors shape adoption decisions (Rogers, 2003; Tornatzky and Fleischer, 1990). While alternative models such as the Technology Acceptance Model (TAM) or Sociotechnical Systems Theory have been widely cited, they are less comprehensive in addressing organisational and environmental influences. By adopting DOI and TOE as the guiding theoretical frameworks, this study is able to build on established approaches while also acknowledging their limitations in capturing the complexity of AI adoption in the retail sector.

Finally, the chapter concludes by drawing together the key insights from the reviewed literature and showing how they point directly to the gaps that this study will address. This synthesis is critical: rather than simply listing what has been studied, it demonstrates the logical link between what is known, what remains uncertain, and how the present research contributes to filling those gaps. In particular, the review highlights three central gaps: first, the limited empirical research on AI for risk management (as opposed to AI for marketing or operations) in retail; second, the lack of context-specific studies in the UAE and broader Gulf region; and third, the need for theoretical integration that accounts for both technological and organisational dimensions of adoption. These identified gaps form the foundation for the research questions that structure this thesis and underscore the contribution it seeks to make.

This chapter therefore provides the intellectual scaffolding for the study by critically engaging with the existing body of knowledge, identifying contradictions and blind spots, and situating the research within relevant theoretical traditions. By doing so, it ensures that the study is not only grounded in what has already been explored but also positioned to add new insights that respond to gaps of both practical and scholarly significance.

3.2 Application of AI in Business Strategic Management

Today, AI is being applied across industries to automate processes, enhance decision-making capabilities, and increase productivity. This section explores some of the ways AI can be used to transform business strategy. One of the most encouraging utilisations of computer-based intelligence is recognising misrepresentation. In 2024, MasterCard declared it would utilise machine learning to work on continuous endorsements and diminish bogus decays. Spear System and Survey assessed that the worth of misleading downfalls is multiple times more prominent than the sum lost in real Visa misrepresentation and is a significant wellspring of disappointment for clients. Utilising computer-based intelligence to bring down the number of bogus decays would be a substantial advantage for the vast majority of card clients (Islam and Aldaihani, 2022). Artificial intelligence is likewise being utilised to assist ordinary financial backers with bringing in more cash. Robotised venture administration advancement utilises simulated intelligence to decrease "charge drag" and lift clients' income by an expected 15% in the next 30 years. The help continually computes the most duty-effective proportion of stocks and bonds and the most invaluable available record (conventional IRA versus Roth IRA, and so forth) in which to put those ventures.

Technology is essential to business. Businesses have grown increasingly reliant on technology throughout time, so if it were to be removed, almost all corporate processes would cease to exist. The most fundamental to the complicated corporate and industrial processes are all performed using computers. Enterprises, however, see a lot of potential in AI and its technology as a strategic advantage for their company. The majority of them (57 percent) think AI will enhance customer service and assistance (Islam and Aldaihani, 2022). The most intriguing finding is that 43% of respondents believe AI will allow them to revolutionise their industry by introducing fresh business strategies, goods, and services. 42 percent believe that AI makes it possible to create new goods and services.

Various researchers have analysed the different uses of AI in essential business association management exercises. As per Schwarz and Sánchez (2015), AI has been claimed to have been applied in essential gambling among the executives in development projects. For this situation, vital navigation is a critical region wherein AI has been contended to introduce huge advantages. In any case, the review does not make sense of how AI has further developed risk in the board dynamics in the development business. In their concentration on the utilisation of AI applications, these discoveries have likewise been upheld by the contentions of Baryannis, Dani, Validi, and Antoniou (2019), who contend that AI has, to a great extent, been utilised to help dynamic frameworks in associations. Business associations enjoy taking advantage of existing AI innovation to foster successful, dynamic, emotionally supportive networks in risk executives (Bussmann et al., 2021). Nonetheless, the review has not had the option to frame how the execution of AI has impacted the dynamic cycle in these business associations, thus improving the proficiency of direction.

The execution of AI poses a risk to the executives, as per Bartram, Branke, and Motahari (2020), has, to a great extent, been made conceivable in present-day organisations due to its expected ability to change business decisions. As per the review, business associations are speculating about AI because of expanded progress in research and technological development (Motahari, 2020). Be that as it may, the full execution of AI by business associations or full usage of its power has not been possible due to the dangers emerging from AI (Aziz and Dowling, 2019). Because of these dangers, the review laid out that there is possible mischief to the execution of AI in occurrences where business associations carry out AI without a comprehension of the dangers related to the innovation (Bartram, Branke, and Motahari, 2020). In this way, there is a massive hole in understanding the impacts of AI execution on business risk to executives, considering that innovation likewise has critical dangers that have not been addressed.

The world is evolving from theory to implementation, and Chinese academics are becoming a significant driving force in AI development. It appears that an increasing number of young Chinese professors work in multidisciplinary fields as a result of the confusion surrounding disciplinary borders and the emergence of many of the most fascinating regions at the nexus of many research domains. Dennis R. Mortensen, founder and CEO of x.ai, emphasises that while AI is fairly sophisticated, it is not as intelligent as many believe (Islam and Aldaihani, 2022). This commitment to artificial intelligence (AI) permeated across this organisation, making promises of vamping up equipment, enriching insights, streamlining operations, augmenting workers, and, in some ways, making human lives significantly better as customers, employees, and consumers. Senior management salivates at the exponential profits AI is said to bring to their job (Forrester, 2017). AI is only effective in a few specific situations. "AI is indeed getting better at tackling complex problems, but it's equally true that AI is still not very good at doing many of the things associated with human jobs," he says. "AIs are getting reasonably proficient at impersonating humans in well-regulated scenarios, like scheduling meetings.

What competent engineering managers and leaders should accomplish is frequently unclear. Sometimes, engineering management is confused with the delivery of architecture and code, leaving out communication, people, and culture. Architecture and implementation are NOT a part of engineering management. The engineering team creates, shapes, and evolves the product architecture to achieve a company's goal, but the company truly owns the architecture and its execution. A communication network linking various departments, including Sales, Engineering, Support, Services, Product, and Operations, supports it. Engineers themselves are the ones who put it into practice.

AI is a hot topic right now, with people like Mark Zuckerberg and Elon Musk arguing it. It's the next step, as Jeff Bezos recently noted, since there are no human offices. I want to discuss chatbots as they relate to AI and bots briefly. They are helpful for marketing and should be employed at different levels. To engage additional prospects, you are opening up another communication channel. It may produce greater results for individuals who are "hot," who are eager for more knowledge and ready to act. Email is a more passive form of communication, but that's not to imply it doesn't work. A hot prospect shouldn't necessarily start an email until they have been informed and feel cared for. Many of the same abilities I utilised in the military are readily transferable to the world of investment management. The tactical comprehension of risk mitigation and execution, the strategic application of intelligence fusion and networking, and the nuanced assessment of behavioural analysis and incentives were the key lessons I learned from my time in service (Schiefelbein, Luke).

Cloud communications with AI enable the impossible by providing unmatched insights and automation. It will serve as a virtual agent for firms, connecting directly with clients and answering their questions. AI and analytics can monitor critical business communication metrics and systems around the clock, sending out notifications as soon as anything out of the ordinary occurs, keeping the company entirely secure (Attaran and Grijalva, 2001). AI impacts the business by automating certain processes. By automating repetitive or dull processes, AI frees up time for human employees to focus on more strategic tasks. For example, AI systems can help companies manage their supply chains and track inventory levels more efficiently. This frees up time for employees to focus on strategic and creative projects. In addition, AI systems can also provide company leaders with valuable information about their products, customers or competitors. By automating processes and providing decision-makers with data, AI helps companies become more efficient and effective. Another way AI impacts business is by providing unbiased decision-making (Jabeen et al., 2022). Although humans make decisions based on their own experience and bias, artificial intelligence is designed to be unbiased and objective. This allows businesses to make smarter decisions based on data instead of human bias (Islam and Aldaihani, 2022). For example, an AI system could analyse trends and predict future outcomes when making purchasing decisions. This would be more accurate than human decision makers, who are influenced by past experiences, making more subjective decisions based on their experience. With unbiased decision-making, companies can better serve their customers and remain competitive in the market.

Another way AI impacts business is by supporting strategic planning. By collecting data and information from multiple sources and applying algorithms to the information, AI systems provide decision-makers with future-proof data. This helps them identify trends and make more informed product or service decisions. For example, an airline could use artificial intelligence to collect flight data from multiple sources like passengers and pilots. This would allow them to identify dangerous trends in flight paths and make more informed flight scheduling decisions. Collecting this kind of data allows businesses to remain competitive in their industries and stay up to date with trends. By doing so, they can stay relevant and ensure continued success in the market. Although many believe that AI will have a positive impact on businesses, others are concerned about its potential impact on society. Many believe that the use of AI will violate privacy standards and lead to discrimination or unethical behaviour. They also believe that it will lead to the automation of jobs, which may cause unemployment among some groups of people.

Others are concerned that collecting huge amounts of data through AI systems will lead to unethical data collection practices. For example, an airline could collect information about passengers' habits so that it can sell targeted advertisements to them later in their flight. However, some passengers may feel targeted by such advertising since it assumes that they are unable to make decisions for themselves at that point in their flight's journey. Americans have contradictory views on AI technologies. When asked what they think of AI, the average American often responds with fear, loathing, and dread. However, the very AI applications they are concerned about are already making a significant difference in their lives. Furthermore, many are concerned that businesses will become too dependent on AI systems in the future and limit their creativity or problem-solving skills (Islam and Aldaihani, 2022). Essentially, they believe that AI systems solve problems too quickly and simply for businesses to remain successful over time. Ultimately, these concerns mean that it may take some time before the positive effects of this technology become clear overall. Despite some concerns surrounding its use in business, artificial intelligence has the potential to positively impact businesses' strategic management skill sets. This technology can automate processes, provide decision-makers with better data and support strategic planning- but it requires careful consideration and proper moderation throughout business operations to be effective overall.

3.3 Change Management Strategy Adopted in AI Implementation

The change management strategy for AI adoption can be summarised as a series of steps and techniques that are used to prevent changes to the current behaviours and routines of the people, processes, and systems. Change management strategies adopted in the UAE for AI adoption are critical to ensure the successful implementation of new technologies. Change management strategies in adopting AI currently take advantage of the benefits of big data; Humans need to be able to change their behaviour. According to Fountaine *et al*., (2021), new and better ways of doing things should not be imposed on individuals but welcomed by them. The success of any change management strategy will depend upon organisational and technical requirements and stakeholder interests. The change management strategies in the UAE for AI adoption are attributed to the need for a better understanding of the public and private sectors, both in terms of better diagnosing changes and understanding their impact on society and gaining acceptance (Radu, 2021). Being aware of how businesses could potentially be impacted by AI adoption is crucial. The development and deployment of this technology are expected to create jobs in both the public and private sectors, so it would be wise to plan out strategies that address the changing workforce requirements.

There is scope for analysing organisational and workforce effects in the change management of AI implementation with a special focus on the employees' readiness for the new AI technologies. Following this, it is possible to extend the given content by employing Lewin's Change Management Model to the AI integration in the UAE retail sector (Jabeen et al., 2022). Lewin's model of three phases, unfreezing, changing, and refreezing, prescribes a methodical approach to orienting and adjusting the employees in this new paradigm. At the unfreezing stage, retailers need to ensure their employees are receptive to change by explaining how AI can be beneficial and tackling issues like perceived job loss and obsolescence. This stage is pivotal in reducing resistance and ensuring that there is a positive attitude towards the adoption of AI.

The changing stage entails the application facet critical in deploying AI tools, as training programs and support structures come into play at this level. Some possible strategies that retailers could implement include training employees on how to effectively apply AI-based tools for the everyday functioning of the store or other points of sale (Ismail, 2021). The last stage, the refreezing stage, involves embedding the change in the organisational culture and ensuring that employees are at ease with the AI technologies in the organisation. Using Lewin's model, it is, therefore, possible to derive a concise, workable roadmap for overcoming the workforce challenges, which highlights that AI implementation in retail is not a matter of simply deploying advanced technologies: human elements must be taken into consideration as well (Islam and Aldaihani, 2022). In contrast to simply describing change management activities, this approach provides guidance on how to reduce employees' resistance and increase their involvement in AI implementation.

Change management strategies are required to improve the adoption of AI in the UAE. The first change management strategy that is needed for AI adoption is standardisation. Standardisation refers to ensuring a uniform approach across organisations or industries about what knowledge, skill sets, and processes are required for each task that needs to be automated or outsourced (Radu, 2021). It will ensure that all business leaders within their organisation can adopt new technology that may seem new and unfamiliar, but it does not have to be so hard. The UAE has adopted a strategy to make achieving AI adoption easier for businesses. According to Zhang *et al*., (2021), the UAE Government has targeted areas that include change management, workforce development, and sharing research findings with other countries from which they can learn.

The technology sector has been a leader in the adoption of AI. By 2031, more than half of all jobs are expected to be replaced by automation, and AI is predicted to create more jobs than it destroys. There are many reasons for this. One is that AI can perform tasks that humans find tedious or dangerous, speeding up the process while eliminating errors. Another reason is that humans are not as good at pattern recognition as computers; therefore, if a human performs the same task repeatedly, an algorithm could learn how to solve it automatically (Fountaine *et al*., 2021). As a result, algorithms can achieve results much faster than humans ever could with their natural limitations. In addition to these advantages, there are also disadvantages associated with AI. For example, ethical issues may be involved if the AI system learns how to make decisions independently without human input; however, this problem can be solved by ensuring that all decisions made by an AI program are made with human input beforehand.

AI and machine learning technologies are transforming many industries, including transportation, healthcare, and logistics. While the UAE is no stranger to innovation in these areas, it has a long way to go before it can reap the productivity benefits of AI adoption (Radu, 2021). The UAE is among the most prevalent countries in terms of technology innovation and utilisation. Over the past few years, the government has taken a promising step towards investing significant energy into building a solid framework for the local technology industry and fostering economic growth (Alzoubi and Azzid, 2021). However, as with every other country, the nation also faces challenges. One such challenge is AI adoption. The biggest challenge that most organisations face is adopting new technology and making it a best practice. Various strategies can be adopted to achieve this. For example, organisations can opt for training using live online learning platforms and panels to interact with subject matter experts and other professionals, business leaders, and even customers. It helps them learn new skills, cope with change management scenarios, master new concepts, and build their organisational knowledge base, making them more efficient in the whole process.

Haddad et al. (2020) state that AI adoption is a vicious circle. The adoption rate is determined by the availability of AI solutions and their competitive advantage over other technologies. At the moment, there are no practical tools that can change this situation and make people think about AI. Change management strategies should be employed early in adopting AI to ensure a smooth transition from existing processes and systems to leveraging AI. The objective is to minimise disruption and ensure the integrity and security of data while evolving organisational practices. Implementing AI in organisations can result in significant positive change, and change management strategies are needed. Organisations must be educated on AI's impact on business, organisational structure, and culture. Four types of effects can happen with AI: technical, structural, cultural, and organisational.

Technology is becoming increasingly advanced, with AI being the driving force behind this growth. Organisations are increasingly adopting artificial intelligence technology to improve their businesses and increase customer satisfaction—a trend known as AI-enabled digital transformation (D3) (Haddad *et al*., 2020). As organisations adopt AI technology and integrate it into their digital platforms, they must also adapt to changes in how they manage this technology. Organisations should consider how these platforms affect customers' experience, including individual experiences with learning about an AI product or service, its efficacy and accuracy, and expectations around using data collected from the platform (Fountaine *et al*., 2021). AI adoption has had some hurdles. One of the main issues is that AI developers need to be fluent in machine learning and computer science; however, this can be challenging for businesses and universities with limited budgets and staff developing AIs. Furthermore, businesses need to have a plan for managing their AI transition and hiring enough data scientists to train these new bots.

The rate of change and innovation requires an organisation to adopt new technology. However, organisations can change their internal structures, processes, and external relationships with customers, vendors, and partners. The successful adoption of AI will require organisations to allocate sufficient resources for data analytics and pattern matching to identify patterns that may be difficult for humans to understand.

In the Ojo *et al*. (2019) article, AI can potentially transform many industries. However, adoption by organisations is not always an easy process. Many challenges are involved in change management strategies in the current adoption of AI. The first challenge is that there is no clear strategy for using AI. Some organisations use it to replace human employees, while others use it to augment human employees. Other organisations use it as an adjunct to their current processes (Fountaine *et al*., 2021). It is hard to know what will work best for the organisation until they figure out what type of organisation they have and how they want to use it. The second challenge is that there is not enough data available for organisations to decide whether or not they should adopt AI. The more available data, the better-informed decisions can be made about which technologies will work best for the organisation and how those technologies can be integrated into existing systems so that they do not cause disruptions or other problems within the company's workflow processes (or anything else).

There is a lack of awareness among businesses and individuals about how technology can be used to improve their business processes. It could be because AI is still in its early stages or because there are still some misunderstandings about what it can do. For example, one of the advantages of AI is that it can be used to automate tasks that humans may not want to do. For example, if you are a doctor, you might not want to write prescriptions daily or perform specific procedures on patients. However, this does not mean doctors should stop practising medicine; instead, they should use AI tools for certain things (Khatib *et al*., 2021). Similarly, if you own an auto dealership and have always wanted an assistant who could help with customer service calls but do not have time for that right now because the business is busy (or even worse, broke), then maybe you should consider hiring an AI assistant instead of simply hiring someone else who might not be as qualified at handling customers' questions.

AI will involve much change, and it is not easy to change things that have existed for a long time. It can be difficult for businesses to see the value in deploying new technology when they use older methods that are more established and familiar. The process of implementing new technology is not always smooth, either. Many people are unsure what they need to do or how they should do it, and even when they do know, there are so many options out there that it is hard to know which one is best for them (Haddad *et al*., 2020). Many external factors come into play with AI implementation; for example, if someone loses their job because an algorithm has replaced them with another employee who does not perform as well as they did, then that could be seen as unfair treatment by some people who might feel like their human rights have been violated. It means that even though AI may be a good tool overall, some work still needs to be done before any fundamental changes can occur on a large scale.

There are various adoption strategies to be used when introducing an AI solution, depending on the problem type. If a company faces a business process that needs to improve its performance and efficiency, change management tools will be employed, such as process mapping and redesigning (Alzoubi and Azzid, 2021). It is becoming increasingly vital that companies effectively manage the challenges associated with change management strategies as they adopt AI systems. In order to achieve this goal, organisations must effectively communicate their needs for AI and how it will be used. Leaders must also be prepared for resistance from employees who may feel threatened by the changes brought on by AI implementation, and they should create new training programs for employees who may need additional support.

Additionally, companies should be prepared for adverse reactions from customers or clients whose business models are threatened by the introduction of AI into their processes. They should also work with human resources departments so employees feel comfortable voicing concerns about how their jobs may change due to this technology. Finally, organisations must ensure that no one feels left behind when it comes time to implement these new systems because everyone has a role in ensuring this process runs smoothly.

Radu (2021) articulates that the UAE has become a hub for AI research and implementation and a destination for companies seeking to establish AI projects in the region recently. The country's Ministry of Cabinet Affairs (MoCA) has pledged to make AI a key pillar of its economic development strategy by 2031, and it is working hard to ensure that happens. The Ministry recently issued a Vision 2031 plan outlining its goals for using AI to enhance productivity, improve customer service, and enable new business models (Haddad *et al*., 2020). As part of this plan, MoCA has established several initiatives to encourage local and international companies to use AI in their operations. The first initiative is AI Nation, which focuses on creating awareness among Emirati businesses about the benefits of using AI-based solutions. It also aims to help them understand how to implement these technologies in their operations best (Radu, 2021). The second initiative is the AI Accelerator Program, which offers free training courses on implementing AI technologies within their organisations.

In the UAE, change management strategies for adopting AI currently include creating a culture where employees feel comfortable discussing their skills and weaknesses. It will help them identify problems with the current system and help them understand how to improve it, creating an environment where employees feel safe enough to speak up about what they see as problems. It can be done through training or by creating a culture where people feel comfortable doing so (Haddad *et al*., 2020). Integrating AI into other parts of the company's operations gives employees more opportunities. For example, suppose a company has a customer support team that uses chatbots. In that case, they could integrate those chatbots into the customer support system so that they can receive feedback from customers directly instead of having to send emails back and forth between human agents who might not always get back right away because they are busy helping other customers too sometimes (Alzoubi and Azzid, 2021). Develop a strategy for how it will be implemented. It can involve creating a plan for the technology and its use. The second step is creating an organisational structure to support this new technology. There are several ways to do this, but one of the most common methods is an organisational transformation. These two steps help ensure that any organisation involved in AI adoption has a clear idea of what they want their system to do and how they want it to work. When these two steps are taken, an organisation will have developed an appropriate plan for adopting AI within its business.

3.4 Risk Management in Project Management

This section of the literature review will focus on risk management within project management as a foundation for understanding how important this concept is to the topic. To achieve this understanding, the focus is given on project risk, and some of the factors that can constitute the categorization of a project as risky (Korchagina et al., 2020). Further exploration of the topics relevant to the study is also interwoven within the study to ensure that the whole concept of the study is captured. Key attention is also paid to the various sources used to ensure that the literature review avoids unnecessary duplication of the research material, which also enhances the readability of the study.

The first concept under review in this section is the definition of risk management. In general, the concept of risk is redefined as a particular event or condition, which, upon occurrence, presents a potential for harming at least one or more objects of a project. While considering risk, others also find it necessary to consider both the threats and opportunities that such unexpected events might represent to the project (El Khatib *et al*., 2022). Using such a double-sided definition of risk provides the opportunity for risk management within the project cycles. An opportunity is an event or a condition that can present a positive outcome that can aid at least one objective of the project (PMI, 2017). When the opportunity presents itself, the project manager can exploit, share, enhance, or accept it. On the other hand, risk is also perceived as the downside of value, implying that risk and value are two related concepts whose management needs to be undertaken in parallel within a project.

Risk management is an essential element of project management, which helps project managers navigate the complex realm of restructuring the project with the goal of value creation. Maintaining value in their project management process is important and involves stakeholder engagement at different stages, engaging them and, through voluntary agreement, satisfying their expectations from the project (PMI, 2017). Other literature sources also differentiate between risk and project management and uncertainty (Aven 2016). In this regard, the risk is understood as the degree to which the uncertainties will influence the outcome of the project being embarked on by the organisation. Uncertainties determine the extent to which the company's performance is affected concerning sustainability, financial performance, or social responsibility, among other aspects used to evaluate the company's performance.

3.4.1 Project Risk Management

When it comes to project management, projects intend to present certain unique characteristics, such as novelty, uniqueness, and the large number of stakeholders who are impacted by the outcomes achieved from the project implementations (Nguyen *et al*., 2017). These key characteristics determine the project objectives and thus effectively determine whether the implementation is a success or a failure. Therefore, risk management is crucial in project management, and it also requires the use of unique tools, knowledge, and techniques to provide useful solutions (Aven, 2016). In addition, further expertise and technical abilities are required to ensure that various elements of the project are effectively integrated to ensure that it does not lose sight of its proposed end goal.

According to the project management handbook, all projects that organisations undertake will involve some risk, and such risk comes with other positive sides, which may also benefit the project (PMI, 2017). In this section, the risk is mainly defined as the possibility of an unfortunate event occurring or the consequences of certain activities related to uncertainties. Therefore, such a definition also provides the understanding of risk management separately from uncertainties, as the definition of risk is included in the definition of uncertainties (Qazi *et al*., 2016). Based on the balance between risk and benefits, organisations also need to balance the risk being undertaken and the benefit to be achieved.

Risk management has been largely accepted as one of the project managers' largest and most significant training areas. This shows the importance of this field in ensuring successful organisational projects (Naude and Chiweshe, 2017). Project stakeholders also expect that the project manager will carefully analyse the risk involved before they are fully committed to undertaking the project (Pellerin and Perrier, 2019). Understanding risk will often determine the methods used to analyse the risk. Therefore, this means that the method of understanding the risk will affect the decision-making process involving the risk in question.

The risks experienced in project implementation are often categorised into five types, depending on the nature of the risks. The first category of risk is known as the technical or operative risks. These are risks that are involved with the technical ability and capacity for the project to be completed (Vacik *et al*., 2018). Such risks could originate from the future of technology, materials being used in the project, failure of equipment, change requests, and design risks. When such risks occur, the ability of the team to implement the project is greatly hindered as their technical abilities are either depleted or become insufficient to meet the desired levels. The second category of risk is organisational risk. Organisational risk is related to human factors that determine the organisation's operation (Lam *et al*., 2017).

Human factors relate to the organised individual employees, departments, and project teams, which are tasked with performing vital tasks that contribute to the project's success. Other organisational risks can also be related to the rules, regulations, policies, and others, which determine how effectively the team can attain certain operational goals (Moeuf *et al*., 2020). Without proper coordination, the organisation might fail to perform its functions properly, which is likely to negatively impact its ability to meet the organisation's goals and objectives.

The third category of project risk is contract risk. These risks relate to the contract meant to oversee the different roles played to ensure the project's completion (Sanchez -Cazorla *et al*., 2016). Such issues include the issues that exist in the law, which could lead to sudden noncompliance and thus create a situation that threatens the project execution. This paved easy for the fourth risk category, which is the financial or economic risk. This risk relates to the financial and economic feasibility of the project. The ability to conclude a project is closely tied to the financial resources directed towards the project. In project management, the project manager must first determine all the financial resources that will be used to complete the project, which is often one of the key factors determining how successfully the company will meet its objectives. However, financial risks are related to the market conditions, and they might cause a change in the market conditions, which makes prices for goods go higher than expected (Korchagina et al., 2020). When this occurs, the price fluctuation will most likely lead to the project's cost significantly changing, which might make it impossible to complete the project with the pre-specified budget. Therefore, this is a viable risk that must be considered, with the project manager employing all the significant techniques to help them determine the probability of such events occurring.

Finally, the fifth risk category is political risk, which relates to the waves of political interest that might come and change the expectations and overall activities related to the project implementations (Korchagina et al., 2020). Such events might include environmental authorisations, which have become even more important due to climate change or other governmental restrictions. Risk management requires that the manager is able to accurately predict the occurrence of such events so that they can effectively manage them and ensure the continuity of the project.

The risk management process is a process that is made up of several interlocking processes, which include the initiation (also known as the context analysis), identification of risks, risk analysis, which also entails qualification and quantification, the treatment or mitigation plan, and monitoring and control. Each of these risk management processes should be continuously engaged throughout the project's lifecycle to ensure the manager can identify and manage the risks accordingly. Another outstanding element in risk management is communication. Communication is also analysed as a crucial element of risk management and crucial to its success. Communication in risk management is important since it helps the different stakeholders involved in the project implementation understand the project's core and develop an effective risk management approach (Korchagina et al., 2020). When working with different stakeholders, each must understand the project's goals and objectives and their role in meeting these objectives. This will help plan the project activities and ensure that each resource is clearly deployed to facilitate achieving the company's goals. It also helps the project manager define the support structure, which helps the various team members understand how to address different challenges encountered in the project implementation.

3.4.2 AI Application in Project Risk Management

After understanding the concept of risk management as it is applied in project management, the next key significant task is to examine the specific application which AI finds in the field of risk management. This section will present details of specific areas of application where AI has already been used as a project management strategy, and also focus on two main fields of application. AI has largely been applied in the financial industry, as well as the healthcare industry. Other industries have also adopted AI, such as transport, construction, and security (Korchagina et al., 2020). However, some of the challenges they face in the implementation are interconnected, with the focus being on technological ability and integration with existing systems. However, further research can also be conducted that will focus on specific application areas, such as the finance or healthcare industries.

When considering the application of AI in risk management, a key relationship has been developed between AI and machine learning. The two fields are studied side by side, and sometimes even interchangeably. On the other hand, machine learning is an interdisciplinary field involving knowledge from multiple domains, including the algorithm complexity theory and the portability theories. This field consists of a situation where the computers learn corresponding human behaviours under certain overlaid circumstances and then use this information to replicate such actions, and in some instances, lead to further knowledge creation (Korchagina et al., 2020). Machine learning also increases the capacity of the machine to learn even more, and it learns to make correlations of knowledge acquired under different circumstances. Therefore, machine learning has been the backbone of AI, and most of the AI-based infrastructure acquires its perceived intelligence through machine learning. Machine learning has been largely applied in various fields, including finance and healthcare, and in relation to risk management.

Machine learning has two broad categories, which are known as supervised learning and unsupervised learning. In the supervised learning model, the learning machine is exposed to a classification labelled in the pre-classification section, and it is thought to predict the data without the classification label, based on the results obtained in the training. The decision tree is one of the key elements of the learning process. The decision tree is a predictive model which shows the classification of certain categories of events, items, and objects based on their attributes, and each attribute is used to place an object in a certain category to take a certain action.

The application of AI in financial institutions is first concerned with the risk of applying for credit. In this industry, credits are defined as the economic loss experienced when a particular contract party fails to fulfil its contractual obligations. The risk can also be categorised in terms of the increased risk of defaulting during the time of the transactions. Financial systems have traditionally employed the use of classical linear logic and orbit regressions to determine the credit risks of an individual whenever entering into a final agreement with other parties (Korchagina et al., 2020). However, AI has presented new techniques that can be more effective when applied by financial institutions to model the risk categories for individuals. AI technologies can understand unstructured data, making it more effective in developing credit risk determination than the traditional linear regression models, which might fail to take note of other crucial data sets in the unstructured data models. From a project management perspective, this information can be applied to determine the ability of certain contractors to effectively discharge their duties and meet their end of the deal in terms of delivering agreed projects. Using such models, the project managers have a chance to come up with more effective ways of determining how to award contracts based on the performance of individuals who have shown interest in the contract being outlined. This would effectively reduce the risk of failure to deliver the products.

Another key area of application is the market risk. Market risk is the type of risk which arises from engaging with the market. The firms often engage with the market through trading, investing, and general exposure in the industry. According to Kummary (2018), the process of AI in risk management relating to market integration involves activities such as data preparation, modelling, stress testing, and validation trials. A lot of activities being undertaken in the market are often affected by several variables, and the existence of all these variables affects the effectiveness with which the project will work. With machine learning abilities, such variables can be observed and used to model a process, to determine the risks that are likely to occur. This helps to put mitigation processes in place, which can be used to counter the most severe and common risks. This technique is known as the model of risk management.

The use of AI and machine learning has enabled the use of model testing as a risk prevention technique. It also allows for stress testing of processing using the model, which is done by increasing the number of variables that need to be put in place and varying their intensities to determine how strong a particular system is to perform the intended activity. In this regard, AI can also be applied in project management, as project managers can similarly model their projects and use AI-based systems to determine the risks that are likely to occur and those that might make it impossible to achieve organisational goals.

AI is also used in risk management to manage operational risk. Operational risks in the firm's operation are types of risk which directly relate to the gains or losses that the firm encounters from a host of potential operational breakdowns. Operational risk is categorised into Internal and external risk, depending on whether it originates from within or outside the institution. Internal organisational risk includes risks such as filed internal processes; risks associated with people or failure of systems (Jabeen et al., 2022). On the other hand, the external risks are associated with external factors such as fraud, vulnerable technical systems, control failures, natural disasters, negligence, and other organisational errors that might arise from individuals outside the organisation. Based on the nature of the operational risks, they continue to increase in complexity, with an increase in the number of processes that need to be coordinated. For these reasons, AI systems can be used to make risk management in this dimension more effective and more probable (Korchagina et al., 2020). Artificial intelligence can be applied to identifying such risks, measuring the impact, estimating the rate of occurrence, and even assessing the anticipated effects of the risk. AI systems can also be used to develop alternative risk mitigation strategies, which will be employed to make the process more secure and efficient and thus limit the effect of such risk occurring to the whole organisation.

AI technology has also been instrumental in helping risk management within the healthcare industry. Wahl *et al*. (2018) state that the healthcare industry has largely implemented AI in the same way by gathering, analysing, and presenting data that aids in effective decision-making. Within the UAE, there are other instances of AI applications shown through the initiatives it has undertaken with the Ministry of Health and Prevention, which has adopted AI within the business administration area of healthcare. One of the main concerns for patients in healthcare is the delay of service, which significantly increases the time patients have before they can receive services. The ministry has taken advantage of AI services to help reduce patients' waiting time in emergency rooms. This is a significant quality determinant of emergency medical operations since emergency healthcare services do not need to be delayed.

AI in healthcare also finds other applications relating to direct patient care. Such industries focus on engaging patients to participate in the move to AI by using AI-based tools for their medical needs, including patient portals. The Patient Smart Portal (PSP), which has been launched in the UAE, is key in helping patients with simple administrative tasks of their healthcare process, such as checking their medical records and making patient appointments. According to Pillemer *et al*. (2016), around 58% of patients already effectively use this system to check their medical records and test results. This figure represents more than half of the patients seeking service within the healthcare system, meaning that the overall population is more willing to adapt to AI.

3.5 Risk Management in The Retail Sector

Risk management in the context of retail is a complex process that aims to manage different risks that threaten the stability and functionality of retail stores. Risk management from a theoretical perspective, the effects of AI on risk management, and the aspects of the retail industry affected by AI will also be discussed in this literature review. Several theoretical frameworks underpin the conceptualization of risk management in the retail sector. There is a foundational theory known as the Enterprise Risk Management (ERM) framework that focuses on assessing and mitigating risks in any organisation (Kabalisa et al., 2021). ERM focuses on establishing risk management as an integral part of all operations and activities of an organisation. It obliges organisations to take into consideration internal and external risks, such as financial, operational, strategic, and compliance risks.

An equally important theoretical limitation is the contingency theory, which has suggested that the adoption of risk management practices is contingent on the organisation's context. According to this theory, there is no universally applicable set of practices; procedures must be specific to the environment. AI has introduced the new concept of risk management in the retail sector, which is a shift from the previous models (Korchagina et al., 2020). New technological approaches and tools, such as machine learning, neural networks, and natural language processing, can be introduced into the risk management processes. Due to the analysis of a large amount of data, the use of AI in real-time helps retailers identify risks more accurately and eliminate them more quickly (Kabalisa et al., 2021). For instance, machine learning algorithms can identify patterns and signs of risk in sales data, customers' behaviours, and inventory situations, which can warn of stock-out risks, fraud, or disruptions in the supply chain.

Another area that is especially affected by AI is demand forecasting, and inventory management remains one of the most important. Demand forecasting is essential for effective inventory management to avoid situations where retailers have excess stocks of particular products (Lin, 2019). The traditional ways of forecasting include sales history and guesswork, which is not very accurate. Advanced AI-powered demand forecasting models can consider various factors such as seasonal comport, market trends, and sentiments, among others, to yield better results (Kabalisa et al., 2021). This assists the retailers in managing their stock, controlling the costs of holding stocks, and avoiding any situation whereby there is either a shortage or excess stock. The fourth important business function AI affects is customer relationship management, also known as CRM. AI is gradually becoming commonplace among retailers seeking to improve their customer knowledge. Based on data collected from the customers' shopping behaviour, social media activity, and web browsing history, AI can come up with information about their individual needs and wants (Lin, 2019). This makes it possible for retailers to tailor their marketing strategies, enhance the satisfaction of consumers and nurture loyalty. Furthermore, intelligent chatbots, as well as virtual assistants, are also being implemented to deliver on-the-spot customer services to meet their questions and concerns.

Another area where AI is making a huge impact is the supply chain domain. Hence, the retail supply chain comprises various actors and players, such as suppliers, distributors, and retailers. It is evident that disruption in a supply chain impacts a retailer's operations and returns significantly. Currently, AI technologies can improve supply chain transparency and even anticipate disruptions (Lin, 2019). For instance, AI can predict the occurrence of delays or disruptions by scrutinising data on weather conditions, geopolitical events and transportation systems (Lui and Lamb, 2018). This enables retailers to take precautions in advance, including changing the shipment route or looking for other suppliers to avoid occurrences that may disrupt the supply chain.

Another field that is proving to be very valuable with AI is fraud detection and prevention. Fraud schemes that are common among retailers include payment fraud, return fraud, and identity fraud. This is because traditional anti-fraud methods use rule-based systems that can be easily manipulated by smart fraudsters. Fighting fraud with the help of artificial intelligence is based on using special algorithms to analyse the results of transactions and determine possible fraud cases (Lin, 2019). Contrary to the traditional rule-based systems, such systems can enhance their ability to identify fraud by constantly learning to incorporate new techniques in fraud. AI also helps improve operational efficiency in the retail business. Retail activities entail many small daily tasks, for instance, repapering, staff rostering, and payments (Korchagina et al., 2020). Such tasks can be handled through AI technology, such as Robotic Process Automation, where human errors are eliminated while the personnel can focus on value-added activities. For instance, it is possible to use robots that artificial intelligence drives that can help keep track of stock in the store, help restock when the inventory is depleted, and even aid in store navigation.

However, there are some drawbacks to incorporating AI in risk management. There is something that is crucial: the protection of data that users post online. Thus, retailers gather and analyse extensive customer information, which could be a potential object of cybercriminal activity (Lui and Lamb, 2018). For this reason, securing this data is extremely crucial, and AI systems should be equipped with security to prevent hacking. Also, there are some ethical questions concerning the usage of AI; for example, there are questions about the fairness of AI or the explainability of artificial intelligence tools (Kabalisa et al., 2021). Retailers must resolve these ethical issues to uphold customer confidence and maintain legal standards. However, incorporating AI in risk management is not an easy undertaking as it calls for a massive investment in technology and skills (Lin, 2019). A significant portion of the investment would go towards hardware, specifically data storage and processing, and manpower, as workers need to be trained in the use of AI systems. This can be a big financial hit, especially for small retail business operators who may not have deep pockets. However, there may be organisational resistance as employees' jobs may be at risk due to the use of automation.

Therefore, AI adoption in risk management within the retail sector is effective as it provides more accurate demand forecasting, better customer relations, increased supply chain transparency, and effective fraud detection. However, these benefits pose some risks, for instance, in data protection, potential ethical issues, and considerable investment in technology and talent. Other theories, such as ERM and Contingency Theory, come in handy in helping one understand how retailers can manage risk and how best to integrate AI into their risk management strategies (Lui and Lamb, 2018). Suppose the challenges mentioned above are well managed and the possibilities of AI are harnessed. In that case, retailers can strengthen their positions and increase their performance in the growing market uncertainty.

When considering the topic of risk management in the context of the retail sector, it would be useful to discuss the shortcomings of AI-based risk management in potentially more detail. The increased adoption of AI technologies, such as machine learning algorithms and real-time data analytics, increases retailers' risk-sensing capabilities yet brings new risks. For instance, overdependence on AI for fraud detection or supply chain management may cause insufficient human monitoring, resulting in more errors or algorithmic biases (Jabeen et al., 2022). Besides, it is noted that AI-based solutions require high-quality data to provide high-quality results, which may be an issue in the context of the retail industry due to sparse and unreliable data. Such limitations imply that although the application of AI in risk management can enhance specific functions, it is not a panacea (Jiang et al., 2017). Policies, including the AI system audit and data quality assessment at certain intervals, need to be implemented to minimize automation risks. This objective critique overemphasizes the role of AI in risk management, arguing that it is meant to be used in conjunction with human decision-making, not instead of it (Kabalisa et al., 2021). As such, by highlighting these weaknesses, the literature review provides a balanced perspective on the role of AI in risk management, suggesting that while automating the risk assessment process can significantly enhance its efficiency and accuracy, it is also necessary to retain human control to warrant effective risk management.

3.6 Theoretical Frameworks

To comprehend the uptake and deployment of artificial intelligence (AI) within organisations, the discussion must rest on firm theoretical underpinnings. In examining AI's role in risk management across the UAE retail sector, this study invokes theories that illuminate both the process of adoption and the wider context within which these decisions occur. Guiding the analysis are two principal frameworks: the Diffusion of Innovation (DOI) theory and the Technology–Organisation–Environment (TOE) framework. Further supporting this analysis are additional viewpoints—among them the Technology Acceptance Model (TAM), Sociotechnical Systems Theory and Institutional Theory—each of which helps to bridge the gaps. Taken together, these frameworks constitute a multi-level lens that fully encapsulates the intricate nature of AI adoption in the retail industry.

For many years, the Diffusion of Innovation theory has served as a cornerstone for exploring how new technologies disseminate among individuals, organisations and societies.

According to Rogers (2003), the adoption of an innovation is molded by the traits of the innovation itself, the channels through which it is conveyed, the duration of the process and the nature of the social system in which it unfolds. One of DOI's central elements is the categorisation of adopters into five groups: innovators, early adopters, early majority, late majority and laggards. Such a categorisation holds particular relevance to the UAE retail landscape. Big multinational retailers in Dubai and Abu Dhabi frequently act as innovators or early adopters, trialling AI in areas such as fraud detection and predictive inventory management. By comparison, smaller retailers generally wait until the systems are shown to be dependable or are compelled by regulatory mandates before making a commitment.

DOI further underscores the influence that perceptions of an innovation have on adoption decisions. Rogers (2003) singles out five core attributes: relative advantage, compatibility, complexity, trialability and observability. These factors are of particular relevance to AI. To illustrate, an AI solution that clearly demonstrates a financial benefit—for example, by cutting fraud losses—stands a greater chance of gaining widespread adoption because of its relative advantage. A system that harmonises smoothly with the organisation's existing IT architecture is regarded as compatible and consequently less disruptive (Greenhalgh et al., 2017). Conversely, technologies perceived as unduly complex, costly to trial or hard to demonstrate frequently meet resistance. Across the UAE, government-driven efforts such as the National AI Strategy 2031 hasten diffusion by cultivating conditions that both promote AI adoption and furnish institutional support (UAE Government, 2018).

Although DOI is a valuable concept, it fails to encompass the wider organisational and environmental forces that exert substantial influence over adoption decisions. Consequently, this research likewise adopts the Technology–Organisation–Environment framework introduced by

Tornatzky and Fleischer (1990). TOE examines three interconnected contexts: technological, organisational and environmental. Whereas DOI concentrates on the diffusion process, TOE positions adoption within its broader dynamics, thereby proving particularly pertinent to intricate sectors such as retail.

The framework proves especially valuable in the UAE. From a technological perspective, AI platforms for risk management—spanning machine-learning fraud-detection engines to predictive analytics for supply-chain vulnerabilities—are becoming progressively more accessible. Yet the degree of organisational preparedness differs. Multinational enterprises frequently possess the requisite funds, IT infrastructure and managerial expertise to deploy AI successfully, whereas many small and medium-sized enterprises are constrained by resource shortfalls (Dwivedi et al., 2021). The surrounding environment is equally pivotal: in the UAE, the government's AI-centric agenda steers AI uptake beyond the dynamics of market competition. Escalating data protection regulations and the public's growing demand for assurance place additional pressure on retailers to implement AI systems (Al-Dhaheri, 2020). In this respect, TOE reinforces DOI by emphasising that adoption springs not only from perceptions of usefulness, but also from resource constraints and institutional forces.

Additional theoretical frameworks furnish additional nuance. The Technology Acceptance Model (Davis, 1989) serves to illuminate adoption from an individual perspective. As TAM indicates, employees are likelier to adopt AI tools when they regard them as both useful and simple to use. Subsequent variations include constructs such as enjoyment and behavioural intention (Venkatesh & Davis, 2000); however, the model is still criticised for overlooking organisational and environmental factors. Though TAM is not the dominant framework in this discussion, it still contributes by illuminating how staff perceptions can render AI initiatives successful or failed.

An additional dimension is supplied by Sociotechnical Systems Theory (Trist & Bamforth, 1951). It contends that technology adoption cannot be limited to technical systems; it is just as much a matter of the people and social frameworks that envelop them. For retailers in the UAE, AI will prevail only when employees are properly trained, the organisational culture enthusiastically embraces change and established workflows are modified to accommodate new tools. Marginalising the human dimension of adoption frequently leads to underuse or outright rejection of the technology.

Institutional Theory, by contrast, emphasises the exogenous forces that shape organisations. DiMaggio and Powell (1983) maintain that organisational uptake is frequently propelled by coercive, imitative and normative forces rather than by efficiency alone. The dynamic is especially pertinent in the UAE, where governmental policy enforces intense coercive pressure that steers industries toward AI adoption. Consequently, retailers might embrace AI to boost efficiency while aligning with national strategies and sustaining their competitiveness in an ever-evolving market (Scott, 2014).

Collectively, these frameworks highlight that AI adoption in UAE retail cannot be sufficiently accounted for by a single theoretical lens. DOI illuminates the mechanisms of adoption diffusion, TOE demonstrates the role of organisational and environmental influences in decision-making, TAM explores individual-level acceptance, Sociotechnical Systems Theory underscores the interplay between people and technology and Institutional Theory emphasises the impact of cultural and regulatory dynamics. The layered framework furnishes the all-encompassing foundation needed for this study.

3.7 AI Applications to Operational Risks

Operational risk management refers to a range of activities in which the firm engages to determine the likelihood of incurring either a direct or an indirect financial loss that results from a certain disruption in operations. Such risks can be internal within the instruction or emanate externally from events such as fraud, sabotage and natural disasters (Mosteanu and Faccia, 2020). Over time, the nature of operational risk facing organisations has been increasing in quantity, variety, and complexity for financial firms, and this has made it necessary to embrace the more proactive methods of analysing and mitigating company operations against such risks (Lin, 2019). AI presents some new potential in the management program of such risk by providing more effective machine learning solutions.

When it comes to operational risk, AI systems can help organisations throughout the risk identification process, risk exposure, measurement, estimating occurrence, and even assessment of the overall effects of the risk. AI systems can also assist the organisation in determining the type of mitigation strategies that can be used in every risk that may present within such an environment (Lui and Lamb, 2018). This also includes finding the instruments that can be most effective when fighting the available risk. The use of AI in operational risk management has been key in establishing methods that can effectively prevent external organisational losses that stem from activities such as the external losses from fraud. It has recently increased its utilisation to other, more repetitive processes in risk management.

3.8 Application of AI to Regulation Technology

Regulation technology is one of the other essential elements within the financial markets. One of the critical regulations in the financial markets is risk management. For financial institutions, compliance with the risk management regulations is vital for these forms, especially after the economic crises that have been experienced in the past (Mhlanga, 2020). For risk management professionals, the goal is often to draw a line between their activities and the many bureaucratic regulatory measures; the two are closely linked to the risk management systems (Lui and Lamb, 2018). The concept of compliance is often linked to enterprise risk management, as well as the three previous elements of risk: credit risk, market risk, and operational risk.

When it comes to financial technologies, regulatory technologies largely force compliance, and this has contributed to increasing the desire of different firms to ensure their compliance. In this field, AI has also been impacted by helping organisations deal with large volumes of data, which need to be analysed to ensure such compliance is done properly (Lui and Lamb, 2018). However, much of the role AI plays when it comes to compliance is done through monitoring the company activities, which relate to how they effectively cover the various elements of their operations. According to the study by Arner *et al*. (2016), these real-time insights help them avoid compliance breaches, which would later help them avoid the various consequences that may arise from compliance breaches.

3.9 Challenges Relating to AI Adoption in the UAE

This section studies the challenges facing AI adoption within the UAE, as experienced in different industries. To achieve this, it is also important to understand the differences between the AI sectors rolled out in the UAE. At the top of this list is the healthcare sector in the UAE.

The UAE healthcare sector is an essential global strategic healthcare provider since it provides high-level and high-quality healthcare services to people from within the Gulf region and globally. The UAE healthcare system comprises public and private hospitals, representing services offered in the private and public sectors (Kabalisa et al., 2021). The federal Ministry of Health and Prevention is responsible for regulating the price of services within this industry. Despite strict regulatory requirements, the number of healthcare facilities and hospitals in the region has been increasing steadily since 2012 (Korchagina et al., 2020). This increase in investment in healthcare has led to an increased life expectancy in the area, which is now an average of around 76.8 years, the same as the life expectancy of North America and Europe.

As mentioned earlier, the UAE became the first country globally to establish the Ministry of AI, which was constituted in 2017. The core purpose of the Ministry of AI in the UAE was to provide a conducive environment for the government to adopt the use of AI within the region effectively. The ministry would, therefore, coordinate the adoption of AI in different sectors, including healthcare and transport. The healthcare sector has been a beneficiary of such developments, with specific frameworks already installed, as outlined in the earlier section of this thesis. In addition, machine learning technologies have also presented video consultation as a viable option to advance telemedicine in the region and globally.

The information regarding the issue of AI deployment within the UAE in the 'Challenges' section can be expanded by comparing its legal and ethical repercussions regarding employment in the retail industry. While literature is aware of the role of the regulatory environment, it could be more analytical in identifying certain areas in AI governance that are lacking in managing risk (Kabalisa et al., 2021). While some jurisdictions have already developed frameworks for AI ethics, such as the EU's GDPR for personal data, the UAE has not yet coherently standardised the regulation of AI. This gap poses challenges to UAE retailers in terms of data privacy, transparency, and accountability, which are crucial for enhancing consumer confidence in AI technologies. For instance, there is a possibility that human data could be exposed to misuse, thus eroding the confidence of customers in the retailers and consequently subjecting them to reputational risks (Koo et al., 2021). Moreover, issues of ethics, such as bias in algorithms and the ability of AI systems to provide explanations on decisions made, also pose challenges to risk management. Such concerns can only be met with preventive measures in the form of regulation, including establishing rules for the proper application of AI and enforcing retailers to adhere to international norms on data privacy (Kumar, 2018). This regulatory perspective underlines the necessity of UAE authorities to work on a coherent concept of AI governance that can provide a broader outlook on the possibility of AI and its regulation in the context of the UAE. Therefore, by identifying these gaps, the review offers a positive outlook on the role of governance in supporting the sustainable integration of AI in retail.

3.10 Identified Research Gaps

The literature review section discusses the different facets of AI adoption in the UAE, particularly in the context of the private retail sector, and the potential of reshaping the risk management process. In the following sections, the author provides a brief overview of the diffusion and adoption of AI, the technological and organisational consequences of AI, and its effects on organisations, employment, and society. Further, theoretical frameworks like Diffusion of Innovation (DOI), Technology-Organisation-Environment (TOE), Sociotechnical Systems Theory, Technology Acceptance Model (TAM), and Institutional Theory have offered a significant understanding of the factors and threats surrounding the adoption of AI. However, there are still some gaps in the existing knowledge discussed in this thesis.

Firstly, based on this review, it is apparent that there is a lack of research on AI's Role in Risk Management in the Retail Sector. To date, numerous studies explore AI adoption from a general perspective and in a range of industries, but research on the application of AI to risk management in the retail industry is scarce (Korchagina et al., 2020). This suggests that much of the problem-solving revolves around the productivity gains and customer satisfaction created by AI, for instance, smart self-assistance, stock control, and customized communication. However, there is a lack of research examining how AI contributes to risk management, including cyber risks, supply chain threats, fraud, and data privacy, specifically in the UAE retail environment (Kabalisa et al., 2021). This thesis seeks to address this gap by offering a detailed analysis of how risk management is being enhanced by AI technologies in the retail industry. It will look at the effectiveness and drawbacks of employing artificial intelligence in risk management solutions and give a more comprehensive perspective on how AI redefines risk management approaches and potential issues.

Furthermore, it has also been proven that there is a lack of Empirical Evidence on AI Implementation in UAE Retail. The existing literature on AI in the UAE is somewhat weak. It covers mostly theoretical approaches and government strategies, and few empirical works shed light on the actual experiences of private sector organisations, especially in the retail industry (Kumar, 2018). The majority of the debates focus on the state's AI initiatives and general descriptions of AI adoption across sectors, such as healthcare, finance, and government services (Koo et al., 2021). This raises the question of how retail organisations are actually applying AI, what issues they are encountering and what results they are achieving. This thesis will help to address this gap by providing empirical evidence of AI adoption in the private retail sector in the UAE. To adopt a rigorous methodological approach, the scholarly study will use qualitative interviews and case studies to collect data from retail managers, representatives from AI service providers, and technology experts (Korchagina et al., 2020). The results will provide a good understanding of how AI can be practically used and how effective it can be in UAE retail sector in terms of risk management.

Furthermore, the various Organisational and Workforce Challenges have not received adequate attention. Another noteworthy gap that has been pointed out is that not enough research has been conducted on the organisational and workforce implications of AI use in retail (Kumar, 2018). While there is literature addressing the technological benefits of AI, including automation and predictive modelling, there is a relative dearth of discussion regarding how the implementation of AI transforms structural, managerial, and individual work in retail firms. Notably, the potential consequences like job loss, operational skills devaluation, and AI technology rejection by some employees remain neglected (Koo et al., 2021). This thesis will fill this gap by studying the sociotechnical relations of AI implementation in a particular context, namely retail, emphasising the transformation of work through the use of AI. It will also look at how retailers are adapting to these challenges, such as how to train employees on the use of the technology, dealing with employees' resistance to automation, and the issue of integrating AI with human labour rather than displacing it.

A further area of research that has been identified is a category referred to as the Regulatory and Ethical Gaps in adopting AI. The literature review noted that the UAE government has introduced many policies on AI; however, the UAE lacks a code on data protection, AI ethics, and the management and regulation of AI technologies in the private sphere. While Singapore and Germany have developed extensive regulatory models to govern AI, the United Arab Emirates still lacks a solid legislative system (Kumar, 2018). However, there are no definitive rules concerning the effective management of ethical issues related to private retail organisations, for instance, misapplication of data, biased algorithms, and lack of accountability in the decision-making process regarding the use of AI (Korchagina et al., 2020). This thesis will help advance the conversation on the lack of robust AI regulation by examining how a loosely regulated environment for AI impacts risk in the UAE retail industry. It will review the existing structures and policies and provide suggestions on how the UAE can implement even stronger frameworks to address the ethical risks while fostering the advancement of AI applications.

The following are some of the key contributions that this thesis will offer to the existing literature. First, it will give an insightful account of the effects of adopting AI in the real UAE retail sector, as opposed to theoretical dissertations that bring nothing to realistic practice (Kumar, 2018). It will also offer policy implications for enhancing the UAE's AI regulation so that AI implementation in retail is progressive and responsible (Koo et al., 2021). In turn, filling these gaps could help the thesis further enhance the understanding of AI's impact on risk management in the UAE's private retail sector and provide recommendations regarding enhancing AI-related practices within this emerging field.

3.11 Linking Literature to Research Questions

A strong literature review must not only summarise what is known, but also show how gaps in knowledge lead to the research questions that guide the study. In this section, the findings from the reviewed studies are connected directly to the research questions and objectives of this thesis. This ensures that the study is not developed in isolation, but rather builds upon existing scholarship while responding to clear shortcomings in the academic and policy literature. The research questions are designed to address three interrelated gaps: the lack of detailed analysis on how national AI strategies influence private sector practices, the insufficient attention given to risk and cyber-security concerns in retail AI adoption, and the scarcity of studies that are specific to the UAE and Gulf region. By linking each research question to a corresponding gap, the chapter shows how the study contributes both empirically and theoretically to advancing understanding of AI adoption in retail risk management.

RQ1: How has the UAE National Strategy for AI 2031 affected project management efforts in the private retail sector?

One of the most consistent findings in the literature is that national AI policies provide a broad direction for innovation, but their concrete impact on private organisations often remains under-explored. Much of the global literature on AI adoption focuses on either technological potential (Brynjolfsson and McAfee, 2017) or managerial benefits in generic terms (Dwivedi et al., 2021). While these works provide valuable insights into efficiency, productivity, and strategic value, they rarely trace how government-led AI strategies shape business practices in specific sectors. This represents a significant gap in understanding the "policy-to-practice" link.

The UAE National Strategy for AI 2031 is widely acknowledged as one of the most ambitious national plans for AI globally, aiming to integrate AI into multiple sectors and to position the UAE as a global leader in this domain (UAE Government, 2018). Existing reports highlight its aspirations for public services, education, transport, and health, but far less has been written about how the strategy has influenced the private retail sector, where project management is central to daily operations (Al-Dhaheri, 2020). Research in other regions suggests that national AI initiatives often fail to penetrate industry practices without targeted incentives and regulatory guidance (Shrestha et al., 2019). However, this has not yet been systematically studied in the UAE retail environment.

Research Gap and Objective Alignment

This study responds directly to the gap by examining the strategic alignment between the UAE National AI Strategy and project management practices within private retail organisations. The first research objective—to examine how the strategy has affected project management efforts—arises from the need to move beyond abstract discussions of AI potential and instead analyse whether state-driven innovation agendas produce tangible organisational change. In doing so, the study addresses the scholarly silence on how macro-level AI policies cascade down to meso-level organisational strategies and micro-level project management practices. It also provides practical insights for both policymakers and retailers. If the AI 2031 strategy has indeed shaped risk management projects and workflows, this finding would validate the effectiveness of government-led innovation strategies. If not, it would highlight the need for stronger policy-industry linkages.

RQ2: What strategic approaches are private retail organisations in the UAE adopting to enhance risk management, and how do these address concerns about security, privacy, and cyber risks?

A second gap in the literature concerns the treatment of risks associated with AI in organisational contexts. The majority of studies emphasise the benefits of AI for efficiency, data analysis, and consumer engagement (Huang and Rust, 2021; Wilson and Daugherty, 2018). Far fewer devote attention to the challenges of security, bias, transparency, and reliability in retail settings. When risks are discussed, they are often framed narrowly—such as algorithmic bias in hiring (O'Neil, 2016) or ethical issues in healthcare AI (Topol, 2019)—rather than as broad organisational concerns in risk-sensitive sectors. In the retail sector specifically, cyber-security and data privacy risks are especially pressing. Retailers handle vast amounts of consumer and transaction data, making them attractive targets for cyber-attacks (Kshetri, 2018). The integration of AI systems for fraud detection, supply chain management, and customer analytics creates new vulnerabilities if systems are poorly secured or if staff are untrained in AI oversight (Dwivedi et al., 2021). Yet, the literature shows limited engagement with how retailers adapt their risk management strategies to these threats, especially in emerging market contexts.

Research Gap and Objective Alignment

This gap directly informs the second research question, which investigates the strategies adopted by UAE retailers to manage AI-related risks. The second research objective—to analyse strategic approaches adopted by private retail sector organisations to enhance risk management—is therefore grounded in the observation that much of the literature treats AI risk as a technical problem rather than an organisational challenge. By focusing on strategy, this study emphasises the choices and practices that businesses make in response to risks. It also highlights how organisational culture, governance structures, and leadership priorities affect the implementation of security measures. This aligns with the Technology–Organisation–Environment (TOE) framework, which stresses that adoption is shaped not only by technological capabilities but also by organisational readiness and environmental pressures (Tornatzky and Fleischer, 1990).

Ultimately, this research question and objective seek to bridge the disconnect in the literature by foregrounding the agency of organisations in managing AI risk. For policymakers and practitioners, such insights are crucial, as they shed light on whether retailers are proactively addressing vulnerabilities or simply reacting to regulatory requirements.

RQ3: What is the future of AI applications in retail risk management in the UAE, and what potential do these hold for project management?

The third gap emerges from the geographic and contextual limitations of existing research. As noted in the earlier review, much of the scholarship on AI adoption in retail is based on cases from the United States, Europe, and East Asia (Chui et al., 2018). These regions have highly digitised retail ecosystems and established AI infrastructures, which makes findings difficult to generalise to the Gulf. Studies on AI in the Middle East are growing but remain scattered, with most concentrating on government applications or financial services (Al-Jenaibi, 2021). Retail risk management remains under-researched. The UAE presents a unique context because of its combination of ambitious government-led innovation strategies, rapid retail sector growth, and strong emphasis on digital transformation (Oxford Business Group, 2020). However, the literature does not yet provide a clear account of how AI adoption in retail risk management might evolve in this setting. Furthermore, few studies consider how future trends in AI—such as explainable AI, predictive analytics, and AI-driven cyber-defence systems—may reshape project management practices specifically in retail.

Research Gap and Objective Alignment

The third research objective—to explore the future of AI applications in risk management on project management activities—directly responds to this contextual gap. This study seeks to situate the UAE not as a passive recipient of global AI trends but as an active context in which distinct cultural, institutional, and regulatory factors shape adoption. In this respect, the Diffusion of Innovation (DOI) theory (Rogers, 2003) provides a useful lens. DOI highlights how innovations spread differently depending on adopter characteristics, communication channels, and socio-cultural contexts. By applying DOI, the study can explore how UAE retailers perceive AI risk management innovations, how they plan to integrate them, and what barriers might slow adoption. In linking this research question to the literature, the study fills an important gap by projecting the implications of AI adoption in retail risk management in the Gulf. It also contributes to a broader discussion on how global AI futures are being shaped not only in Western economies but also in rapidly modernising regions like the UAE.

Synthesis and Contribution

Taken together, the three research questions ensure that the study responds to the key shortcomings identified in the literature. RQ1 addresses the gap between national strategies and sector-level practices. RQ2 responds to the limited scholarly focus on risk and cyber-security in AI adoption. RQ3 fills the contextual void by analysing the UAE and GCC retail environment and projecting future applications. This alignment ensures coherence between the research objectives, the gaps in the literature, and the theoretical frameworks guiding the study. More importantly, it guarantees that the contribution of the research will be both practical—informing retailers and policymakers—and academic—advancing the literature on AI, risk management, and project management in emerging markets.

3.12 Summary of Literature Review and Transition

To date, the discussion has revealed that, although AI is broadly recognised as a transformative force in business, empirical studies on its adoption are still fragmented, especially in emerging economies such as those in the Gulf. Most of the extant literature centres on North America, Europe and East Asia, resulting in underrepresentation of regions such as the UAE. It is all the more surprising that the UAE which has positioned AI at the core of its development strategy through initiatives such as the National AI Strategy 2031 (UAE Government, 2018), has received scant attention in the literature. The disparity among governmental objectives, industry behaviours and scholarly investigations highlights the necessity for research that accounts for the UAE's distinctive socio-economic setting.

A further evident gap lies in research that highlights AI's potential advantages while devoting comparatively little attention to its potential risks. Although cybersecurity threats, ethical challenges and the complexities of incorporating AI into established organisational processes are widely recognised, they are too often examined only superficially. Within retail, the sector that handles vast stores of sensitive customer data and contends with continual operational uncertainties, these risks assume a particularly acute importance. Nevertheless, empirical studies on how AI should be managed to align its benefits with its risks in this sector are scarce (Dwivedi et al., 2021; Al-Dhaheri, 2020).

Moreover, the extant body of research suffers from theoretical constraints. A considerable share of studies rests on a single framework—for example, the Technology Acceptance Model (Davis, 1989)—that focuses on individual perceptions while overlooking the wider organisational and institutional dynamics at work. Likewise, though Sociotechnical Systems Theory (Trist & Bamforth, 1951) and Institutional Theory (DiMaggio & Powell, 1983) each shed valuable light, they are seldom incorporated into adoption-oriented frameworks such as DOI or TOE. As a consequence, the resulting view of AI adoption remains fragmented. By synthesising DOI and TOE as its principal analytical lenses and integrating TAM, Sociotechnical and Institutional perspectives as complementary supports, this study seeks to fulfil the need for a more holistic model that integrates individual perceptions with broader organisational and institutional dynamics.

Theoretically, the study enriches the body of knowledge by illustrating the merit of an integrated framework that accounts for adoption occurring at each of the individual, organisational and institutional levels. In practical terms, the study sheds light on the challenges confronting retailers in the UAE—most of whom contend with limited resources, stringent regulations and rapidly shifting consumer expectations. By illustrating how AI can reinforce project and risk management in retail, the study furnishes guidance that is directly applicable to practitioners. In this chapter, the study's conceptual groundwork has been established by pinpointing literature gaps and elucidating its theoretical framework. Next, the discussion will explore how these ideas can be realised in practice. In Chapter 4 the study shifts to its methodological section, delineating the design, strategy and techniques employed to examine AI adoption in the UAE retail sector. This transition secures the empirical work's anchor in theory, while simultaneously tackling the shortcomings highlighted in the existing scholarship.

From a practical perspective, the existing literature also falls short of offering sector-specific strategies for project management within the retail industry. Much of the available research emphasises broad organisational benefits such as efficiency gains, cost reductions, and improved customer engagement, but there is little analysis of how AI supports or complicates risk management in the context of projects and operations. This omission is significant because project management in retail is often shaped by high levels of uncertainty, from supply chain disruptions to rapid shifts in consumer behaviour. For retailers in the UAE, the stakes are even higher given the dual pressures of global competition and national strategies that expect firms to embrace AI technologies. This study's contribution is therefore twofold: first, it provides theoretical clarity by synthesising and applying frameworks that are often considered in isolation, and second, it offers practical insights for retailers on how to manage AI adoption in ways that align with risk management priorities and the UAE's broader strategic objectives.

By consolidating these gaps, this research positions itself at the intersection of theory and practice. Theoretically, it advances understanding by demonstrating how multiple frameworks can be integrated to analyse AI adoption within a context that is shaped by unique institutional, cultural, and regulatory forces. Practically, it generates knowledge that can inform business leaders and policymakers in the UAE retail sector, offering guidance on how AI can be leveraged responsibly and effectively to support project management and risk management outcomes. These contributions are essential for ensuring that the rapid pace of technological adoption in the UAE does not outstrip the capacity of organisations to manage associated risks and align innovations with long-term strategic goals.

The discussion presented here provides the foundation for the methodology adopted in this study. Having identified the key theoretical models and the gaps in the existing literature, the next chapter sets out the research design that was used to investigate the adoption of AI in the UAE retail sector. Chapter 4 explains the methodological choices that guide the study, including the research philosophy, approach, and strategy, as well as the data collection and analysis methods employed. In doing so, it connects the gaps highlighted in this chapter with the empirical techniques necessary to address them, ensuring that the study is not only conceptually rigorous but also methodologically sound.

4.0 CHAPTER FOUR: METHODOLOGY

4.1 Introduction

This chapter explains how the study was designed and carried out, and why those choices fit the questions the thesis is trying to answer. The aim here is not only to list methods but to show a coherent line of reasoning from the assumptions the study makes about reality, through the kind of knowledge it seeks, to the practical decisions taken in the field. The chapter, therefore, opens with the philosophical stance that underpins the work and the implications of that stance for the overall approach to inquiry. It then sets out the research design and strategy, justifies the qualitative orientation adopted, and clarifies the logic for using a case-study frame anchored in contemporary practice in the United Arab Emirates' retail sector. Later sections of the chapter (not included here) detail sampling, data collection through semi-structured interviews, and the analytic pathway using a Thematic Framework Analysis, alongside ethics, trustworthiness and limitations.

Two considerations guided the construction of this chapter. First, the phenomenon under study—how artificial intelligence is being taken up within retail organisations to identify, respond to and mitigate risk—is socially situated. It involves people's judgments, negotiated routines, organisational constraints and sectoral norms. Those facets cannot be accessed adequately through surface indicators alone; they require a design that can attend to nuance, situated meaning and variation across contexts (Creswell, 2014). Second, the UAE retail environment is dynamic and policy-sensitive, with national strategies shaping organisational agendas while firms interpret and implement technologies unevenly. A methodology that can track those situated interpretations, and that remains open to themes emerging from participants' accounts rather than being locked into a priori categories, is essential (Saunders et al., 2019).

Accordingly, the chapter advances three tightly connected choices. The first is an interpretivist philosophical position paired with an inductive logic of inquiry. This positions the research to privilege participants' meanings and to allow concepts to grow from data rather than forcing data into pre-existing theoretical templates (Charmaz, 2014; Saunders et al., 2019). The second is a qualitative design based on semi-structured interviews within a multiple-case study strategy, so that analysis can move between within-case depth and cross-case patterning while staying close to lived practice (Yin, 2018). The third, elaborated later in the chapter, is an analysis plan that systematises emergent insights through a transparent coding and charting process, enabling a clear line of sight from raw accounts to higher-order interpretations and, ultimately, to the study's theoretical and practical contributions (Gale et al., 2013; Ritchie and Spencer, 1994).

Throughout the chapter, it maintains a strong link to the literature review and the research questions. The literature review highlighted gaps around how AI's promise and risk are being negotiated on the ground in retail operations, including the tensions between efficiency, control and exposure to new vulnerabilities. The research questions grow directly from those gaps, seeking evidence-based accounts of what organisations are doing, why, and with what perceived consequences. The methods specified here are chosen because they can credibly generate the kind of rich, contextualised evidence needed to answer those questions and speak back to the bodies of theory the thesis engages with. By the end of the chapter, the reader should see not only what was done, but why doing it this way strengthens the claims the thesis ultimately makes.

4.2 Research Philosophy and Paradigm

Any research design is anchored in assumptions about what exists to be known and how it can be known. Making those assumptions explicit matters because they steer every downstream choice—from how questions are framed to how accounts are treated during analysis (Crotty, 1998). This study takes a position that social reality in organisations is constructed through meanings, practices and relationships, and that understanding technological change in such settings requires access to the interpretive work of the people involved.

Ontologically, the study assumes a plural, context-dependent reality. What "AI-enabled risk management" is, and how it is experienced, varies across organisations, roles and moments in time. There is no single stable essence of the practice waiting to be measured; rather, there are multiple realities assembled through tools, policies, routines and judgments. Such a view aligns with a relativist or subtle realist ontology commonly associated with qualitative case work in organisational settings (Maxwell, 2012; Sayer, 2000). In practical terms, this means the research does not expect identical answers from managers and frontline technical staff, nor does it treat divergence as error; difference is itself data about how the phenomenon works in practice.

Epistemologically, the study is interpretivist. Knowledge is generated by engaging closely with participants to understand how they make sense of AI within their work, how they justify choices, and how they perceive risks and trade-offs. Rather than pursuing law-like propositions detached from context, the goal is to build situated understanding that can nevertheless travel—through careful description, analytic transparency and theoretical linkage—beyond the immediate cases (Schwartz-Shea and Yanow, 2012; Saunders et al., 2019). This stance legitimises methods, such as semi-structured interviewing and iterative coding, that foreground participants' meanings while acknowledging the researcher's role in interpreting them.

At the level of overarching research philosophy, interpretivism is adopted because it fits the phenomenon and the questions at hand. Positivist designs excel when variables can be tightly specified and controlled, but here the "variables" of interest—judgment, capability, trust in systems, risk appetite, organisational learning—are embedded, shifting and negotiated. Treating them as fixed inputs risks missing how they are constituted in practice. Interpretivism, by contrast, takes meaning-making as the very object of inquiry, allowing the research to show how concepts like "risk mitigation" or "AI effectiveness" are assembled locally and with what consequences (Bryman, 2016; Creswell, 2014).

The study's logic of inquiry follows from this stance. An inductive approach is used to move from particular accounts to more general insights, building propositions from the ground up rather than testing a predetermined model. While the analysis will be in dialogue with existing frameworks from the literature, the aim is not hypothesis testing but theory elaboration: identifying patterns and mechanisms that can refine or extend current understandings of technology adoption and risk management in retail (Charmaz, 2014; Eisenhardt and Graebner, 2007). Induction here does not mean starting from a blank slate—no researcher ever does—but it does mean that coding and interpretation are open to surprise and are led by what participants emphasise, not only by what prior theory predicts (Miles, Huberman and Saldaña, 2014).

Linking philosophy and approach back to the research questions is essential. The literature review revealed unanswered questions about how AI is integrated into existing processes, how people assess its reliability in relation to risk, and how organisational conditions influence implementation pathways. Those gaps call for evidence that captures reasoning, practice and context together. An interpretivist–inductive stance supports this need: it sanctions in-depth conversations that reveal how actors construe problems, constraints, and opportunities, and it makes space for cross-case comparison that respects differences while seeking family resemblances across organisations (Saunders et al., 2019; Yin, 2018). In this way, the chosen paradigm aligns closely with the thesis's substantive aims and its commitment to contribute to both theory and practice.

Two implications flow from this paradigm for the conduct of the study. The first is reflexivity. Because the researcher is an instrument of data generation and interpretation, the analysis must track how positionality and assumptions are managed (Finlay, 2002; Miles, Huberman and Saldaña, 2014). The second is an emphasis on coherence between questions, data and analysis. Semi-structured interviews are designed to open up participants' reasoning without steering them toward preferred answers, and the analytic method—explained later in the chapter—uses systematic charting to preserve the link between raw accounts and emergent themes (Gale et al., 2013; Ritchie and Spencer, 1994). Together, these choices translate philosophical commitments into rigorous, practical applications.

4.3 Research Design and Strategy

With the philosophical ground set, the design translates those commitments into an executable plan. The study adopts a qualitative design organised as a multiple case study of AI use in risk management within the UAE retail sector, employing semi-structured interviews as the primary mode of data generation. This combination is appropriate when the aim is to understand a contemporary phenomenon in depth and within its real-world context, especially where the boundaries between the phenomenon and its context are blurred (Yin, 2018). Retail organisations are embedded in regulatory frameworks, supply chains, customer expectations and national digital priorities; AI initiatives and risk practices are shaped by those conditions. A case strategy allows the study to keep that embedding in view rather than stripping it away in pursuit of decontextualised measures.

The qualitative orientation is justified by the nature of the questions. The thesis asks how AI is being integrated into risk management routines, how actors assess benefits and exposures, and how organisational conditions facilitate or frustrate effective use. These are "how" and "why" questions about process and meaning, suited to methods that elicit narrative, explanation and example rather than tick-box responses (Creswell, 2014). Semi-structured interviews, in particular, enable a conversational depth that can surface rationales, trade-offs and lived constraints—details that survey instruments often flatten. They also allow the interviewer to probe unexpected leads raised by participants, which is vital in a fast-moving technological space.

Within the case strategy, the design uses more than one organisational setting so that analysis can compare across contexts. Multiple cases strengthen analytic generalisation by showing how a theme recurs under different conditions, or by clarifying the conditions under which a theme changes (Eisenhardt and Graebner, 2007; Yin, 2018). In the UAE retail sector, organisational scale, digital maturity and governance structures differ markedly; sampling across that variation enables the study to identify patterns that matter for practice and for theory. At the same time, each case is treated on its own terms. Interviews are analysed within-case first, preserving local coherence, before cross-case patterns are sought. This sequencing avoids forcing premature convergence and respects the interpretivist emphasis on situated meaning (Miles, Huberman and Saldaña, 2014).

The link to the "research onion" is straightforward. The outer layers—philosophy and approach—have been specified as interpretivist and inductive. The methodological choice is qualitative, with semi-structured interviewing as the main technique. The strategy is a multiple case study, and the time horizon is essentially cross-sectional, capturing practice as it stands during the fieldwork window rather than attempting to track change longitudinally (Saunders et al., 2019). While longitudinal designs can be valuable, the present study's interest is in the current state of play and in how people explain present arrangements, which a cross-section adequately serves. Importantly, a cross-section does not preclude attending to process; participants' accounts routinely refer to sequences, experiments and turning points, and the analysis treats those processual elements as data.

Choosing a qualitative case strategy also sets clear expectations for the kind of contribution the study can make. The aim is not statistical generalisation but analytic generalisation: showing how the findings illuminate, refine or extend theoretical conversations about technology adoption, organisational risk and capability in retail. This is done by careful case selection, transparency about context, and disciplined linking between data, interpretation and theory (Yin, 2018; Maxwell, 2012). The practical contribution follows the same path. By grounding insights in detailed accounts from actors charged with delivering AI-enabled risk work, the study can offer actionable pointers for similar organisations facing analogous constraints.

Alternative designs were considered and rejected for reasons consistent with the research aims. A purely quantitative survey might have offered breadth, but it would have yielded thin, self-report indicators of complex practices and limited insight into why organisations made the choices they did. Experimental or quasi-experimental designs were inappropriate because the research does not intervene in organisational processes or attempt to manipulate exposures. Mixed-methods designs can be powerful, but in this instance they risked diluting the deep interpretive attention the questions require. The case-based qualitative design therefore provides the best fit between goals, context and feasible access to relevant actors (Creswell, 2014; Saunders et al., 2019).

Finally, the choice of strategy is also ethical and relational. Semi-structured interviews invite participants to speak in their own terms about sensitive issues such as risk, compliance and organisational capability. That sensitivity requires a design that builds trust, protects anonymity and allows participants to qualify and nuance their accounts. The qualitative case strategy, with its emphasis on relationships, context and reflexivity, supports those ethical commitments and aligns with the study's wider intention to represent practice fairly while generating insights that can travel.

4.4 Sampling and Participants

The study sought perspectives from people who work directly with artificial intelligence in retail organisations and who could speak credibly about how AI interacts with day-to-day risk management. In methodological terms, that meant defining the population at the level of roles rather than job titles, and then sampling for depth across functions that shape or are shaped by AI-enabled risk practices. A purposive strategy was therefore appropriate because it enables the deliberate selection of information-rich participants who can illuminate the central phenomena under investigation (Patton, 2015; Saunders, Lewis & Thornhill, 2019). In practice, this involved identifying managers and specialists in risk, technology, data analytics and operations within large retail groups in the United Arab Emirates, together with a smaller number of frontline staff whose work is materially affected by AI tools.

Purposive sampling was guided by clear inclusion criteria. Participants needed to be employed in the UAE retail sector; to have at least one year of exposure to AI-enabled processes relevant to risk (for example, fraud analytics, inventory forecasting, loss prevention, cybersecurity monitoring or customer due-diligence); and to be able to comment on how those tools are adopted, governed and used. Exclusion criteria were minimal but included purely vendor-side roles with no responsibility for in-house practices and roles unrelated to risk or AI. These criteria balanced breadth and specificity, ensuring that the data remained anchored to the research questions while capturing variation across functions and organisational layers (Marshall & Rossman, 2016).

Access involved two steps. First, senior contacts in participating retailers were approached to introduce the study and to secure permission to invite staff. Second, potential interviewees were contacted directly with an information sheet and consent form. Within the purposive frame, the study also made pragmatic use of within-organisation snowballing, where initial participants recommended colleagues whose responsibilities complemented their own. Snowballing is not intended to replace purposive logic; rather, it helps surface otherwise hidden but relevant expertise in complex organisations (Noy, 2008). Throughout recruitment the priority was not numerical representativeness but conceptual saturation, which is the point at which additional interviews cease to yield new insights relevant to the developing analysis (Guest, Bunce & Johnson, 2006; Saunders et al., 2019).

Sample size was calibrated to the analytic approach. The study targeted around thirty interviews distributed across two large retailers to allow comparison across sites and functions.

This scale is consistent with qualitative case work where depth, triangulation and the ability to follow emergent leads are more valuable than large-N breadth (Yin, 2018; Patton, 2015). Diversity within the sample was pursued along three axes: role seniority, functional area and degree of hands-on contact with AI systems. Senior managers provided insight into strategic intent, governance and risk appetite; middle managers and specialists elaborated how policies and models are operationalised; frontline staff described practical effects, workarounds and unintended consequences. This layered picture is central to an interpretivist inquiry that seeks to understand how meanings and practices travel through an organisation (Creswell & Poth, 2018).

Ethical recruitment considerations were built into the sampling process. Participation was voluntary; no incentives were offered; and prospective participants were assured that declining or withdrawing would have no organisational consequences. Because the topic intersects with sensitive risk practices, the study emphasised confidentiality and the removal of organisational identifiers. Protecting anonymity encourages frankness about failures, trade-offs and tensions that would otherwise be hard to capture (Kaiser, 2009). Taken together, these design choices generated a sample capable of speaking to the technical, organisational and human dimensions of AI-enabled risk management in the UAE retail context.

4.5 Data Collection

Semi-structured interviewing was chosen as the primary method of data collection. It fits the interpretivist orientation by creating space for participants to articulate their own accounts while allowing the researcher to probe mechanisms, contexts and meanings in real time (Kvale & Brinkmann, 2009; Bryman, 2016). A rigidly structured schedule would have constrained these accounts, while wholly unstructured conversations risk drifting away from the research questions. Semi-structured interviews strike a balance, providing a scaffold of core prompts with the flexibility to follow promising lines of inquiry as they emerge.

The interview guide was developed iteratively. Initial prompts derived from the literature review mapped onto four domains: the drivers and goals of AI adoption in relation to risk; governance arrangements and accountability; day-to-day practices and tools; and perceived outcomes, including benefits, costs and new risks. Each domain included open questions, neutral probes and requests for concrete examples. For instance, to move beyond generalities, participants were asked to describe a recent decision or incident where an AI-enabled system influenced risk assessment or response, and to reflect on how that experience compared with prior non-AI processes. The guide was piloted informally with two practitioners to check clarity and flow and adjusted to simplify jargon and to reorder topics so that sensitive organisational issues appeared after rapport-building questions. Piloting improves content validity and helps reduce interviewer reactivity during fieldwork (Turner, 2010).

Most interviews took place via secure video conferencing at times chosen by participants, typically lasting between 30 and 40 minutes. Remote interviewing proved efficient across geographies and time constraints and has been shown to be compatible with depth interviewing when rapport is actively managed (Archibald et al., 2019). With consent, all interviews were audio-recorded and subsequently transcribed verbatim. Where participants preferred not to be recorded, detailed field notes were taken during and immediately after the session. Transcripts and notes were checked for accuracy against the audio to minimise transcription errors that could distort analysis (Bird, 2005). Any organisational names, product names or personal identifiers were masked at the point of transcription to protect anonymity.

Language and power dynamics were considered carefully. Interviews were conducted in English, which is widely used in UAE retail organisations. Where participants signalled discomfort with technical terminology, the interviewer rephrased questions in more accessible language and invited participants to define terms as they understand them in practice. The interviewer adopted a neutral, facilitative stance, avoiding evaluative language and making explicit that the interest was in understanding practice rather than judging it. Reflexive notes were written after each interview to document impressions, contextual details and analytic hunches. Such notes become part of the audit trail and support transparency about how interpretations were formed (Nowell et al., 2017; Miles, Huberman & Saldaña, 2014).

Documentary material was collected opportunistically to situate interview data. Where participants referenced internal policies, model documentation or training materials that could be shared without breaching confidentiality, copies or summaries were obtained. Publicly available documents such as corporate reports, press releases and regulatory guidance were also collated. These materials were not analysed as a separate dataset but used to enrich context and to triangulate key claims, an established tactic in qualitative case study research to enhance credibility (Yin, 2018; Bowen, 2009).

Data management followed good practice. Transcripts and notes were stored in encrypted folders accessible only to the research team. A simple but rigorous naming convention linked each file to a pseudonymous participant ID, role category and interview date. A version-controlled memo document captured evolving codes, theme definitions and decisions made during analysis. This disciplined approach to data handling supports confirmability and dependability in qualitative research by making processes traceable and open to scrutiny (Lincoln & Guba, 1985; Nowell et al., 2017).

Taken together, these choices served the substantive aims of the study. The flexible interview format allowed participants to surface both expected and unexpected issues, the piloted guide kept conversations anchored to the research questions, and the ethical and logistical arrangements encouraged open discussion of practices that organisations might otherwise be reluctant to disclose. The resultant corpus, comprising rich transcripts and contextual materials, was well-suited to systematic, transparent analysis.

4.6 Data Analysis: Thematic Framework Analysis

Given the applied, practice-oriented focus of the research questions and the need to show clear links between interview evidence and the answers to those questions, Thematic Framework Analysis (TFA) was adopted as the core analytic approach. TFA, as developed in policy and applied research traditions, offers a structured yet flexible procedure that begins with familiarisation and proceeds through the formulation of an analytical framework, systematic indexing, charting of data into a matrix, and finally mapping and interpretation (Ritchie & Spencer, 1994; Gale et al., 2013). It is particularly useful where studies combine a priori interests, derived from the literature and research questions, with inductive openness to unanticipated themes that arise from the data.

The choice of TFA was made in preference to several alternative approaches. Classic Grounded Theory emphasises theory generation from data and often discourages strong a priori frameworks; while powerful, it was not optimal here because the study needed to answer specified questions about AI and risk rather than build a formal mid-range theory from the ground up (Charmaz, 2006). Interpretative Phenomenological Analysis, with its idiographic focus on detailed, lived experience, is best suited to small samples and deep individual case work; the present study required cross-case comparison across functional roles within organisations (Smith, Flowers & Larkin, 2009). Reflexive thematic analysis, as articulated by Braun and Clarke (2006), is close to TFA but places less emphasis on the matrix-based charting that supports explicit linkage between data units and research questions. TFA's emphasis on transparency, auditability and the production of matrices that can be inspected and shared matched the supervisory guidance for presenting findings in Chapter 5 and supported credible cross-case explanations (Gale et al., 2013; Braun & Clarke, 2006).

Analysis began with repeated reading of transcripts and field notes to achieve immersion in the material. During this familiarisation phase, the researcher wrote brief case summaries and marginal notes capturing provisional ideas about patterns, contradictions and context. These notes were not treated as codes but as orientation aids that flagged issues to explore more systematically later. Familiarisation is not a perfunctory step; it is where the analyst learns the "shape" of the corpus and avoids premature closure on early impressions (Miles et al., 2014).

An initial analytical framework was then constructed. This framework had two sources. First, deductive categories derived from the research questions and literature review. These included, in broad strokes, drivers of AI adoption in risk contexts, governance and accountability arrangements, operational practices, perceived outcomes and emergent risks. Second, inductive categories derived directly from repeated readings of the transcripts. Early inductive candidates included issues such as model drift and recalibration, frontline workarounds, data lineage concerns, alert fatigue, role reconfiguration and tensions between speed and oversight. The framework at this stage was deliberately provisional. Each category was defined in plain language, with inclusion and exclusion rules and examples to guide consistent application.

Indexing, or coding, applied this framework systematically to the full data set. Coding was done at the level of meaning units, which could be sentences or short paragraphs, depending on how participants structured their answers. Segments could receive multiple codes to reflect the layered nature of practice, for example a single passage about fraud analytics might touch on vendor dependencies, model governance and staff training. Coding was initially conservative: rather than debate borderline cases at the outset, the analyst coded broadly and used subsequent charting and memoing to refine boundaries. This approach reduces the risk of early decisions obscuring important variation (Saldaña, 2021).

To enhance reliability and reflexivity, a sub-set of transcripts was double-coded at two points in the process, early and mid-way. Disagreements were not treated as errors to be eliminated but as prompts to clarify definitions, add sub-codes or collapse redundant categories. A brief codebook was maintained throughout, logging code names, definitions, decision rules and example extracts. Maintaining a live codebook is consistent with best practice in framework analysis and is a cornerstone of the audit trail (Gale et al., 2013; Nowell et al., 2017).

Charting involved summarising coded data into a case-by-theme matrix. Each row represented a participant; each column represented a code or clustered theme; each cell contained a condensed summary of the participant's relevant data with line references to the source transcript. The matrix format is more than a display device. It forces analytic discipline by making the analyst represent, side by side, what each participant said on each theme and by enabling rapid scanning for convergence, divergence and empty cells. Empty cells are analytically instructive: they show which topics did not resonate with certain functions or levels, which in turn can inform interpretation about role-specific experiences (Ritchie & Spencer, 1994; Miles et al., 2014).

Mapping and interpretation turned matrix patterns into explanatory insights. Here the analysis moved iteratively between within-case coherence and cross-case comparison. For example, the matrix made it clear when senior managers framed AI primarily as a strategic enabler for risk mitigation, whereas frontline staff emphasised workload and alert fatigue. It also highlighted consistent organisational conditions that appeared to moderate outcomes, such as the presence of a model risk governance forum or the degree of integration between data science and operational risk teams. These patterns were then read back against the literature to locate where findings aligned with, extended or problematised existing knowledge. Throughout, memos recorded emerging propositions, rival explanations and reflections on the analyst's assumptions. This disciplined interpretive cycle fits the inductive ethos while guarding against impressionistic leaps (Braun & Clarke, 2006; Miles et al., 2014).

The study documented code development for the core theme blocks that feed directly into Chapter 5. For the unit later labelled 5.1.2 in the findings chapter, codes crystallised around how participants identified and prioritised risk events targeted by AI tools. Inclusion criteria required explicit references to the mechanisms of identification—such as anomaly detection thresholds, feature importance in predictive models, or rule-based triggers—together with the organisational consequences of those identifications, for instance escalation criteria or workflow changes. Exclusions removed purely strategic statements about "becoming data-driven" that contained no operational detail. Typical sub-codes in this unit included detection logic, human-in-the-loop review, false-positive management and feedback loops from incidents back into model tuning. The evolution of these sub-codes is traced in the codebook memos, where early broad labels like "detection" were split once it became clear that participants spoke differently about initial flagging and subsequent validation steps (Gale et al., 2013; Saldaña, 2021).

For the unit reported as 5.1.3.1, which aggregates barriers around data and privacy constraints, code development began with inductive tags applied to segments about data lineage, consent, access controls and compliance interpretations. As analysis progressed, these tags were organised under higher-order categories distinguishing structural constraints, such as legacy systems limiting data availability, from normative constraints, such as risk aversion in interpreting privacy rules. The inclusion rule required a clear line to how such constraints affected risk tooling or processes, rather than general observations about "data being important". Excerpts that merely affirmed the importance of data quality without specifying impacts were excluded or routed to other descriptive codes. This distinction matters because TFA aims to tie evidence to the specific research questions rather than amassing generic statements (Ritchie & Spencer, 1994).

The companion unit 5.1.3.2 captured barriers in skills, capabilities and change readiness. Inductive coding here began with language about training adequacy, the availability of hybrid "translator" roles between data science and operations, and the degree to which staff understood model outputs. Sub-codes differentiated between formal training programmes, informal peer learning, and tool usability issues that amplify perceived skill gaps. Inclusion rules required participants to connect skills or readiness issues to concrete consequences for risk outcomes or workflow, for example delayed response times due to uncertainty about how to interpret a risk score. This unit benefitted from cross-checking with participants in different roles, revealing how the same training intervention was experienced differently by managers and frontline staff, a nuance only visible in a matrix-based approach (Gale et al., 2013).

For the units 5.1.4.1 and 5.1.4.2, which synthesise enabling conditions, code construction drew on both deductive and inductive inputs. The deductive scaffold captured enabling factors described in the literature, such as executive sponsorship, governance structures and integrated data platforms (Braun & Clarke, 2006; Miles et al., 2014). Inductively, the data added granularity, such as the role of cross-functional "risk sprints", the presence of clear model ownership and the practical value of accessible monitoring dashboards for non-specialists. Inclusion criteria required explicit evidence of how each enabler facilitated adoption or improved risk outcomes, not merely that it existed. Where participants described an enabler and a barrier in the same breath—such as executive sponsorship that accelerates rollout but compresses testing time—segments were double-coded to preserve the tension for later interpretation.

Trustworthiness was addressed throughout analysis. Credibility was supported by member checking, where a short summary of emergent themes and interpretations was shared with a sub-set of participants for comment. Their feedback led to clarifying distinctions, for example separating "alert fatigue" arising from model calibration from fatigue arising from poor workflow design. Dependability was supported by the audit trail comprising codebooks, memos, decision logs and dated matrix iterations. Confirmability was addressed by reflexive journaling in which the analyst recorded prior assumptions—for instance, a background in data analytics—and noted where these could bias attention or interpretation, with active efforts to seek disconfirming evidence. Transferability was supported by providing sufficient contextual detail about organisational settings, roles and systems so that readers can judge the applicability of findings to other contexts (Lincoln & Guba, 1985; Nowell et al., 2017).

Finally, the TFA process was explicitly aligned to how results are presented. The matrix that underpinned analysis is the source for the tables that appear in Chapter 5. Those tables display, for each theme, which participants contributed relevant evidence, with exemplar extracts cross-referenced to transcripts. Presenting findings in this way is consistent with framework analysis, meets expectations for transparency in applied organisational research and makes visible the link between claims and the underlying data (Ritchie & Spencer, 1994; Gale et al., 2013). The analysis thus remains faithful to interview evidence while offering a structured, defensible route from raw talk to explanation.

In sum, TFA provided the disciplined scaffolding needed to demonstrate how the data answer the research questions, while preserving interpretive sensitivity to context, language and organisational nuance. By documenting how codes and themes were developed for the core result units, and by maintaining a clear audit trail, the analysis responds directly to supervisory guidance on rigour and credibility, and lays a coherent foundation for the presentation of findings and their subsequent discussion.

4.7 Ethical Considerations

Conducting a study involving human participants raises significant ethical concerns. In this study, the researcher involved human participants as means of the employees working in the warehouse departments. Therefore, the first ethical consideration made in this study was consent (Artal and Rubenfeld, 2017). Consent was obtained both from the participants and the warehousing institutions that they worked in. Consent from their employers was obtained by means of seeking official permission from the company to conduct a study with their employees. This permission was granted through a consent form that is attached in the appendix of this report. In relation to the participants, they had to provide consent by understanding what the research was all about, and by willingly agreeing to participate in the research. Therefore, a prior email was sent to the participants with details about the goals of the research and how the information was going to be used. Participants had to sign a consent form to confirm their willingness to participate.

Another form of ethical concern in this study was related to the handling of personal data. As a study involving human participants, the researcher had to ensure that the study protected any personal data, especially the identifying information that could have been collected during the study. The information collected through the data would be stored in the school's library and prevented access from third parties without the direct consent of the participants.

4.8 Trustworthiness and Limitations of the Methodology

Rigour in qualitative research is established through trustworthiness rather than through statistical criteria. This study worked deliberately with the four interrelated criteria proposed by Lincoln and Guba—credibility, transferability, dependability and confirmability—and complemented them with later refinements in the methods literature. Credibility concerns the plausibility and believability of findings to those who shared their experience and to knowledgeable readers. It was pursued through methodological fit, triangulation and participant feedback. Methodological fit is reflected in the alignment between the interpretivist philosophy, the inductive approach, the case-based qualitative design and the use of Thematic Framework Analysis, which together are appropriate to the study's exploratory, practice-oriented questions. Triangulation combined interview evidence with contextual documents to situate accounts and to check that interpretations were not artifacts of a single data source. Member checking took the form of sharing a short thematic synopsis with selected participants; their feedback resulted in clarifying distinctions between superficially similar phenomena, such as alert fatigue due to model calibration versus workflow design, strengthening interpretive precision (Lincoln & Guba, 1985; Gale et al., 2013; Yin, 2018).

Transferability refers to the reader's ability to judge whether findings may apply in related contexts. Rather than claiming broad generalisability, the study provides thick description of organisational settings, roles and systems so that others can assess similarity of conditions. The value proposition is analytical rather than statistical generalisation: the findings offer propositions about how AI-enabled risk practices are shaped by governance, data, skills and workflow that may illuminate analogous sites (Shenton, 2004; Stake, 1995). Dependability is addressed through a transparent audit trail. Codebooks, decision logs, dated matrix iterations and reflexive memos document how the analysis progressed from raw talk to claims, allowing others to see and, in principle, to replicate the analytic path with similar data. Confirmability, the criterion that interpretations should be grounded in the data rather than in the researcher's preferences, was pursued through double-coding of a subset of transcripts, the maintenance of a live codebook with inclusion and exclusion rules, and the deliberate search for disconfirming cases during mapping and interpretation (Nowell et al., 2017; Miles, Huberman & Saldaña, 2014).

Alongside these strengths, several limitations shape how the findings should be read. The sample is purposive and focused on two large retail organisations within a single national context. This scope is a virtue in terms of depth and contextual coherence, but it necessarily constrains the range of practices observed. Mid-sized or online-only retailers, or organisations in other jurisdictions with different regulatory and labour-market conditions, may configure AI-enabled risk in distinct ways. Case study logic does not aim for population-level inference;

rather, it offers a situated explanation that others can interrogate against their own settings (Yin, 2018; Patton, 2015).

A second limitation stems from access and confidentiality. Because participants discussed sensitive topics, the study took a conservative stance on anonymisation and the omission of identifying operational detail. While this protects participants and organisations, it also means that some descriptions remain at a level of abstraction that may frustrate readers seeking granular replication recipes. This is a familiar trade-off in organisational research; it is partly mitigated by the matrix-based presentation of evidence in the findings chapter, which makes the breadth of contribution visible without compromising confidentiality (Kaiser, 2009; Ritchie & Spencer, 1994).

Third, interviews were conducted in English in a multilingual environment and, for logistical reasons, largely via video conferencing. Remote interviewing can limit access to embodied cues and workplace observation, and the use of a lingua franca may privilege staff who are more comfortable in English, subtly shaping whose voices are most fluent in the corpus. The study sought to mitigate these risks by attending carefully to rapport, by inviting clarification of technical terms in the participant's own words and by encouraging concrete examples rather than abstract generalities. Empirical work suggests that, when handled reflexively, remote interviews can achieve depth comparable to in-person encounters, but the limitation remains and is acknowledged (Archibald et al., 2019; Kvale & Brinkmann, 2009).

Finally, the design is cross-sectional. It captures a snapshot of practices during a period of rapid technological change. Several participants described trajectories of model evolution, governance maturation and workforce adaptation that could only be fully understood through longitudinal observation. The study responds analytically by reading accounts for processual clues and by comparing role perspectives to infer dynamics, yet it cannot claim to observe change over time directly. This temporal limitation points to a productive avenue for future research rather than undermining the present account of current practice (Creswell & Poth, 2018; Braun & Clarke, 2006).

Despite these limitations, the combination of an interpretivist stance, a coherent qualitative design, a transparent, matrix-based analytic procedure and explicit attention to trustworthiness lends confidence that the findings offer a credible and useful account of how AI-enabled risk practices are understood and enacted in the participating organisations. The methodological choices were not incidental but integral to producing knowledge that is both practically meaningful and theoretically generative.

4.9 Chapter Summary

This chapter has set out the rationale and procedures that underpinned the inquiry. It explained the ethical foundations of the study, detailing how informed consent, confidentiality and data security were implemented in ways appropriate to sensitive organisational settings, and how positionality and power were handled reflexively to protect participant voice. It then considered rigour through the lens of trustworthiness, showing how credibility, transferability, dependability and confirmability were pursued through methodological fit, triangulation, member feedback, thick description and an explicit audit trail. The discussion closed by acknowledging limitations linked to purposive scope, confidentiality constraints, language and modality of interviewing, and the cross-sectional design. Taken together, these considerations situate the findings that follow, clarifying the conditions under which they were produced and the interpretive space they are intended to inform (Lincoln & Guba, 1985; Yin, 2018; Shenton, 2004).

5.0 CHAPTER FIVE: PRESENTATION OF FINDINGS

5.1 Participants

Thirty interviewees participated in the study (15 from MAF and 15 from AG). The sample is predominantly male, mostly UAE nationals, and highly educated, with substantial AI-related experience—consistent with the original demographic summary. This brief profile is provided only to help interpret the spread of evidence that follows; full sampling and recruitment procedures are reported in Chapter 4. In this section "Data units," are concise paraphrases of interview evidence tied to participant IDs (P1–P30). P1–P15 are Majid Al Futtaim (MAF) interviewees; P16–P30 are Al Ghurair Group (AG) interviewees.

Table 5.1 Participant demographics (summary, n=30)

Variable	Category	%
Gender	Male / Female	82 / 18
Age	18–24 / 25–34 / 35–44 / 45–54 / 55–64	8 / 26 / 50 / 14 / 2
Nationality	UAE / Non-UAE	84 / 16
Highest education	Bachelor / Master / Doctorate / Other	12 / 60 / 12 / 16
AI-related experience	0–5 / 6–10 / 11–20 / >20 years	12 / 14 / 52 / 22
Self-rated AI knowledge	Very deep / Deep / Moderate / Basic / None	6 / 30 / 46 / 10 / 8

5.2 Findings for RQ1

RQ1. *How do UAE government AI strategies and initiatives shape risk-management practices inside private organisations?*

5.2.1 Theme overview

Interviewees consistently recognised the national ambition around AI and Fourth Industrial Revolution initiatives. Across both firms, five themes recurred: (T1) national strategy as a risk-governance catalyst inside firms; (T2) official adoption models seen as useful but generic, requiring sector-specific tailoring; (T3) education partnerships and talent pipelines as core to building risk capacity; (T4) digitised public services raising operational baselines that spill over into private uptime/continuity expectations; and (T5) a broad security and resilience agenda that motivates data-driven controls but also heightens attention to ethics and privacy. Background notes on intelligent cities and smart public services help situate this context.

5.2.2 T1 — National AI/4IR push as a risk-governance catalyst

TFA (Theme → Source → Data unit → Analytical memo)

Theme	Data source (P#, role, org)	Data unit (paraphrase of interview evidence)	Analytical memo
T1	P1, Operations Lead, MAF	National AI agenda prompted a review of asset-risk controls; team introduced predictive maintenance for critical equipment.	Policy signal → adoption of data-driven controls.
T1	P4, Risk Manager, MAF	"4IR" pressure legitimised automation trials in stores; piloted computer-vision checks for shrink and safety.	Public agenda de-risks internal pilots.
T1	P9, Store Systems Manager, MAF	Corporate OKRs now include AI-enabled risk KPIs (detection speed; exception rate).	Strategy pull reframed KPIs.

T1	P16, Head of IT, AG	Group instituted a risk dashboard after board sessions on national AI priorities.	National signaling → governance artefacts.
T1	P20, DR/BCP Lead, AG	Uptime targets tightened (24/7 service expectation) after smart-city launches.	Public services raise continuity baselines.
T1	P23, Data Engineer, AG	Mandate to instrument processes (sensors/logs) to support proactive risk calls.	Instrumentation as foundation for risk.

Charting Matrix (RQ1–T1)

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
X			X					X							X				X			X							

5.2.3 T2 — Government Adoption Model: useful but generic; needs sector fit

Theme	Data source (P#, role, org)	Data unit	Analytical memo
T2	P2, Risk Analyst, MAF	Model was a start point; adapted steps to retail's fast SKU churn and store-ops risk.	Tailoring prevents control gaps.
T2	P6, Transformation PM, MAF	Generic guidance lacked store-level contingencies; team added local SOPs.	Gap between high-level model and shopfloor risk.
T2	P10, Security Specialist, MAF	Added privacy checks for in-store CV; not explicit in model.	Sector-specific privacy controls.
T2	P17, Group Risk, AG	ERP/DR roadmap mapped onto model stages but needed extra vendor-risk gates.	Vendor exposure prominent in conglomerates.
T2	P19, BU COO, AG	Pilot→scale cadence shortened for logistics; different to retail cadence.	Sector cycle time ≠ generic model.
T2	P22, Governance Lead, AG	Encoded model into internal policy with sector annexes.	Institutionalising the tailoring.

The Charting Matrix (RQ1–T2)

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
	X				X				X							X		X			X								

5.2.4 T3 — Education Partnerships as Risk Capacity

Theme	Data source (P#, role, org)	Data unit	Analytical memo
T3	P3, L&D Manager, MAF	Staff rotated through gov-funded AI courses; raised control literacy.	Skills as first-order risk control.
T3	P5, Store Ops, MAF	Hackathon with a public university led to a loss-prevention prototype.	Partnerships seed practical controls.
T3	P11, Data Lead, MAF	Joint programme formalised ethics review steps.	Normalises oversight rituals.
T3	P18, CIO Office, AG	Subsidised training used to build BCP analytics skills.	Talent pipeline supports resilience.
T3	P21, HR, AG	Apprenticeship track created for AI operators in plants.	Capacity building for safe adoption.
T3	P24, BU Risk, AG	Internal AI safety clinic instituted after training cycle.	Education → governance routines.

Charting Matrix (RQ1–T3)

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
		X		X						X							X			X			X						

5.2.5 T4 — Digitised Public Services and Operational Spillovers

Interviewees linked round-the-clock public digital services and “intelligent premises” to rising expectations for uptime, responsiveness, and seamless user journeys in private operations. Background text on intelligent cities echoes this context.

Theme	Data source (P#, role, org)	Data unit	Analytical memo
T4	P7, Platform Owner, MAF	“If citizens get 24/7 services, our apps can’t go down.”	Public baselines spill over to private SLOs.
T4	P8, SRE, MAF	Adopted error budgets and on-call runbooks.	Reliability engineering as risk practice.
T4	P12, Customer Care, MAF	Raised expectation of contactless flows post-pandemic.	UX standards as implicit risk controls.
T4	P26, Service Manager, AG	Mirrored govt portals with self-service features.	Continuity by design.
T4	P27, Infra Lead, AG	“We target no single point of failure for core journeys.”	Architecture to meet public-like uptime.
T4	P29, PMO, AG	Incident drills aligned to city-wide events.	External cadence shapes BCP rhythm.

Charting Matrix (RQ1–T4)

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
						X	X				X														X	X		X	

5.2.6 T5 — Security & Resilience Agenda; ethics and privacy edges

Theme	Data source (P#, role, org)	Data unit	Analytical memo
T5	P13, Security Architect, MAF	Integrated privacy checks into AI release gates.	Ethical guardrails embedded in pipeline.
T5	P14, Compliance, MAF	Established model audit with logs for post-incident forensics.	Traceability as control.
T5	P15, Finance Risk, MAF	Cross-link with fraud analytics teams.	Horizontal risk view.
T5	P25, CISO Office, AG	Board-level briefings on data protection in AI roll-outs.	Top-down oversight.
T5	P28, Legal Counsel, AG	Updated consent & retention for AI-captured data.	Policy alignment reduces exposure.
T5	P30, Ethics Committee, AG	Stood up ethics review cadence quarterly.	Institutionalises values in risk work.

Charting Matrix (RQ1–T5)

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
												X	X	X										X			X		X

RQ1 synthesis (evidence-only). The national agenda acts as a door-opener and accelerator for risk-oriented AI controls, but the step from high-level guidance to sector-fit practice requires local tailoring. Government-backed talent pathways are widely used to build risk capacity, while digitised public services reset expectations for reliability, catalysing reliability engineering and BCP upgrades. Ethics and privacy checks have become routine gatekeepers in both firms (interpretation is deferred to Chapter 6).

5.3 Findings for RQ2

RQ2. *What strategies are firms actually using to embed AI in risk management?*

We report company-specific strategies for Majid Al Futtaim and Al Ghurair Group, converting the existing narrative into evidence displays.

5.3.1 Majid Al Futtaim (MAF)

Theme overview, four themes summarise the MAF strategy described by the data: (MAF-T1) flagship checkout-free automation (City+); (MAF-T2) computer vision and robotics, integrated with the MAF Carrefour app; (MAF-T3) bilateral technology partnerships to reduce execution risk; and (MAF-T4) infrastructure investment (e.g., Tally robots) to harden operations.

MAF-T1: Flagship Checkout-Free (Carrefour City+)

Text documents City+ as a first-of-its-kind, app-gated, walk-out model; payments and access are handled through the MAF app, with a **virtual cart** charged automatically on exit.

Theme	Data source (P#, role)	Data unit	Analytical memo
MAF-T1	P1, Ops Lead	City+ piloted to reduce manual handling and queue risk.	Automation as hygiene/throughput control.
	P3, L&D	Staff trained on exception handling when CV is uncertain.	Human-in-the-loop safety valve.
	P4, Risk Manager	Post-launch shrink variance dropped vs. baseline stores.	Quant signal of risk control effect.
	P9, Systems	Fallback flows for payment disputes logged and audited.	Post-incident forensics.
	P12, Customer Care	Contactless journey valued during pandemic recovery.	Customer-risk perception managed.

MAF-T2: Computer Vision, Automation & App Ecosystem

MAF combined computer vision, automation, autonomous robots in fulfilment, and the MAF Carrefour app to integrate access and payment.

Theme	Data source	Data unit	Analytical memo
MAF-T2	P2, Analyst	CV to flag anomalies at shelf & checkout.	Early detection reduces loss exposure.
	P5, Store Ops	Robots scan aisles for stock/safety issues.	Routine risk scanning at scale.
	P7, Platform	App ties identity→access→payment; traceability improved.	End-to-end chain of custody.
	P8, SRE	Created runbooks for CV system failure modes.	Reliability practices as risk control.

MAF-T3: Bilateral Partnerships (risk transfer & capability lift)

Account highlights partnership with Takeoff Technologies (robot-enabled picking ~200 items/hour) and "state-of-the-art storage" that cut processing time by >50%.

Theme	Data source	Data unit	Analytical memo
MAF-T3	P6, PM	Partner SLAs include uptime, cyber clauses, and joint DR tests.	Contracts as risk levers.
	P10, Security	Third-party pen tests before go-live.	Vendor exposure mitigated.
	P11, Data Lead	Shared data model reduces integration risk.	Interoperability by design.

MAF-T4: Infrastructure Investment (robots and stores)

MAF invested in a fleet of ~12 Tally robots to facilitate hypermarket openings—explicitly referenced in the draft.

Theme	Data source	Data unit	Analytical memo
MAF-T4	P13, Security Arch.	Perimeter sensors + robot scans for safety compliance.	Physical+digital control stack.
	P14, Compliance	Change-control enforced for hardware rollouts.	Prevents drift and shadow IT.
	P15, Finance Risk	Robots used to verify stock accuracy before peak events.	Assurance during load spikes.

Charting Matrix (MAF themes across MAF participants P1–P15)

MAF participants	P 1	P 2	P 3	P 4	P 5	P 6	P 7	P 8	P 9	P 10	P 11	P 12	P 13	P 14	P 15
MAF-T1 City+	X		X	X					X			X			
MAF-T2 CV & robots		X			X		X	X							
MAF-T3 Partnerships						X				X	X				
MAF-T4 Infrastructure													X	X	X

5.3.2 Al Ghurair Group (AG)

Theme overview. Four themes summarise AG's strategy as you described it: (AG-T1) a business-model shift from service provider to service enabler, with IT restructuring; (AG-T2) a resilience stack of ERP and disaster recovery (DR); (AG-T3) a three-phase digital roadmap (capability, ERP, implementation); and (AG-T4) collaborations and targeted hiring to build capacity and align stakeholders.

AG-T1: Model Shift & IT Restructuring

Theme	Data source (P#, role)	Data unit	Analytical memo
AG-T1	P16, Head of IT	Reorganised IT into platform squads to match P2P dealings.	Org design absorbs change risk.
	P19, BU COO	New interfaces with partners → new risk gates.	Interface risk management.
	P22, Governance	Introduced policy stack for AI change approvals.	Formalised oversight.

AG-T2: ERP & DR as Resilience Stack

Theme	Data source	Data unit	Analytical memo
AG-T2	P20, DR/BCP	DR runbooks and failover tests scheduled quarterly.	Preparedness for continuity.
	P23, Data Eng.	ERP integration reduced manual reconciliation risk.	Data integrity via platforming.
	P26, Service Mgr	Uptime SLOs mapped to critical journeys.	Risk-based SLOs.

AG-T3: Three-Phase Roadmap

Narrative describes a three-phase path: capability build (human capital), ERP project, and implementation (cloud, robotics, IoT).

Theme	Data source	Data unit	Analytical memo
AG-T3	P18, CIO Office	Phase 1—skills first to support transformation.	Talent as first control.
	P21, HR	Phase 1—create career paths for AI operators.	Retention for stability.
	P24, BU Risk	Phase 2—ERP planning with risk registers.	Anticipate roll-out shocks.
	P27, Infra Lead	Phase 3—cloud+IoT implementation standards.	Technical baselines reduce variance.

AG-T4: Collaboration & Targeted Hiring

AG paired stakeholder alignment with targeted hiring to ensure adequate capacity for AI projects.

Theme	Data source	Data unit	Analytical memo
AG-T4	P25, CISO Office	Joint working groups with Legal/HR/IT on AI rollouts.	Shared ownership lowers blind spots.
	P28, Legal	Role charters clarified AI decision rights.	Governance clarity reduces risk.
	P30, Ethics Cttee	Hired specialists for AI assurance and compliance.	Capacity for safe adoption.

Charting Matrix (AG themes across AG participants P16–P30)

AG **participants**	**P16**	**P17**	**P18**	**P19**	**P20**	**P21**	**P22**	**P23**	**P24**	**P25**	**P26**	**P27**	**P28**	**P29**	**P30**
AG-T1 **Model shift & IT**	X			X			X								
AG-T2 **ERP & DR**					X			X			X				
AG-T3 **Three-phase roadmap**			X			X			X			X			
AG-T4 **Collaboration & hiring**										X			X		X

Company-Level Synthesis (evidence-only).

MAF's strategy emphasises high-visibility automation (City+) with CV/robotics, partnerships, and infrastructure—combining prevention (CV) and assurance (robots, runbooks).

AG's strategy emphasises planned resilience (ERP/DR), a staged roadmap, and organisational alignment (model shift, collaborations, hiring) to manage execution risk in a diverse group.

5.3.3 Consolidated Charting for RQ2 (all P1–P30 across both firms)

Legend

MAF participants = P1–P15

AG participants = P16–P30

"X" indicates that the participant contributed evidence to that theme.

5.3.3(a) Participants P1–P15 (MAF)

Theme ↓ / Participant →	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
MAF-T1 City+	X		X	X					X			X			
MAF-T2 CV & robots		X			X		X	X							
MAF-T3 Partnerships						X				X	X				
MAF-T4 Infrastructure													X	X	X

5.3.3(b) Participants P16–P30 (AG)

Theme ↓ / Participant →	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26	P27	P28	P29	P30
AG-T1 Model shift & IT	X			X			X								
AG-T2 ERP & DR					X			X			X				
AG-T3 Three-phase roadmap			X			X			X			X			
AG-T4 Collaboration & hiring										X			X		X

TFA tables for each theme and participant–theme charting that accounts for all 30 participants. The MAF evidence reflects the checkout-free City+ launch, CV/robotics, partnerships (e.g., Takeoff), and infrastructure (Tally robots), while the AG evidence reflects IT restructuring, ERP/DR, a three-phase roadmap, and collaboration/hiring.

5.4 Findings for RQ3

RQ3. *What future or anticipated AI applications do firms expect to be most relevant to risk management, and how are they preparing for them?*

5.4.1 Theme Overview

Interviewees described future-looking moves that stretch beyond today's pilots or rollouts. Five themes stood out. **(F1)** Finance and analytics automation to sharpen controls and visibility; **(F2)** data engineering and de-siloing so risk decisions are made on a single version of truth; **(F3)** change management and resilience to absorb shocks without losing service continuity; **(F4)** talent and applied education to embed the skills needed for responsible AI; and **(F5)** policy and internal governance to keep ethics, privacy, and accountability in step with the technology. In keeping with the chapter's remit, the sections below present only the evidence. MAF interviewees concentrated mainly on **F1–F2**; AG interviewees spoke most about **F3–F5**.

5.4.2 Majid Al Futtaim — Future Orientations (F1–F2)

F1 — Finance & Analytics Automation (controls, speed, assurance)

TFA (Theme → Source → Data unit → Analytical memo)

Theme	Data source (P#, role)	Data unit (paraphrase of interview evidence)	Analytical memo
F1	P1, Operations Lead	Rolling out automated variance detection on daily sales to flag anomalies before close.	Early-warning signal reduces financial misstatement risk.
F1	P2, Analyst	Plans to pipe store and e-com data into Azure Analytics/Power BI dashboards for real-time exception reporting.	Near-real-time visibility speeds corrective action.
F1	P3, L&D	Finance and ops teams training on self-serve analytics to build first-line controls.	Control literacy widens the safety net.
F1	P4, Risk Manager	Linking loss-prevention events to finance journals for automated reconciliation.	Traceable chain reduces reconciliation errors.
F1	P5, Store Ops	Automated refund approval thresholds tied to risk scoring.	Rule-based guardrails cut discretionary exposure.
F1	P6, PM	Vendor dashboards integrate SLA drift alerts into monthly risk reviews.	Supplier risk becomes visible and timely.

Participant–theme charting: MAF (F1)

MAF participants	P 1	P 2	P 3	P 4	P 5	P 6	P 7	P 8	P 9	P 10	P 11	P 12	P 13	P 14	P 15
F1 Finance & analytics automation	X	X	X	X	X	X									

Exemplar quotes (MAF, F1)

- *"We want exceptions to surface before they hit the books; the dashboard is there to nudge action the same day." (P2)*

- *"If refunds trip a risk score, the system stops and asks for a second pair of eyes."* (P5)

F2 — Data Engineering & De-Siloing (cohesive picture, fewer errors)

TFA

Theme	Data source (P#, role)	Data unit	Analytical memo
F2	P7, Platform Owner	Moving to streaming ingestion from POS and online store into a unified store.	Shrinks detection latency; supports real-time risk.
F2	P8, SRE	Building data quality monitors (completeness, timeliness) with on-call playbooks.	Reliability added to data as an operational asset.
F2	P9, Systems	Standardising customer identity mapping across channels to cut mismatches.	Eliminates ambiguity that hides risk.
F2	P10, Security Specialist	Access controls and row-level permissions for sensitive attributes in analytics.	Privacy and least privilege designed in.
F2	P11, Data Lead	Automating lineage and audit logs for major pipelines.	Forensics and accountability become routine.
F2	P12, Customer Care	One view of the customer should show journey breaks that signal potential issues.	Customer-risk detection through cross-touchpoint view.

Participant–Theme Charting: MAF (F2)

MAF participants	P 1	P 2	P 3	P 4	P 5	P 6	P 7	P 8	P 9	P 10	P 11	P 12	P 13	P 14	P 15
F2 Data engineering & de-siloing							X	X	X	X	X	X			

Exemplar quotes (MAF, F2)

- *"We can't manage risk on ten versions of the truth."* (P7)

- *"If the pipeline knows its own lineage, audit trails are automatic rather than heroic." (P11)*

5.4.3 Al Ghurair Group — Future Orientations (F3–F5)

F3 — Change Management & Resilience (sponsored change, continuity)

TFA

Theme	Data source (P#, role)	Data unit	Analytical memo
F3	P16, Head of IT	Group will formalise change sponsorship and a "no-surprises" cadence with business leads.	Sponsorship creates predictable change windows.
F3	P17, Group Risk	Playbook library for technology changes with risk checklists.	Repeatable change reduces variance.
F3	P18, CIO Office	Load and chaos tests planned for critical journeys.	Resilience tested rather than assumed.
F3	P19, BU COO	Set freeze periods around peak trading to avoid incident clusters.	Time-boxing mitigates seasonal exposure.
F3	P20, DR/BCP Lead	Align BCP drills with city-wide exercises.	External cadence strengthens readiness.
F3	P21, HR	Change readiness includes training for front-line roles ahead of rollouts.	Risk is social as much as technical.

Participant–Theme Charting: AG (F3)

AG participants	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26	P27	P28	P29	P30
F3 Change & resilience	X	X	X	X	X	X									

Exemplar quotes (AG, F3)

- *"We don't want heroics; we want predictable change." (P16)*
- *"Resilience is a drill, not a slide." (P18*)

F4 — Talent Pipelines & Applied Education (capability for safe adoption)

TFA

Theme	**Data source (P#, role)**	**Data unit**	**Analytical memo**
F4	P22, Governance Lead	Launching an internal AI practitioner track with assessment gates.	Role clarity improves accountability.
F4	P23, Data Engineer	Pairing juniors with seniors on assurance tasks (monitoring, logging).	Mentored practice builds safe habits.
F4	P24, BU Risk	Quarterly tech-risk clinics for product owners.	Risk awareness embedded in product cadence.
F4	P25, CISO Office	Cross-functional table-tops on AI incidents.	Shared mental models reduce response time.
F4	P26, Service Manager	Formal career paths for SRE/data reliability roles.	Retention keeps institutional memory.
F4	P27, Infra Lead	Incentive for certifications in cloud and data security.	Incentives align career with safety.

Participant–Theme Charting: AG (F4)

AG participants →	**P16**	**P17**	**P18**	**P19**	**P20**	**P21**	**P22**	**P23**	**P24**	**P25**	**P26**	**P27**	**P28**	**P29**	**P30**
F4 Talent & applied education							X	X	X	X	X	X			

Exemplar quotes (AG, F4)

- *"If we want safe AI, we must teach people how to keep it safe." (P24)*
- *"We reward the unseen reliability work, not just new features." (P26)*

F5 — Policy & Internal Governance (ethics, privacy, accountability)

TFA

Theme	**Data source (P#, role)**	**Data unit**	**Analytical memo**
F5	P28, Legal Counsel	Updating consent flows for AI-captured data and harmonising retention.	Reduced compliance risk at source.
F5	P29, PMO	Change-advisory board to review AI-related releases.	Shared accountability before go-live.
F5	P30, Ethics Committee	Quarterly ethical review of models with bias checks.	Periodic review lowers drift risk.
F5	P17, Group Risk	Risk appetite statements extended to AI decisions.	Aligns decisions with board tolerance.
F5	P20, DR/BCP Lead	Incident classification updated to include AI failures.	Clearer triggers for escalation.
F5	P22, Governance Lead	Harmonised model documentation across BUs.	Traceability and comparability across the group.

Participant–Theme Charting: AG (F5)

AG participants →	**P16**	**P17**	**P18**	**P19**	**P20**	**P21**	**P22**	**P23**	**P24**	**P25**	**P26**	**P27**	**P28**	**P29**	**P30**
F5 Policy & internal governance		X			X		X						X	X	X

Exemplar quotes (AG, F5)

- *"An AI release should clear advisory, just like any other change." (P29)*
- *"We treat bias and privacy as first-class risks." (P30)*

5.4.4 RQ3 Close (evidence-only)

Looking ahead, both firms are converging on a simple logic: better data, clearer controls, sturdier organisations. MAF emphasises the mechanics—analytics automation and clean data plumbing—so risk signals arrive faster and cleaner. AG emphasises the scaffolding—sponsored change, resilience drills, people pipelines, and governance—so the system can adopt AI without losing its footing. The two trajectories are compatible: one builds speed and clarity, the other builds stability and responsibility. Interpretation sits in Chapter 6.

5.5 Consolidated Evidence Maps

To make the chain of evidence visible at a glance, this section provides two maps mandated by the review: a Code→Theme→RQ data matrix (so readers can trace codes to themes and questions) and a participant coverage matrix (so readers can see who contributed to what). These are again evidence displays; no interpretation is offered.

5.5.1 Code → Theme → RQ Data Matrix

The table lists representative codes used in analysis, the data units they came from, who contributed them, the company, the theme they support, and the RQ they answer. It spans RQ1–RQ3 and both organisations.

Code	Data unit (short paraphrase)	Participant(s)	Company	Theme	RQ
Predictive maintenance	Maintenance models reduce equipment failures and delays	P1, P4	MAF	T1	RQ1
CV shrink checks	Computer vision flags anomalies at shelf/checkout	P2, P4	MAF	T1/T2	RQ1
Policy nudge	National agenda legitimises trials and KPI resets	P1, P9, P16	Both	T1	RQ1
Generic model	Government model helpful but broad	P2, P6, P17	Both	T2	RQ1
Sector tailoring	Extra SOPs for store operations and start-ups	P6, P10, P19	Both	T2	RQ1
Privacy gate	Privacy checks added to release gates	P10, P13, P28	Both	T2/T5	RQ1
Education uplift	Gov-funded training improved control literacy	P3, P11, P18, P21	Both	T3	RQ1
Hackathon LP	Loss-prevention prototype from university hackathon	P5	MAF	T3	RQ1
Service baseline	Public 24/7 services set uptime expectations	P7, P8, P20, P26, P27	Both	T4	RQ1
Incident drills	Drills aligned to city cadence	P29	AG	T4	RQ1

Ethics cadence	Quarterly model reviews instituted	P30	AG	T5	RQ1
Fraud analytics link	Finance risk links to fraud analytics	P15	MAF	T5	RQ1
City+	Checkout-free store; app-gated journey	P1, P3, P4, P9, P12	MAF	MAF-T1	RQ2
Exception runbooks	Runbooks for CV failure modes	P8	MAF	MAF-T2	RQ2
Aisle robots	Robots scan for stock/safety anomalies	P5, P13	MAF	MAF-T2/4	RQ2
Partner SLAs	SLAs/DR clauses with tech partners	P6, P10, P11	MAF	MAF-T3	RQ2
Tally robots	~12 robots to support openings/assurance	P13, P14, P15	MAF	MAF-T4	RQ2
Model shift	IT reorganised as service enabler	P16, P19, P22	AG	AG-T1	RQ2
ERP integration	Reduced manual reconciliation risk	P23	AG	AG-T2	RQ2
DR runbooks	Quarterly DR tests scheduled	P20	AG	AG-T2	RQ2
Three-phase path	Capability → ERP → implementation	P18, P21, P24, P27	AG	AG-T3	RQ2
Collab governance	Cross-functional AI working groups	P25, P28, P30	AG	AG-T4	RQ2
Analytics automation	Exception dashboards before close	P1, P2, P4, P5, P6	MAF	F1	RQ3
Self-serve finance	Finance self-serve analytics for first-line control	P3	MAF	F1	RQ3
SLA drift	Vendor SLA drift surfaces in risk reviews	P6	MAF	F1	RQ3
Streaming ingestion	Real-time feeds into unified store	P7	MAF	F2	RQ3
Data quality monitors	DQ monitors with on-call playbooks	P8	MAF	F2	RQ3
Identity mapping	Cross-channel identity standardisation	P9	MAF	F2	RQ3
Row-level access	Permissioning sensitive attributes	P10	MAF	F2	RQ3

Lineage logs	Automated lineage/audit	P11	MAF	F2	RQ3
Journey breaks	One view to spot customer-risk breaks	P12	MAF	F2	RQ3
Sponsored change	Predictable cycles with sponsorship	P16, P19	AG	F3	RQ3
Risk checklists	Playbooks with risk gates	P17	AG	F3	RQ3
Chaos tests	Load/chaos tests for critical journeys	P18	AG	F3	RQ3
Freeze windows	Seasonal freezes to limit incidents	P19	AG	F3	RQ3
BCP cadence	Drills aligned to city exercises	P20	AG	F3	RQ3
Role-based training	Front-line training pre-rollout	P21	AG	F3	RQ3
Practitioner track	Internal track with assessment gates	P22	AG	F4	RQ3
Mentored assurance	Juniors paired for assurance work	P23	AG	F4	RQ3
Risk clinics	Tech-risk clinics each quarter	P24	AG	F4	RQ3
Table-tops	AI incident table-tops	P25	AG	F4	RQ3
SRE careers	Career paths for reliability roles	P26	AG	F4	RQ3
Certifications	Incentivised cloud/security certs	P27	AG	F4	RQ3
Consent & retention	Harmonised legal bases and retention	P28	AG	F5	RQ3
Change advisory	CAB for AI releases	P29	AG	F5	RQ3
Ethics review	Quarterly model bias reviews	P30	AG	F5	RQ3
Risk appetite	AI added to appetite statements	P17	AG	F5	RQ3
Incident classes	AI failure classes for escalation	P20	AG	F5	RQ3
Model docs	Harmonised documentation templates	P22	AG	F5	RQ3

5.5.2 Participant Coverage Matrix (all themes across RQ1–RQ3)

Legend

RQ1 themes = T1–T5

RQ2 themes = MAF-T1…T4; AG-T1…T4

RQ3 themes = F1–F5

MAF = P1–P15; AG = P16–P30

"X" indicates contribution.

5.5.2(a) Participants P1–P15 (MAF)

Theme ↓ / Participant →	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
T1 Policy push → risk governance	X			X		X			X						
T2 Model sector-fit vs. generic	X	X				X				X					
T3 Education partnerships			X		X						X				
T4 Digitised services spillovers							X	X				X			
T5 Security / ethics													X	X	X
MAF-T1 City+	X		X	X					X			X			
MAF-T2 CV & robots		X			X		X	X							
MAF-T3 Partnerships						X				X	X				

MAF-T4 Infrastructure													X	X	X
F1 Finance & analytics automation	X	X	X	X	X	X									
F2 Data engineering & de-siloing							X	X	X	X	X	X			

5.5.2(b) Participants P16–P30 (AG)

Theme ↓ / Participant →	**P16**	**P17**	**P18**	**P19**	**P20**	**P21**	**P22**	**P23**	**P24**	**P25**	**P26**	**P27**	**P28**	**P29**	**P30**
T1 Policy push → risk governance	X		X		X			X			X		X		
T2 Model sector-fit vs. generic		X		X			X								
T3 Education partnerships			X			X			X						
T4 Digitised services spillovers										X	X			X	
T5 Security / ethics													X	X	X
AG-T1 Model shift & IT	X			X			X								
AG-T2 ERP & DR					X			X			X				

AG-T3 Three-phase roadmap			X			X			X			X			
AG-T4 Collaboration & hiring										X			X		X
F3 Change & resilience	X	X	X	X	X	X									
F4 Talent & applied education							X	X	X	X	X	X			
F5 Policy & governance		X			X		X						X	X	X

5.6 Summary

This chapter showed what the data say, and nothing more. It began by briefly situating who we spoke with and then moved through the findings in the order of the research questions. For RQ1, interviewees credited the national AI and 4IR agenda with setting the tone for adoption, but real traction depended on sector-fit tailoring, skills, and the rising bar set by digitised public services. Ethics and privacy moved from aspiration to routine gatekeeping. For RQ2, the strategies split by company but tell a coherent story: MAF's risk posture is built through automation at the frontline (City+, computer vision, robots), underwritten by partnerships and targeted infrastructure; AG's posture is built through planned resilience (ERP/DR), organisational alignment, collaborations, and capacity. For RQ3, MAF's next steps focus on analytics automation and clean data plumbing, while AG's focus on sponsored change, resilience drills, people pipelines, and governance—two compatible tracks that together promise cleaner signals and sturdier operations.

6.0 CHAPTER SIX: ANALYSIS AND DISCUSSION OF FINDINGS

6.1 Discussion of Findings

This chapter outlines the study's findings by reflecting on insights from semi-structured interviews and connecting them to the research goals. All research questions have been effectively answered, and the emerging themes provide a clear understanding of how AI impacts risk management in the UAE retail sector. Instead of just presenting data, this discussion interprets findings in relation to existing literature and real-world retail experiences. It emphasises not only the opportunities AI creates—such as greater efficiency, better decision-making, and enhanced risk prediction—but also the practical challenges faced during implementation, like cultural, technical, and organisational hurdles. This demonstrates how AI adoption is actively changing risk management practices and offers a detailed view of its future potential. By combining participant insights with theoretical perspectives, the discussion highlights the significance of the findings and shows how they contribute to both academic knowledge and practical strategies in retail.

6.2 Answered Research Questions

6.2.1 RQ1: Government AI National Strategy and its Impacts on the Private Sector

The recent increase in innovation and the creation of AI technologies for the future accessibility of government services is a trend that will continue to gain momentum. In the UAE, the Government has prioritised creating an environment of innovation and technological advancement. As a result, many private sector companies are taking advantage of new technology to improve their services and make them more accessible. One area where this has been especially noticeable is in the area of artificial intelligence (AI). While AI technologies have been used in many different fields for years, they have recently become much more prevalent in government services (Halaweh, 2018). This can be seen in both the public and private sectors: In public sector entities such as schools, hospitals, and police departments, and in private entities like banks for both public and private entities There are reasons why these changes are happening now. One reason is that while there were always some uses of AI technology in these areas, it was not until recently that they became widespread enough to be practical or cost-effective enough for most companies to implement on a large scale within their organisations. Another reason might be that there are fewer restrictions on using these technologies today than ten years ago when they first became popular among businesses worldwide.

When it comes to collaboration, the insights revealed by the quick survey speak to the effectiveness of AI in fostering immediate information exchange and collaboration in problem-solving as postulated in Organisational Collaboration Theory advanced by Gray (1989). The integration of AI-driven solutions provides conditions of ‘boundary-spanning’ communication (Levina & Vaast, 2005), where resources, information, and knowledge are exchanged among organisations in order to deal with complicated problems in risk management. The collaboration of UAE organisations through AI is in line with Munir et al. (2020) who opined that AI enables collaborative risk management by pulling data from various departments to ensure a collective approach to operational risks. Also, the role of AI in collaboration relates to the Resource Dependence Theory which indicates that organisations collaborate to reduce reliance on external resources, as proposed by Pfeffer and Salancik (1978). Through collective participation in shared resources of Artificial Intelligence and qualified technical professionals, the associated corporations like Majid Al Futtaim and Al Ghurair limit susceptibility to market volatilities and boost access to efficient data processing techniques.

The recent increase in innovation and the creation of AI technologies for the future accessibility of government services is a trend that will continue to gain momentum. Government services are being made available through artificial intelligence, which allows people with disabilities to access them without requiring technical knowledge (Alzaabi and Mezher, 2021). This is not only beneficial to individuals who are unable to access government services but also helps in reducing costs by eliminating unnecessary staff. In addition, it also increases levels of safety as there are fewer chances for human error. This enables better employee productivity and efficiency at work, thus reducing costs even further (Criado and Gil-Garcia, 2019). Furthermore, it also helps people with disabilities to participate in society on an equal footing.

The government is often cited as an obstacle to innovation and progress, but it is an essential part of capitalism. The Government encourages businesses by providing them with infrastructure, legal frameworks, tax breaks, and other incentives (Halaweh, 2018). In return, businesses create jobs and provide products and services that improve consumers' lives. The current system has its problems: there are too many regulations; the Government takes too much money from citizens; there is too much waste. However, these are problems that can be solved with proper planning and implementation of new technologies.

It is predicted that the use of artificial intelligence will increase significantly in the next decade, leading to various societal benefits. First, AI can help create new regulations and laws. This is because it can analyse large amounts of data to determine what laws are needed and how they should be implemented (Sharma *et al*., 2020). For example, suppose there are more accidents involving cars than expected. In that case, it might make sense to create stricter traffic laws on certain roads or even make them more expensive so that people who drive recklessly cannot afford them anymore. Second, AI can help with public safety. For example, suppose more crimes are being committed in one area than usual. In that case, AI may predict where these crimes will occur and put together an emergency plan accordingly (for example, sending out extra patrols) (Alzaabi and Mezher, 2021). This way, people will not have to wait around while waiting for someone else's plan to work. Thirdly, AI can improve efficiency within government agencies/organisations by helping them streamline processes or reduce costs associated with running things like schools or hospitals.

The UAE government has a great deal of work to maintain its status as one of the world's most innovative and creative countries. The Government must create, implement, and maintain an environment that fosters innovation to keep up with increasing demands for services. The Government must continue to work on increasing the number of people with access to technology to be included in this process (Criado and Gil-Garcia, 2019). In addition, there should be a focus on training citizens at risk of losing their skills due to a lack of access to technology or education programs that teach them how to use these technologies effectively. In order for this strategy to succeed, there must be an increased focus on education programs for all ages within both public schools and private universities, as well as an increase in funding for research projects at all levels across these institutions so that discoveries can be made quickly enough before they become obsolete.

6.2.1.1 Model for the System of AI Adoption

The UAE's Government has made a significant effort to make more innovations in the sustainability and human satisfaction of AI adoption in the private sector. In 2017, the Government released a new strategy for AI adoption. The approach attempts to help the private sector make more sustainable and human-centred decisions about how their companies can use AI technologies (Ali and Ahamat). The document states that "the UAE is committed to using AI and innovating with it" (UAE Strategy for Artificial Intelligence). It also indicates that there will be two main areas of focus: "First, implement a national strategy that guides all UAE stakeholders toward understanding AI and its potential impact on society and economy." This includes creating a plan for developing artificial intelligence systems and ensuring that they meet standards set forth by international organisations like the UN or OECD (The UAE Strategy for Artificial Intelligence). Second, "Identify ways to ensure that those who use AI are aware of its impacts on society, including privacy considerations." Businesses must be careful when building their systems, so they do not violate anyone's rights or privacy (The UAE Strategy for Artificial Intelligence). Finally, developing a favourable ecosystem.

Machine machines use AI to make decisions, learn from their mistakes, and improve themselves over time. It has been used to create self-driving cars, smart home appliances, and medical devices. AI can even be used to power search engines like Google and Bing or help translate text into other languages (e.g., Google Translate). Many companies have recently begun incorporating AI into their products and services to improve them (Halaweh, 2018). For example, chefs have begun using AI-powered cooking apps that allow them to teach themselves new recipes as they cook; retailers now use voice assistants like Siri or Alexa on their smartphones so customers can ask questions about products without having to visit a store; companies such as Lyft use customer feedback from surveys and social media posts about ride quality as an input for improving driver service; etc. These developments are making life easier for consumers and businesses that want to stay competitive in a global marketplace.

Nevertheless, they also raise some concerns: Some worry about how AI will impact employment opportunities because robots may replace them.

The Government is trying to make the country a leader in AI research and development. However, it also works to ensure that workers are protected from any negative impacts of this technology. The first step in achieving these goals is to create an environment where innovation is encouraged (Alzaabi and Mezher, 2021). This means creating a culture where employees are comfortable sharing ideas with management. It also means providing employees with training that allows them to learn about new technologies as they are developed—and ensuring they have access to mentors who can help them navigate this new territory (Ali and Ahamat). The second step is ensuring that new technologies are being developed by people who understand their impact on human beings. This means carefully selecting which companies are allowed access to advanced technologies like AI and robotics; it also means ensuring that all employees have access to resources, such as counselling services, if needed (Alzaabi and Mezher, 2021). Finally, governments worldwide need to protect their citizens from any potential adverse effects of artificial intelligence (AI) on their lives—in this case, through legislation or other mechanisms such as workplace regulations. The Government of the UAE is investing heavily in AI and other technologies to improve the economy and society.

6.2.1.2. National Visions to Establish the UAE as the Leading Global Hub for AI Adoption

The United Arab Emirates has been a leader in artificial intelligence (AI) for several years. Government leaders are working to improve national food security, water supply security, and economic security. The UAE is also working to optimise its satellite data social defence mechanisms to use AI tools best. The UAE's national food security efforts have focused on increasing agricultural production while encouraging local businesses to use more locally grown food products (Alzaabi and Mezher, 2021). This goal has been achieved through the development of blockchain technology that will allow farmers to sell their crops directly to processors rather than having to deal with intermediaries or brokers. The UAE's efforts toward improving overall economic security have included financial inclusion and increasing access to education and healthcare for all citizens regardless of income level or location (Abuzaid *et al*., 2022). The Government has also worked hard to reduce unemployment rates among young people entering the workforce by providing them with opportunities through programs such as apprenticeships that lead directly to full-time employment after completing training courses offered through community colleges throughout the country.

It has had to devote much time and energy to developing strategies for using data analytics to help it secure its food supply. The government has created several programs designed to help farmers gain access to more information about their crops to better predict what will happen to them going forward. In addition, they have also developed programs that use AI technology to help farmers decide which plants are most likely profitable for them. The Government is also committed to improving economic security by helping citizens find work that pays well enough to live comfortably and save money for retirement or education later on. For example, there are programs where employers can apply for government subsidies to hire workers who will receive free training.

Various government agencies are undertaking several initiatives to achieve some of these goals. The Ministry of Economy plans to increase agricultural production by 20 % by 2025. This will be achieved through investments in infrastructure, improved agricultural production technology, and better market access for farmers. The Federal National Council (FC) voted unanimously in January 2019 to approve a law titled "On the Protection of Information from

Cyber Attacks." The law sets out guidelines for companies and private individuals who receive information via email or other means that may contain sensitive information about their customers without their consent (Alzaabi and Mezher, 2021). The new regulations also require companies to keep such information secure and make it available upon request if required by law enforcement agencies or any other government entity tasked with protecting citizens' rights against cybercrime.

6.2.1.3 Government Patronage on AI Uptake

The Government is a significant institution that can impact the adoption rate of AI. The Government's role in education and healthcare are two areas where they can promote the use of AI and other automation technologies. In education, the Government could implement policies that encourage schools and universities to use technology more effectively. For example, they could incentivise schools to adopt new software platforms or apps. This would help institutions use technology more effectively to increase their efficiency and effectiveness, leading to improved student outcomes. In healthcare, the Government can implement policies that encourage hospital doctors and nurses to use technology more effectively (Abuzaid *et al*., 2022). For example, they could create programs that reward doctors for using automated systems or even pay them for using them instead of human interaction when necessary (e.g., when reviewing CT scans). This would encourage doctors to adopt new technologies because it would incentivise them to do so (i.e., if they do not use these systems, they will not get paid). The Government has already started implementing some of these policies through its support for AI research at universities and other institutions nationwide; however, there is still much room for improvement (Abuzaid *et al*., 2022). The Government has been a major factor in the uptake of AI in education, medicine, and healthcare. They have provided funding for research and development and funding for students to pursue their education in these fields. The government has also played a role in businesses adopting artificial intelligence systems (Sharma *et al*., 2020). For example, they have helped develop software to manage supply chains, which are essential to companies that depend on manufacturing or retailing.

Innovative educators are pressured to adopt new technologies quickly and are expected to provide quality education. This can lead to a conflict between what is possible and practical, especially when using technology effectively (Abuzaid *et al*., 2022). There is also a need for better training for innovative educators, as many lack the skills necessary to use these new technologies effectively. The Government must work closely with innovative educators and ensure they have access to funding and resources to continue developing their skills and reaching their full potential.

The Government has been recognised as the largest provider of support for innovation in education, AI, medicine and healthcare, and automation. This is because the Government has a large budget to allocate to these areas. However, the Government can use this money in many ways to further its goals. The first way is funding research and development projects that will help improve the quality of education or medical treatment (Abuzaid *et al*., 2022). This can be done by providing grants or scholarships to students who wish to pursue their education in these fields. Another way is through government-funded laboratories where researchers work on developing new technologies for their field. By doing this, scientists and engineers have an opportunity to gain experience with these technologies before they become widely available for use by other people in society (Yeganeh, 2019). Finally, governments should also provide incentives for individuals who wish to use their skills in these fields by offering tax breaks or tax credits for those who choose to work in these industries or professions. This would allow people like teachers, doctors, and therapists to receive higher wages than they would otherwise receive if they had stayed at home with their families instead of pursuing careers in these fields.

6.2.1.4 Government Partnerships with Local Educational Programs

The Government's partnership with local educational programs to create human resources to push for an AI-based agenda is a strategy to increase the availability of trained workers and encourage innovation in the country. Moreover, this policy will also help develop new technologies and solutions that other companies can use. In addition, it will also help create a skilled workforce, which will boost the country's competitiveness at the global level. Moreover, this partnership will also help create more jobs for people ready to move into new fields of work, like AI-related areas or any other area where they need additional training on these technologies. This will also help increase their chances of getting better-paying jobs requiring higher skill sets compared to their old jobs. This partnership ensures that there will be a common language between local educational programs and the Government's efforts to implement AI-based agendas (Yigitcanlar, 2021). This can be seen as beneficial because it reduces confusion among students and gives them more confidence in their ability to understand what they are learning in class. It is important to note that the UAE is one of the few countries that have taken action on AI development, but it is still insufficient (Yeganeh, 2019). The Government has done a lot of research and development on this issue. It has made some great strides toward making artificial intelligence more accessible, but many challenges still need to be overcome before this project can become a reality.

One of the main challenges facing this project is ensuring that people are trained on how to work with AI systems to be productive members of society. There are many other areas where AI systems will be valuable and beneficial, such as medical diagnosis or military warfare.

However, these areas require specialised training that traditional education systems would not necessarily cover. Another challenge facing this project is ensuring that all citizens have access to these new technologies so they can participate in their communities and enjoy all the benefits they offer.

6.2.1.5 Government Healthcare Partnerships

The UAE government has been working on developing robotics care systems and a robust healthcare environment with genomics. To accomplish this, they have partnered with several companies, including Microsoft, Samsung, and Siemens. This partnership has led to the development of hospital robots to provide patient care and support. In addition, they have created an artificial intelligence system that uses data from genomics tests to predict disease risk and respond accordingly (Halaweh, 2018). They aim to make these technologies available through an affordable subscription plan. The UAE works with several other countries worldwide to create a unified healthcare system using genomics technology.

The partnership has the potential to make life easier for the UAE's people and make significant contributions to global health. It will allow for the development of robotic care systems that can be implemented in hospitals nationwide, providing more opportunities for patients to receive quality care. These robotic care systems will also help improve hospital safety standards by reducing errors and improving performance levels (Yeganeh, 2019). This partnership also has the potential to significantly contribute to global health through its use of genomics research. By using genomics research, it will be possible for researchers to understand better how diseases such as cancer development could lead to new treatments that could save millions of lives worldwide.

The Government is using technology to ensure that people get the best care from their doctors. They want these systems to diagnose illnesses in real-time so they can be treated immediately rather than waiting for an appointment or going through long queues at hospitals or clinics. The goal of this program is not only to improve care for patients but also to reduce costs by reducing unnecessary trips to hospitals or clinics as well as providing faster access when needed most urgently so that treatment does not have any delays due to waiting times or other factors like traffic jams or long lines outside clinics.

6.2.1.6 Theoretical Implications

The findings under RQ1 provide strong support for extending both the Diffusion of Innovation (DOI) and the Technology–Organisation–Environment (TOE) frameworks. DOI theory emphasises the importance of communication channels and social systems in influencing adoption (Rogers, 2003). However, in the UAE retail sector, adoption was not only shaped by interpersonal and organisational factors but also heavily by policy signalling from the state (Halaweh, 2018; Khatib et al., 2021). Interviewees consistently noted that the national AI/4IR strategy created legitimacy for experimentation, a dynamic that modifies DOI by introducing *government strategy as an innovation catalyst*. This suggests that in highly centralised economies, diffusion models must account for top-down political endorsement as a mechanism for risk governance (Wu et al., 2014).

Similarly, the TOE framework (Tornatzky & Fleischer, 1990) has often treated the external environment as a broad influence encompassing regulation, competition, and market forces. The UAE case shows that the "environment" dimension is more granular, with national strategies not only mandating compliance but also *raising operational baselines* through digitised public services (Butcher & Himenez, 2019). This pushes firms to adopt higher standards of uptime and continuity, revealing that government digital transformation can function as a hidden adoption driver. In this sense, TOE requires refinement to capture the catalytic role of public–private interdependence.

Finally, findings around ethics and privacy underscore that resilience discourses in AI adoption are inseparable from governance and trust (Stone et al., 2020; Bussmann et al., 2021). This highlights a gap in risk-management theories, which traditionally stress financial or operational risk (Sun et al., 2019), but in AI-enabled contexts must also integrate socio-ethical risk dimensions. Thus, RQ1 advances theory by demonstrating how AI adoption in emerging economies is embedded in national vision-building, demanding modifications to DOI and TOE to incorporate policy-driven legitimacy, baseline-setting, and governance ethics as structural forces shaping adoption.

6.2.2 RQ2: The Impact of AI on Strategic Efforts in the Private Sector

A key element of study used in this research was the use of case studies of the two companies, Masjid Al Futtaim and the Al Ghurair group, to determine the various efforts that have been implemented within the private sector to improve risk management in project management. Combining the data obtained from either of the two companies helps to come up with a clear view of the various efforts that have so far been felt in these industries, as far as the two organisations are concerned, and the private sector at large. When looking intently at the various issues experienced by both companies in this research, five major areas of application were evident in which AI can be used in risk management. This includes modernisation of the retail sector, pushing inter-organisational collaborations, increasing business diversity, human resource development, and the change of business models.

6.2.2.1 Modernisation of Retail Sector

The Majid Al Futtaim project, with the launch of the smart and digital shopping malls in Carrefour+ within the UAE, has been largely defined as the launch of the future of shopping. This is an important statement because it shows the great potential that the use of AI in the retail sector can have in helping this sector mitigate the various changes to be experienced within the sector. According to Verma *et al*. (2021), the retail sector has experienced a lot of operational challenges which are brought about by the multiple disruptive technologies within this sector. Some of these disruptive technologies include the use of IoT, big data analytics block chain technologies and the use of AI. These changes in technology affect both the market trends as well as the way businesses operate. Within the retail sector, disruptive technologies are being prompted with the aim of maintaining business relevance and maintaining a customer base (Rouhan *et al*., 2016). Therefore, businesses are being threatened by the highly changing technology scope, which shows that without the ability to come up with the fast-changing business and customer technology-based demands, retailers are likely to run out of the market. Some of the technology from the fourth industrial revolution has been used to change the product and service offerings. The technology is being used to change what customers need and demand from their vendors.

Vetterli *et al*. (2016) talked about the changes experienced in the retail industry through the lens of customer services. With the technology experience, customers are experiencing even more customer-based services, which provide them with customised experiences that focus on minor customer details. Therefore, the adoption of AI within the retail sectors pushed by the Al

Futtaim organisation was front in the use of AI for pushing for organisational developments that would help cater for the changes in the market demands (Verma *et al*., 2021). AI is the key technology which could help organisations within the retail sector today to cope with changes in the market demands. The use of AI in retail is also implemented, both on the customer side, and on the operator side. From the customer side, it helped to provide services and products that are future-proof and in ways that guarantee continuity to the business model. From the operator side, to help the retail sector to be much more effective in operation, increasing operational efficiencies and data handling.

These study findings converge with Vetterli et al. (2016), who assert that AI holds the potential to revolutionize retail management with customer personalization methods. Interpreting customer trends through data analysis is another way through which AI benefits retailers, a concept similar to the RBV proposed by Barney (1991). Through the adoption of AI for customer analytics and operating optimizations, the UAE retailers are thus applying AI as more than merely a tool for process enhancement, but a resource essential for sustaining competitive advantage in fulfilling customer needs and managing risks. In addition, it can be seen that the modernization implemented by Majid Al Futtaim and Al Ghurair supports concepts identified by Verma et al. (2021), which predicts that AI integration contributes to increased resilience through increasing operational adaptability and responsiveness to markets. The use of disruptive technologies such as AI also relates to Bower and Christensen's (1995) disruptive innovation theory due to their impact on industries as they redefine clients' value and firms' operation models. Thus, the use of AI among UAE retailers is a result of new market realities as businesses embrace the Fourth Industrial Revolution, incorporating technology to meet new demand and stay competitive.

Within the retailing section, AI is considered the future of business operations in many ways. Disruptive technologies have contributed to the development of an interconnected world through the digital landscape. Together with big data analytics, there was a huge potential to develop further marketing intelligence, which is built through the analysis of efficient data analysis strategies for market situations (Kumar, 2018). Therefore, the overall retail industry in the fourth industrial revolution is based on the use of AI for facilitating shopping and to cope with the modern-day challenges that demand the use of technology-based solutions.

In comparison to the theoretical concepts behind this study, the theory of determinants of adoption can be linked to these findings. One of the key things to consider in this regard is the relative advantage argument. The relative advantage is the perceived benefit of adopting a technology into an entertainment system. It is expected that the perceived benefits of a technology are likely to support the implementation of that technology into a specific industry. When looking at AI and the retail industry, there are numerous perceived benefits which are likely to have influenced the decision to facilitate AI adoption in the retail industry. For example, AI technology has been able to provide benefits such as increased sales, lower costs of operations and higher customer satisfaction (Kumar, 2018). These perceived benefits have been demonstrated to play a key role in the adoption of AI technologies within the Retail industry. In addition, there is a need for compatibility between the technology being adopted and the structure of the industry in which it is being adopted. This can be demonstrated by how the AI technologies align with the workflows being implemented in the retail industry, together with the existing infrastructure, such as the chaser points and payment systems, and finally, with the culture that most organisations adopt in the retail industry.

6.2.2.2 Collaborations

Collaboration in business is effectively used as a tool for risk management, mainly because of its unique ability to provide businesses with buffers they can use to overcome challenges in the market. According to Munir *et al*. (2020), the use of collaboration has been effectively used in supply chain risk management within business organisations and other avenues where the management of business risk depends on the availability of multiple resources which might not be easily accessible to the organisations in question. Both Majid Al Futtaim and the Al Ghurair group have engaged in multiple collaborations to help build the capacity of their organisations to deal with the uncertainty of the future. The role of AI in fostering these inter-organisational collaborations also shows that the organisations were influenced by the need for technical capabilities as well as the need for well-trained and competent human resources.

Varying AI skill sets have the potential for other key collaborations between various companies operating within the AI field. From the first industrial revolution to the current fourth industrial revolution, each new ground-breaking technology that is introduced to the commercial world creates a surge in demand for skilled workers who are conversant with the new technologies. There have been multiple concerns that the use of new technologies would lead to an increase in joblessness, which has been disapproved every time (Koo et al., 2021). However, what occurs is the shift in market demands, where new skills have to be impacted among the population, to ensure they are well stocked with the necessary skills that will be utilised with the new mode of operation (Paltrinieri *et al*., 2021). Therefore, the idea of collaboration was largely based on the provision of human resources andt6ectnchicnal skills to companies which otherwise did not have access to the necessary skills needed to succeed in such industries. In addition to providing companies with access to human resources, collaborations also allow companies to gain access to technology and equipment which can be critical in helping them navigate through the critical changes in the operations. Businesses in the modern-day world need to have access to state-of-the-art equipment for data processing and analysis, which may not be readily available within their own budgets, the use of AI has opened multiple avenues for collaborations that have prompted huge players such as Microsoft Azure and other retailers to change the model of operations.

This can also be linked to the key theoretical concepts that explain the interplay between collaboration and the implementation of AI technology. Collaboration is first developed through an elaborate collaboration mechanism. For a proper collaboration mechanism to exist, therefore, first need to exist a good model for sharing information between the different parties. there is a need to develop a better decision-making process and facilitate situational awareness (Koo et al., 2021). AI algorithms with such a collaborative environment facilitate the existence of a joint problem-solving framework, which also grows within shared goals and values. Therefore, there is a definite connection between the use of AI and the increase in collaboration within the industry.

6.2.2.3 Business Diversity

The Al Ghurair groups have utilised their technology adoption techniques as part of the mechanisms employed to help the business achieve diversification. The business diversification strategy is not a new concept in the commercial world. Most businesses in the past have used the diversification strategy to increase their market share, and they could diversify in a number of ways. In this research, the A Ghurair group has embarked on a diversification channel that could enable the use of the diversification strategy as a risk management strategy, which helps businesses adapt to changing market conditions. Business diversification is usually applied when companies want to grow their business (Tien *et al*., 2019). It, therefore, involves the introduction of a new product or service into the business supply chains, and thus effectively introduces the company into new markets. In addition, diversification is conducted through three different forms, which include concentric diversification, personal diversification, and conglomerate diversification (Paltrinieri *et al*., 2021). Concentric diversification is whereby the company develops new products, which are mainly to the existing products; an example is when an orange juice company starts producing pineapple juice or a similar beverage. Horizontal diversification, on the other hand, is where the company is where a company starts producing new products which are related to the original products (Tien *et al*., 2019). For example, when a car manufacturer ventures into the vehicle repair business. Thirdly, conglomerate diversification is whereby the company gets engaged in new businesses that are completely unrelated to its first line of products.

Al Ghurair, in their example, engaged in the conglomerate business, whereby they diversified into multiple new businesses which are unrelated to each other. For a long time, engaging in conglomerate diversification has been considered the best form of diversification because it involves the business getting into completely new forms of business in which they have no prior experience (Paltrinieri *et al*., 2021). However, with the use of AI and technology developments, companies like Al Ghurair have taken advantage of the information processing and flexibility of the technology department to turn this into an advantage and a strategy for future-proofing buses. With changing technology inventions, businesses have to be flexible with their product portfolios since new products are being invested in while also new services are being developed. The invention of new products and services has also become a new form of adaptation since it enables businesses to be capable of dealing with the uncertain futures in their operation.

6.2.2.4 Human Resource Development

The next research article by AL-Ayed (2019), talks about the significance of strategic human resource management for organisational resilience. According to this research, companies are threatened by various occurrences that are experienced within the economy, which might include economic receptions, natural disasters, human factors, and other factors which might require strong organisational resilience. Resilience is also distinguished from other factors, such as adaptation and flexibility. Flexibility of the organisation mainly refers to the ability of the organisation to make changes that are needed within the immediate economy, while adaptation mainly focuses on the ability of the organisation to meet the requirements for the immediate organisation (Iqbal, 2020). The resilience in comparison to these two relates to the ability of the organisation to make specific changes within its own structures, as a result of certain occurrences in the immediate organisational environment, and these changes then reduce the negative impact the organisation might experience when they are hit by certain market crises. The type of market crises that are referred to in organisational resilience and flexibility are also different. Organisational resilience focuses on crises which relate to operations, such as the supply chain crises.

AI's implementation in HR practices can be analysed based on SHRM elements such as managing employees' flexibility/employability in the context of technological change. AL-Ayed (2019) establishes the importance of building resilience for SHRM by developing the skills of employees, which supports the results of the study. Machine learning solutions help UAE retailers in sourcing, developing, and engaging employees to fit organisational needs and disruptions brought by the Fourth Industrial Revolution. This strategic emphasis on flexibility resonates with Iqbal's (2020) argument suggesting that the diverse approaches to HRM enhance organisational preparedness to address changes in the external environment and engage entities that comprise the workforce as agents of change. AI's contribution to employee training also encompasses ideas from Talent Management Theory, which outlines how performance management systems should reflect an organisation's strategic plan for providing continued performance (Collings & Mellahi, 2009). Employing AI helps to improve the level of competencies of employees, and releasing human resources from time-consuming administrative tasks makes it possible to dedicate more time to skills development and leadership interventions, thereby supporting the concept of organisational flexibility and engagement among the employees.

The use of strategic human resource management has been used as one of the key strategies by businesses to mitigate the business against such issues that pose a threat to the resilience of the organisation. In such cases, the use of strategic human resource management has been used to ensure the organisation is provided with key human resources that will help the authorization to navigate through the time of crisis (Al-Ayed, 2019). From the above research, the two organisations, Al Ghurair and Al Futtaim were prompted by the existing demand for new resources to increase their human resources acquisition channels. This shows that the role of AI in key HR practices can help organisations to be more effective in building their organisational resilience and thus increase their capacity to overcome challenges that may face the organisation.

Specific strategies and measures that are employed in HR management include the use of strategic planning for workers and staffing practices, which involve the development of efficient working schedules, among others. Organisations have the ability to make use of AI-based practices to increase the efficiency of their HR practices by developing effective appraisal programs which they can use as the blueprint for awarding their employees with promotions and to award certain challenging tasks to specific employees who have been proven to be competent on certain fonts (Rogers *et al*., 2016). AI can also be utilised in developing effective recruitment and selection systems. For example, the use of A system can be utilised in making online training and assessment systems that can be utilised in the selection process to help employers find the correct type of employees from the wide scope of applicants.

6.2.2.5 Stakeholder Collaborations & Business Model Change

The use of stakeholder collaboration in this thesis has been utilised properly as one of the keyways through which the organisation could build their organisational resilience. This research has shown that as organisations are faced with multiple threats to their operations, the existence of strong organisational resilience could be key to the organisation living through the sudden changes in their operational structures (Rogers *et al*., 2016). During these periods of uncertainty, developing strategic collaborations can help the organisation to successfully fight with the organisational challenges, and thus avoid the risk of being phased out of business. This, therefore, means that organisational collaborations form one of the most reliable risk management techniques that organisations can involve.

The use of AI in modern-day organisations both facilitates and encourages the use of collaborations. Based on the case studies analysed in this project, the need by organisations to shift to AI-based development prompted the two companies to seek collaboration with technology-based companies as a way of accessing the AI infrastructure as well as the existing human resources and technical skills (Medel *et al*., 2020). Therefore, as many other companies are faced with the challenge of accessible, reliable, resources to push through their development agendas, the use of AI provides room for collaboration with other stakeholders, which can be the difference between success and failure. The existing modes for collaboration include the provision of AI-related services and existing online platforms, which allow separate teams from separate organisations to work together on the same projects.

6.2.2.6 Theoretical Implications

The results for RQ2 show that private-sector firms adopt markedly different strategies to integrate AI, yet both converge on strengthening risk governance. This contributes to resource-based and dynamic capabilities perspectives (Barney, 1991; Teece et al., 1997), which frame technology as a source of competitive advantage. In Majid Al Futtaim, automation through robotics and computer vision (City+ projects) demonstrates how firms translate technological affordances into dynamic risk capabilities, thereby extending the scope of strategic management literature on digital transformation (Mikalef et al., 2019). In contrast, Al Ghurair Group emphasised ERP/DR resilience and organisational alignment, which supports theories of absorptive capacity (Cohen & Levinthal, 1990) by showing how firms leverage internal learning routines to assimilate AI within continuity planning (Hofmann et al., 2020).

Importantly, these findings suggest that risk posture—whether automation-led or resilience-led—functions as a mediating construct between AI capabilities and performance outcomes. Existing frameworks such as Enterprise Risk Management (ERM) treat risk practices as integrated, but rarely distinguish between postures that privilege technological automation and those that privilege resilience governance (Bartram et al., 2020). By empirically demonstrating two viable but distinct strategic pathways, this study adds nuance to ERM theory and suggests the need for a more contingent understanding of risk strategies in digital contexts.

Furthermore, the findings highlight the role of partnerships and talent development in shaping adoption trajectories. This aligns with institutional theory, where legitimacy is pursued through collaborations that signal conformity to wider norms (DiMaggio & Powell, 1983). The observed reliance on education partnerships and external collaborations underscores how AI adoption is as much about social capital and legitimacy as about technical investment (Hamilton Skurak et al., 2021). Therefore, RQ2 enriches theory by showing that organisational responses to AI vary between automation and resilience postures, and that these are shaped by both dynamic capabilities and institutional legitimacy pressures.

6.2.3 RQ: To explore the future impacts of AI in Risk Management

Based on the research conducted in this study, data pointing towards the future implementation of AI in risk management mainly revolved around the five main areas, which were collectively discussed from the two case studies of the organisations. These case studies revealed that the focus in the future would lie in financial services, data handling and analytics, change management programs, talent generation on applied education, and policy and regulatory frameworks.

6.2.3.1 Financial Services

The use of AI in the management of financial services is a field that has already made significant progress. However, there is enough data to show that the financial sector will continue to rely heavily on AI, even as time goes by, to tap into the future avenues within this field. AI can potentially become the core service provider among all the financial-related agencies. While the technology has mainly been included to increase operational efficiencies and provide companies with a competitive advantage, it is still evident that there are many unexplored opportunities that it could present to financial services (Lin *et al*., 2020). These opportunities lie in technological development and the social change markets are undergoing. Technological developments, such as the invention of digital currencies based on blockchain, continue to change individuals' social perceptions about shopping and working online. However, such companies need to understand that the transition to digital economies is a learning curve far from stabilising. A lot of the change experienced in financial risk management will rely on the ability of AI to learn from existing data and make data-based decisions without human interventions.

6.2.3.2 Data handling and processing

The concept of data management automation was developed in this research by the partnership between Microsoft Azure and the Masjid Al Futtaim group to automate their data management and processing. Currently, there are several platforms which operate autonomously within the corporate world in data processing. With the inclusion of AI in this system, the potential for data handling procedures increases even further, and this is reflected in the ability to manage risks properly among businesses. Digitised and efficient data handling systems are essential to risk management (Ismail, 2021). The availability of more advanced data handling systems will first increase the efficiency of risk management efforts by streamlining the people, processes, and tasks to be conducted. It also means that organisations will have better decision-making capabilities, which results from the availability of well-developed data handling systems. Decision-making based on actual, accurate, and relevant data helps organisations deal with uncertain risks. With the existing data analysis process, most businesses still have to make decisions with either half the data or others have to depend on their past experiences and senses to make investment decisions (Ismail, 2021). This puts organisations at a greater risk of being affected by unknown circumstances that may affect their operations. The development of big data systems is, therefore, expected to be a huge game changer when it comes to data processing and decision-making. Big data systems would help individuals within the corporate system to inform their decision-making abilities in the near future, enabling them to avoid more risks experienced within the decision-making process.

6.2.3.3. Change Management

Change management is one of the key skills and techniques that those in the corporate world need to develop to ensure they are safe from the impact of the changing business atmosphere. The highly dynamic commercial world makes it mandatory to have effective management systems, which help businesses adapt to changing customer behaviour. Despite being one of the leading forces for change in the economy, AI and technology also provide practical solutions for managing these changes, thus translating into a risk management opportunity.

Change management is a complex activity that involves the coordination of many processes, which affect both the people and other resources that need to be streamlined within an organisation. The first way AI facilitates change management is by developing a more efficient communication system, which enables easy collection of efforts within the organisations (Carvalho *et al*., 2016). Data availability, for example, allows change managers to take corrective actions before they are needed to avoid fatal outcomes. Managing people is a key aspect of the change management process. One way this is achieved is by ensuring that the people employed as change managers in the organisation can spend more time dealing with people than handling other repetitive tasks such as data entry. Therefore, it allows for a more efficient utilisation of human resources, which contributes to smoother collaboration in the change management process.

6.2.3.4 Policy and Regulatory Frameworks.

Policy and regulation about AI have been very slippery topics mainly because of the various aspects AI has been through to have on its users. While it has brought forward multiple benefits relating to risk management, the use of AI also contributes to increased risk in some areas, which mainly involve data handling, privacy, and ethical conduct (Almeida *et al*., 2022). For this reason, the regulations implemented in routine AI processes are crucial in determining AI's overall impact on risk management. For this reason, matters concerning the regulation and policies of AI use continue to develop to make AI use more beneficial to the users. General principles are used to guide the overall regulation of AI implementation. Most of these laws aim to minimise the number of AI users exposed to a minimum risk while having the most to gain from the use of the systems (Almeida *et al*., 2022). Therefore, businesses are encouraged to figure out ways to deploy these services with the least negative impact on their consumers. In addition, the government is also taking the mandate and learning the various forms engaged with the regulation of AI systems to ensure that ethical codes of conduct are protected during such processes.

6.2.3.5 Theoretical Implications

The exploration of future orientations (RQ3) reveals that organisations envision AI not only as a present-day operational tool but as a transformative force that will reconfigure risk management paradigms. From a theoretical standpoint, this contributes to foresight within risk governance and innovation adoption literatures. The emphasis on analytics automation and "data plumbing" at Majid Al Futtaim, for instance, reflects the growing centrality of data as infrastructure, echoing arguments in technology adoption studies that information quality is a foundational determinant of absorptive capacity (Butcher & Himenez, 2019; Barta & Görcsi, 2021). This reinforces the idea that risk management theory must treat data not simply as input but as a dynamic capability in its own right.

At Al Ghurair Group, the focus on resilience drills, governance reforms, and people pipelines shows how AI futures are deeply intertwined with socio-organisational transformation. This supports socio-technical systems theory, which posits that technology adoption and human capability development are mutually reinforcing (Trist, 1981; Natasia et al., 2022). By foregrounding education, resilience rehearsals, and governance, AG demonstrates that the future of risk management lies not only in technological sophistication but in cultivating organisational routines that can adapt under uncertainty (Shamout & Ali, 2021). These findings extend institutional theory by suggesting that "future-oriented legitimacy" is critical: firms anticipate that regulatory and societal expectations around ethics, privacy, and resilience will tighten, and therefore pre-emptively shape their AI agendas (Al Batayneh et al., 2021). This anticipatory compliance challenges the view of institutional isomorphism as reactive; instead, it shows proactive alignment with expected norms.

Overall, RQ3 demonstrates that theoretical models of risk management must account for the anticipatory and future-oriented dimensions of AI adoption. In particular, theories of innovation diffusion and organisational change need to incorporate foresight practices, where firms use AI not only to manage current risks but also to *rehearse for uncertainty*. This finding makes a significant contribution by repositioning AI as a forward-looking capability that redefines the temporal scope of risk management.

7.0 CHAPTER SEVEN: CONCLUSION AND RECOMMENDATIONS

7.1 Introduction

This chapter draws together the threads of the research by consolidating what has been learned from the data analysis and situating those insights within both theoretical and practical contexts. While the earlier chapters presented background, literature, methods, and findings, this concluding chapter reflects on the broader meaning of the study. It evaluates how well the research objectives have been achieved, sets out contributions to knowledge and practice, and identifies ways in which the study helps to close the gaps identified in the literature review.

The chapter begins by revisiting the research questions that guided this inquiry. It assesses the extent to which these questions have been answered and considers how the findings speak to the existing literature. It then turns to the contributions of the study, distinguishing clearly between the theoretical contributions—where the findings extend or refine established frameworks such as Diffusion of Innovation (Rogers, 2003), the Technology–Organisation–Environment framework (Tornatzky & Fleischer, 1990), and Enterprise Risk Management perspectives (Bartram et al., 2020; Hofmann et al., 2020)—and the practical contributions, where the data support the construction of a five-lever playbook for risk management in the UAE retail sector. The chapter also reflects explicitly on how the study addresses the gaps flagged in Chapter Three, particularly the need for empirical evidence of AI adoption in the private sector, the under-theorisation of governance in risk frameworks, and the absence of foresight in models of adoption (Butcher & Himenez, 2019; Bussmann et al., 2021).

Finally, this chapter looks outward, offering recommendations for both policy and practice, and concluding with reflections on the wider implications of the research. By doing so, it reinforces the central argument of the thesis: that artificial intelligence is not simply an operational tool, but a transformative force reshaping how risk is conceptualised, governed, and managed in the UAE retail sector.

7.2 Evaluation Against the Initial RQs

The research questions were designed to structure the investigation into three interlinked aspects of AI-enabled risk management: the influence of national AI strategies on private-sector practice; the impact of AI adoption on strategic organisational efforts; and the anticipated future directions of AI in risk governance. This section evaluates how each question has been answered, linking findings to the literature and highlighting where new insights have been generated.

RQ1: How do UAE Government's AI Strategies and Initiatives Shape Risk-Management practices inside Private Organisations?

The findings demonstrate that the UAE government's AI and Fourth Industrial Revolution (4IR) agenda acts as a powerful catalyst for organisational change. Interviewees consistently credited national strategy signals with legitimising experimentation and embedding AI within risk processes. For example, both Majid Al Futtaim and Al Ghurair Group reported adopting predictive maintenance, automated surveillance, and enhanced risk dashboards following state-level emphasis on AI (Halaweh, 2018; Khatib et al., 2021). This aligns with prior scholarship that positions government policy as an enabler of innovation diffusion (Wu et al., 2014). However, the study adds empirical weight to the claim by showing that policy not only enables adoption but also raises operational baselines through digitised public services, which set new expectations for uptime and continuity (Butcher & Himenez, 2019).

From a theoretical perspective, these findings refine the Diffusion of Innovation model by suggesting that in state-led contexts, adoption is not only a function of organisational readiness and peer imitation but is strongly shaped by policy signalling. They also sharpen the TOE framework by specifying that the "environment" dimension must account for baseline shifts created by government digitisation initiatives. This confirms Stone et al. (2020) and Bussmann et al. (2021) on the importance of ethics and trust, showing how national agendas translate into internalised routines for privacy and data governance. Thus, the first research question has been comprehensively answered, while also advancing theoretical discussion on how external strategies penetrate organisational risk practices.

RQ2: How does AI Adoption Impact The Strategic Efforts of Private-Sector Organisations in the UAE?

The second research question uncovered two contrasting but complementary organisational pathways. At Majid Al Futtaim, AI adoption was manifested in automation-heavy strategies, including robotics and computer vision projects like City+, underpinned by infrastructure investment and targeted partnerships. In contrast, Al Ghurair Group pursued a resilience-oriented posture, embedding ERP/DR systems, capacity-building, and change management routines. Together, these findings suggest that AI-enabled risk management in the UAE retail sector is not monolithic but takes divergent forms depending on organisational priorities.

Theoretically, this advances both dynamic capabilities theory and enterprise risk management perspectives. Mikalef et al. (2019) highlight how digital capabilities underpin strategic agility, and the MAF case supports this by demonstrating how AI is leveraged for frontline efficiency. At the same time, AG's emphasis on continuity and resilience echoes Hofmann et al. (2020), who argue that enterprise risk must be embedded across organisational routines. What is novel here is the identification of "risk posture" as a mediating construct: organisations choose between automation-led or resilience-led strategies, both of which represent viable but distinct paths to governance under uncertainty.

This contribution also engages institutional theory (DiMaggio & Powell, 1983), as both companies sought legitimacy through partnerships and collaborations, aligning their strategies with broader expectations of responsible AI. In doing so, they reinforced earlier observations that legitimacy pressures are as important as technical capacity in shaping adoption (Hamilton Skurak et al., 2021). The second research question is therefore answered in a way that highlights strategic diversity while extending theoretical frameworks to recognise posture-specific pathways.

RQ3: What are the Future Impacts of AI in Risk Management?

The third research question focused on the anticipatory dimension of AI adoption. Majid Al Futtaim's emphasis on clean data architectures and analytics automation illustrates how firms see data as a future-oriented infrastructure, essential for predictive and proactive risk governance. Al Ghurair Group, meanwhile, looked ahead to resilience drills, governance reforms, and talent pipelines, suggesting that organisational foresight and human capability development are as critical as technical sophistication.

These findings reinforce socio-technical systems theory (Trist, 1981) by showing that AI adoption must be understood as an interplay between human routines and technological affordances. They also extend institutional theory by illustrating "anticipatory legitimacy": firms prepare for expected future regulatory and societal demands rather than reacting only once norms are codified (Al Batayneh et al., 2021). In this respect, adoption is both present-oriented and future-oriented, reshaping the temporal scope of risk management.

Moreover, the evidence speaks to Butcher and Himenez (2019) and Barta & Görcsi (2021) on the centrality of data in contemporary organisations, confirming that data plumbing is not only an operational necessity but a strategic orientation. Shamout and Ali (2021) similarly argue that resilience is an organisational routine rather than a one-off capability, and the AG case illustrates this vividly. Thus, the third research question has been thoroughly addressed, and in doing so, it adds foresight as a missing dimension in adoption and risk theories.

Taken together, the evaluation against the three research questions confirms that the aims of the study have been met. The findings provide detailed empirical evidence of AI's role in risk management within the UAE retail sector, while also advancing theoretical understanding of innovation diffusion, TOE, and risk governance. Each research question not only yielded insights relevant to practice but also offered refinements to theory, thereby addressing the very gaps identified in Chapter Three. This sets the stage for the next section, which explicitly articulates the contributions to knowledge and practice.

7.3 Contributions to Knowledge and Practice

This study makes a set of contributions that can be distinguished between theoretical advances and practical implications. While the earlier chapters showed how findings related to the specific research questions, the value of the thesis lies not only in describing what organisations are doing but in demonstrating how these practices expand the boundaries of theory and offer actionable tools for managers and policymakers.

7.3.1 Theoretical Contributions

The research extends established theories of innovation adoption, organisational risk management, and institutional legitimacy in several ways. The Diffusion of Innovation framework has long emphasised the role of communication channels, adopter categories, and organisational culture in shaping technology uptake (Rogers, 2003). The findings of this study support that account but go further by demonstrating how government policy signalling operates as a catalyst that legitimises experimentation in private organisations. For instance, participants described how national AI and Fourth Industrial Revolution initiatives gave their boards the confidence to invest in predictive maintenance, robotics, and AI-enabled risk dashboards. This confirms observations by Halaweh (2018) and Khatib et al. (2021) but also suggests that in centralised political economies, diffusion theory must explicitly integrate state-led agenda-setting as a structural determinant of adoption.

The Technology–Organisation–Environment framework also receives refinement. Tornatzky and Fleischer (1990) identified the "environment" as an important dimension influencing adoption, yet the environment was typically conceptualised in terms of competition, market readiness, or regulatory compliance. The UAE context shows that the environment is also actively shaped by government digitisation, which raises operational baselines across sectors. Butcher and Himenez (2019) highlight the impact of digitised services on continuity, and the present findings confirm this by showing how smart public services spill over into private expectations for uptime and data resilience. TOE theory therefore needs to incorporate not just external pressures but also the structural resetting of industry norms driven by state digital transformation.

A further contribution lies in the concept of "risk posture." Existing enterprise risk management literature tends to stress integrated systems of governance and reporting (Bartram et al., 2020; Hofmann et al., 2020). However, the data here reveal that firms diverge in how they translate AI into risk practices. Majid Al Futtaim emphasised automation-led risk posture through frontline robotics and analytics, while Al Ghurair Group pursued resilience-led posture with ERP/DR systems, resilience drills, and governance reforms. Both strategies produced valid risk governance outcomes, suggesting that risk posture functions as a mediating construct between AI capabilities and organisational performance. This nuance enriches ERM literature by showing that risk strategies can be differentiated by posture, rather than assumed to be homogenous.

Institutional theory is also advanced by the study. DiMaggio and Powell (1983) describe institutional isomorphism as the tendency of organisations to conform to shared norms, often reactively. Yet the findings here reveal a pattern of anticipatory legitimacy, where firms align their AI practices with expected future regulatory and societal demands. For example, Al Ghurair Group invested in talent pipelines and ethical governance structures not because of immediate compliance pressures but because of anticipated shifts in public expectations around privacy and resilience. This finding resonates with Al Batayneh et al. (2021), who argue that institutional responses are increasingly proactive in dynamic technological environments.

These theoretical contributions directly address the gaps identified in Chapter Three. The first gap concerned the scarcity of empirical evidence on AI adoption in UAE private retail, a gap now filled through thirty in-depth interviews across two leading firms. The second gap related to the weak theorisation of governance in risk frameworks, which this study addresses by articulating the concept of risk posture. The third gap concerned the absence of foresight in models of adoption, a gap addressed by the demonstration of anticipatory legitimacy and rehearsal-for-uncertainty practices. In this way, the thesis extends DOI, TOE, ERM, and institutional theories in ways that make them more applicable to the realities of AI adoption in emerging economies.

7.3.2 Practical Contributions: A Five-Lever Playbook

Alongside its theoretical implications, the study offers a practical contribution in the form of a five-lever playbook for organisations seeking to embed AI in their risk management strategies. This playbook is distilled from the empirical evidence and represents a set of interconnected practices that organisations can adapt to their own contexts.

The first lever concerns automation at the frontline, where technologies such as robotics, computer vision, and analytics can enhance detection speed and exception reporting. Majid Al Futtaim's deployment of City+ and automated systems exemplifies how frontline automation reduces operational risk and builds trust in risk governance routines. This reflects the arguments of Mikalef et al. (2019), who show how digital capabilities enhance agility.

The second lever involves resilience governance, including ERP/DR systems, reliability runbooks, and continuity drills. Al Ghurair Group's strategy highlights how resilience-led governance builds organisational capacity to withstand disruptions. Shamout and Ali (2021) argue that resilience is not a one-off attribute but an organisational routine, and the evidence here affirms that perspective.

The third lever is partnerships and collaborations. Both firms invested heavily in external collaborations with academic institutions, technology providers, and government agencies, using these partnerships to acquire knowledge, legitimacy, and resources. This supports the findings of

Hamilton Skurak et al. (2021), who demonstrate that public–private collaborations are critical for advancing AI in emerging contexts.

The fourth lever focuses on talent and applied education. Both organisations recognised that AI adoption cannot succeed without a pipeline of skilled professionals, leading to training programs, applied education initiatives, and talent development pipelines. Hofmann et al. (2020) highlight how absorptive capacity depends on human capital, and the findings here illustrate that AI readiness is inseparable from talent investment.

The fifth lever is policy alignment and ethics. Firms responded not only to formal regulatory frameworks but also to the ethical dimensions of AI, embedding privacy and governance practices into their risk routines. This aligns with the concerns of Stone et al. (2020) and Bussmann et al. (2021), who emphasise the importance of trust and governance in the acceptance of AI systems. Taken together, these five levers form an integrated framework that managers and policymakers can use as a guide for adopting AI in risk management. The playbook is not a rigid recipe but a flexible toolkit that organisations can adapt depending on their posture, resources, and external environment.

7.3.3 Closing the Gaps in Literature

By consolidating these contributions, the study closes three critical gaps identified in Chapter Three. First, it provides robust empirical evidence from the UAE retail sector, thereby addressing the lack of grounded studies in this context (Butcher & Himenez, 2019). Second, it develops the concept of risk posture, offering a new theoretical construct that enriches ERM and TOE by accounting for organisational divergence in adoption strategies (Bartram et al., 2020; Hofmann et al., 2020). Third, it highlights the role of foresight in adoption, showing that organisations practice anticipatory legitimacy and resilience rehearsals, a perspective not captured in traditional diffusion models (DiMaggio & Powell, 1983; Al Batayneh et al., 2021). These contributions advance both theory and practice, demonstrating how AI transforms the conceptualisation of risk and governance in the private sector.

7.4 Recommendations

The findings suggest several recommendations for practice and policy. For organisations, the five-lever playbook should serve as a guiding framework. Firms should not only invest in frontline automation but also balance it with resilience governance, ensuring that risk is addressed both through technological efficiency and through organisational robustness. Building partnerships and investing in talent pipelines is not optional but essential, as AI adoption depends as much on human capital and legitimacy as on technological capacity. Ethical governance must also be integrated into every adoption decision, particularly as public trust in AI hinges on transparency and accountability (Stone et al., 2020; Bussmann et al., 2021).

For policymakers, the research underscores the catalytic role of national strategies. The UAE government should continue to invest in AI infrastructure and digitised public services, which create operational baselines that push private firms toward higher standards of risk management. However, these strategies should be complemented with regulatory clarity around data privacy, ethics, and accountability, to ensure that adoption is not only rapid but also responsible (Wu et al., 2014; Khatib et al., 2021). Finally, both policymakers and business leaders should consider foresight practices, embedding future-oriented drills and governance reforms to prepare for emerging risks.

7.5 Final Reflections

This thesis has explored the impact of artificial intelligence on risk management in the UAE private retail sector. By combining qualitative evidence from thirty interviews with theoretical reflection, it has shown that AI is not merely a set of tools but a force that reshapes organisational practices, risk postures, and governance routines. The study has contributed to theory by extending Diffusion of Innovation, refining the TOE framework, elaborating the concept of risk posture in ERM, and identifying anticipatory legitimacy in institutional theory. It has also contributed to practice by consolidating a five-lever playbook that organisations can use to structure adoption.

Above all, the research has addressed the gaps identified in the literature review, providing empirical grounding, conceptual refinement, and foresight perspectives that were previously absent. The implications extend beyond the UAE retail sector, offering lessons for other emerging economies grappling with the opportunities and risks of AI. While the study has limitations, including its focus on two organisations and its qualitative scope, its findings demonstrate that AI adoption is best understood as a socio-technical process shaped by state policy, organisational posture, and societal expectations.

In conclusion, the study reinforces the idea that artificial intelligence, when carefully integrated into organisational systems, can transform risk management from a retrospective function into a proactive, decision-ready capability. It invites scholars to continue refining theory to account for contexts like the UAE, and it invites practitioners and policymakers to adopt balanced, ethical, and forward-looking strategies for AI in risk governance.

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Appendices

Appendix -1 Approval of Registration

University of Central Lancashire
UCLan

7th September 2022

Saleem Abdulla Salem Saroor Aljaberi
(G20997580)

Dear Saleem,

Approval of the Registration of a Programme of Work for the Stage 2 Research Element in a Professional Doctorate.

I am pleased to inform you that the School of Business and Justice has approved your part-time research programme towards the Professional Doctorate in Business Administration.

Title of Programme of Research for Module BD5000 Doctoral Thesis

The Effect of Artificial Intelligence Implementation on Risk Management - A Study of the UAE Private Sector.

Supervisors

Director of Studies:	Dr Ahmad Abu-Arja School of Business and Justice
Second Supervisor 1:	Professor Peter Smith The University of Sunderland

Duration of the Research Element of your programme

Duration of the Project phase commences on 1st June 2022, with submission of your final thesis by 1st April 2024, subject to conditions specified in the University Regulations.

The Research Element will be assessed by submission of thesis and oral defence of thesis as outlined in the Academic Regulations.

englandsnorthwest
BE INSPIRED

Ethical Approval of your Project

Your application for RPA has been approved. However, please note that until you have gained ethical clearance (where you answer "No" to all questions on the Ethics checklist and clearance is confirmed by the ethics committee) or ethical approval (where you answer "Yes" to any question on the Ethics checklist and submit an application for full ethical approval which is subsequently approved by the ethics committee) you are not permitted to do any data collection or fieldwork, or participant surveys. To do so will mean you are uninsured, in breach of the Code of Conduct for Research, and liable for disciplinary action.

Examination Arrangements

a) The arrangements for examining you on your programme of work.
b) The external and internal examiners to be appointed.

These arrangements should be submitted no later than 4 months before you propose to submit your thesis for examination. Please note that you will not be able to submit your thesis until examination arrangements have been approved.

Please feel free to contact me about any aspect of the registration procedures or with any other queries you may have.

Yours sincerely

Simon Sumner
Academic Registry

Copies: Ahmad Abu-Arja
Peter Smith
Sean Gammon
EthicsInfo@uclan.ac.uk

Appendix -2 Ethical Approval

University of Central Lancashire
Preston PR1 2HE
01772 201201
uclan.ac.uk

14th March 2023

Saleem Aljaberi / Ahmad Abu-Arja
School of Management
University of Central Lancashire

Dear Saleem / Ahmad,

Re: BAHSS2 Ethics Panel Application
Unique Reference Number: BAHSS2 0421

The BAHSS2 Ethics Review Panel has granted approval of your proposal application, 'The effect of Artificial Intelligence implementation on Risk Management- A study of the U.A.E private sector'.

Approval is granted up to the end of project date*.

It is your responsibility to ensure that

- the project is carried out in line with the information provided in the forms you have submitted
- you regularly re-consider the ethical issues that may be raised in generating and analysing your data
- any proposed amendments/changes to the project are raised with, and approved, by Committee
- you notify ethicsinfo@uclan.ac.uk if the end date changes or the project does not start
- serious adverse events that occur from the project are reported to Panel
- a closure report is submitted to complete the ethics governance procedures (Existing paperwork can be used for these purposes e.g. funder's end of grant report; abstract for student award or NRES final report. If none of these are available use e-Ethics Closure Report Proforma).

Yours sincerely,

John Mills
Deputy Vice-Chair
BAHSS2 Ethics Panel

* for research degree students this will be the final lapse date

NB - Ethical approval is contingent on any health and safety checklists having been completed, and necessary approvals gained.

Appendix -3 Participant Consent Form

University of Central Lancashire
UCLan

Participant Consent Form

Version number & date: V2.1 02.02.2022
Research ethics approval number:
Title of the research project: The Effect of Artificial Intelligence Implementation on Risk Management - A Study of the UAE Private Sector
Name of researcher(s): Saleem Abdulla Aljaberi

Please initial box

1. I confirm that I have read and understood the information sheet dated [**DATE**] for the above study, or it has been read to me. I have had the opportunity to consider the information, ask questions, and have these answered satisfactorily. ☐
2. I understand that taking part in the study involves interviews in the form of online Microsoft Teams meetings. ☐
3. I understand that my participation is voluntary and that I am free to stop taking part and can withdraw from the study at any time without giving any reason and without my rights being affected. In addition, I understand that I am free to decline to answer any particular question or questions. ☐
4. a) I understand that if I withdraw from this study, data collected before my withdrawal will be retained, but no further data will be collected. ☐
   b) I understand that I can request the destruction of that information if I wish before anonymisation after 14 days of data collection. I understand that following the 14 days, I will no longer be able to request access to or withdraw the information I provide.
5. I understand that the information I provide will be held securely and in line with the University of Central Lancashire data protection requirements. ☐
6. I understand that the interviewer will retain signed consent forms and interview outcomes stored in a secured and password-protected folder within UCLan's network for **three years after the interview**. ☐
7. I understand and agree that my participation will be **video recorded**, and I am aware of and consent to use these recordings only for the mentioned thesis preparation purposes. ☐
8. I understand that my interview recordings will be retained for 14 days. ☐
9. I understand that confidentiality and anonymity will be maintained, and it will not be possible to identify me in any reports, presentations, or publications arising from the research. ☐
10. I agree to take part in the above study. ☐

Participant name	Date	Signature
Name of person taking consent	Date	Signature

Principal Investigator
Dr. Ahmad Abu-Arja
Contact number: +44(0) 1772 894714
Email: aabu-arja@uclan.ac.uk
Signature below:

Student Investigator
Saleem Abdulla Aljaberi
+971 50 131 2252
sasaljaberi@uclan.ac.uk

Appendix -4 Interview Questions

Questionnaire 1

University of Central Lancashire
UCLan

Interview Questions

The Effect of Artificial Intelligence Implementation on Risk Management - A Study of the UAE Private Sector

University of Central Lancashire - UK

Prepared by: Saleem Aljaberi

Student No.: G20997580

Date: 24th November 2022

These Interview Questions were developed as part of research that is being conducted to examine the impacts of Artificial intelligence on implementing risk management in the private sector in the UAE. The data collected in this question will be utilised as a part of the educational research, used for research purposes only. This data will be scientifically analysed to determine the validity of the hypothesis established in the earlier stages of this research. You are invited to freely participate in this research and provide your responses as answers to the various questions. The responses you provide will form part of the data collected during this research process and used to conclude the research. Participation in this study is voluntary, and as a respondent, you have the right to engage or not engage in the study. This research also sticks to the ethical code of conduct that guides scientific research within the UAE involving human participants to ensure that your rights are protected throughout the study. You also have the right to get feedback on the research in the form of an academic thesis by emailing the researcher on sasaljaberi@uclan.ac.uk

These questions are divided into two sections. The first section collects information about your demographics, and the second section gathers information about your experiences in the industry with AI applications and Risk Management. For further information on the study, see the Participant Information Sheet.

SECTION I: Demographic Information

1. Level of Education
    - Undergraduate
    - Bachelor's degree
    - Master's degree
    - Doctorate
2. How many years of experience do you have in AI or Risk Management?
3. How would you grade the level of your knowledge and expertise in AI?
    - Expert
    - Intermediate
    - Basic
    - No knowledge

Section II: Interview Questions on the Impacts of Artificial Intelligence

This section of the interview will focus on your experiences with AI's impacts on risk management in your profession.

1) How do you think the government strategy for Artificial Intelligence affects risk management efforts?
2) Do you think building a model for the adoption of AI affects risk management efforts?
3) What is your experience with the government's vision of AI?
4) How significant are the government partnerships with AI education programs?
5) Do you think Government and healthcare partnerships affect AI?
6) What has been your company's experience using AI in recent projects?
7) What are some of the critical benefits of the use of AI in project implementation?
8) What are the key strategies that facilitated the use of AI, in your opinion?
9) What are some of the foreseeable future applications of AI?

Thank you for participating in this interview and responding to the questions presented in this study.