THE IMPLICATIONS OF INTEGRATING ARTIFICIAL INTELLIGENCE INTO DATA-DRIVEN DECISION-MAKING

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ABSTRACT

Integrating artificial intelligence (AI) into data-driven decision-making offers advantages like increased performance, reduced costs and improved organisational efficiency; however, there are associated risks. The study employs a PRISMA protocol to systematically review academic articles from Scopus, ScienceDirect, and Web of Science databases to determine whether the risks AI pose are worth the rewards they offer. Literature trends reveal a growing interest in AI-driven decision-making, with significant research gaps in African contexts. The study indicates that AI is highly utilized for decision-making to foster competitiveness in manufacturing, finance, healthcare, education, and transport. Identified risks include bias, discrimination, privacy issues, and cybersecurity threats. It is highlighted that businesses need to address concerns about privacy, fairness, and transparency. Policymakers must develop ethical and legal standards besides regular monitoring and auditing of AI uses to mitigate risks.

OPSOMMING

Die integrasie van kunsmatige intelligensie (KI) in data-gedrewe besluitneming bied voordele soos verhoogde werkverrigting, verlaagde koste en verbeterde organisatoriese doeltreffendheid; daar is egter gepaardgaande risiko's. Die studie gebruik 'n PRISMA-protokol stelselmatig om akademiese artikels van die Scopus-, ScienceDirect- en Web of Science-databasisse te hersien om te bepaal of die risiko's wat KI inhou die belonings werd is wat dit bied. Die literatuurtendense toon 'n groeiende belangstelling in KI-gedrewe besluitneming, maar met aansienlike navorsingsgapings in Afrika-kontekste. Die studie dui aan dat KI baie gebruik word vir besluitneming om mededingendheid in vervaardiging, finansies, gesondheidsorg, onderwys en vervoer te bevorder. Geïdentifiseerde risiko's sluit in vooroordeel, diskriminasie, privaatheidskwessies en kuberveiligheidsbedreigings. Die studie beklemtoon dat besighede bekommernisse oor privaatheid, regverdigheid en deursigtigheid moet aanspreek. Beleidmakers moet etiese en wetlike standaarde ontwikkel, benewens die gereelde monitering en ouditering van KI-gebruike om risiko's te versag.

1. INTRODUCTION

In today's era, marked by Industry 4.0 and characterised by a combination of digital technologies with physical systems, the basis of and driving force behind growth and change is incorporating artificial intelligence into data-driven decision-making [1]. Indeed, significant progress in cyber-physical systems, the Internet of Things, and cloud computing are at the root of fundamentally changing the dynamics of how businesses operate, how governments function, and how humans interact with technology [2], [3]. At its core, AI is a revolutionary machine – a machine that can quickly process vast quantities of data to unlock critical insights and drive highly informed decision-making processes with previously unseen efficiency and accuracy [4].

For example, predictive maintenance algorithms in manufacturing show the efficiency of AI in enhancing operational efficiency and improving manufacturing processes. Besides, predictive analytics performed with AI is capable of helping companies to predict and fix failures in their equipment, thus saving on downtime, resource allocations, and maintenance costs [5], [6]. In the health sector, AI-driven diagnostic tools are changing the dimension of medical imaging, since they enable timely disease detection, quality patient outcomes, and organised treatment procedures [7], [8].

AI algorithms also help to analyse critically the financial sector markets and forecast consumer behaviour to let financial institutions make the most appropriate investment decisions and personalise their services to clients [9], [10]. Another advantage of AI solutions is that they increase the delivery of public services in many domains, such as traffic management and disaster response [11], [12]. Last, apart from industry, AI has affected society in several ways, such as optimised traffic management, improved environmental monitoring, and improved educational conditions [13], [14], [15].

Despite AI's advantages, several ethical issues arise from its acceptance in society, including the biases it causes and the transparency deficit it carries [16], [17]. For instance, a lack of clarity might arise when making data-driven decisions, whereby there is a need to question who to hold responsible for any untrustworthiness [8]. Other ethical problems and biases may also come through in decision-making, leading to discriminatory decisions [17]. Last, broader risks threaten society, such as AI-infected viruses and a lack of human autonomy. As a result, it is essential to implement strategies for using AI [18], [19].

Because of the risks that are posed by using AI for data-driven decision-making, an essential question is: "Is the use of AI for competitive advantage worth the associated risks it poses?"

To answer this question, this study intends to analyse the implication of integrating AI into data-driven decision-making with the help of the following research questions:

RQ1: What are the benefits of using AI in data-driven decision-making?

RQ2: What are the risks of using AI in data-driven decision-making?

RQ3: Which sectors mainly use AI for decision-making?

RQ4: What strategies do organisations use to address issues when using AI for data-driven decision-making?

Thus this paper should give clear insight into AI's multifaceted economic, environmental, and social impacts on decision-making and, ultimately, offer strategies for future research endeavours.

2. METHODOLOGY

2.1. Introduction

This section presents an amended version of the methodologies used by [20] and [21] to analyse the literature and to extract its main findings. This methodology first outlines the strategy to narrow the literature search, then screens the literature and extracts and analyses the relevant data. The methodology is carried out this way to ensure clarity and comprehensiveness.

2.2. Search Strategy

As this research paper aimed to determine the implications of integrating AI into decision-making, an in-depth examination of 'artificial intelligence for data-driven decision-making to gain a competitive advantage' was initially conducted to lay the foundation for formulating the literature review questions.

Once the review questions had been formulated, they were broken down into distinct keywords to create the search terms illustrated in Table 1. This involved using Boolean operators, since these would ensure that the retrieved literature consisted only of articles containing one or both search terms in order to explore the relevant sources comprehensively [22].

Table 1: Search terms used to obtain literature

Search terms	
1	Artificial intelligence) AND (data-driven decision-making)
2	(Artificial intelligence) AND (decision-making) AND (risks)
3	(Artificial intelligence) AND (decision making) AND (advantage)
4	(Industry 4.0) AND (data-driven decision making)

The search terms were then run through three search engines – Scopus, ScienceDirect, and Web of Science – since those databases are compatible with Boolean operators and have been considered to be of a high standard [23]. Apart from the abovementioned platforms, the search terms were run through Google Scholar to broaden the search and to ensure that no scholarly works were left unexamined.

2.3. Study selection

After the literature retrieval, a thorough screening and selection process followed the steps according to the preferred reporting of items for systematic reviews and meta-analyses (PRISMA) statement, as shown in Figure 1. According to the statements proposed by [24] and [25], the PRISMA statement outlines the steps used to limit the initial set of studies into a final set and, in so doing, to make the review sound by increasing its methodological quality.

As described by the PRISMA statement, the retrieved literature was subjected to strict screening against the pre-defined inclusion and exclusion criteria shown in Table 2, during which we examined the relevance of each study to the research objective. The specific inclusion and exclusion criteria were chosen to ensure that only recent articles of a high academic quality were included, as the research questions required credible information on the latest implications of AI. According to [26], the PRISMA screening process is used, as it includes only the most relevant studies for analysis so that the literature that is obtained is as fine-tuned as possible.

Table 2: Inclusion and exclusion criteria used to narrow down literature

Inclusion criteria	Exclusion criteria
Studies published between 2018 and the present.	Studies published as conference proceedings.
Studies are available in full text in English.	Studies printed in hard copy.
Studies published in journals.	
Studies are peer reviewed.	

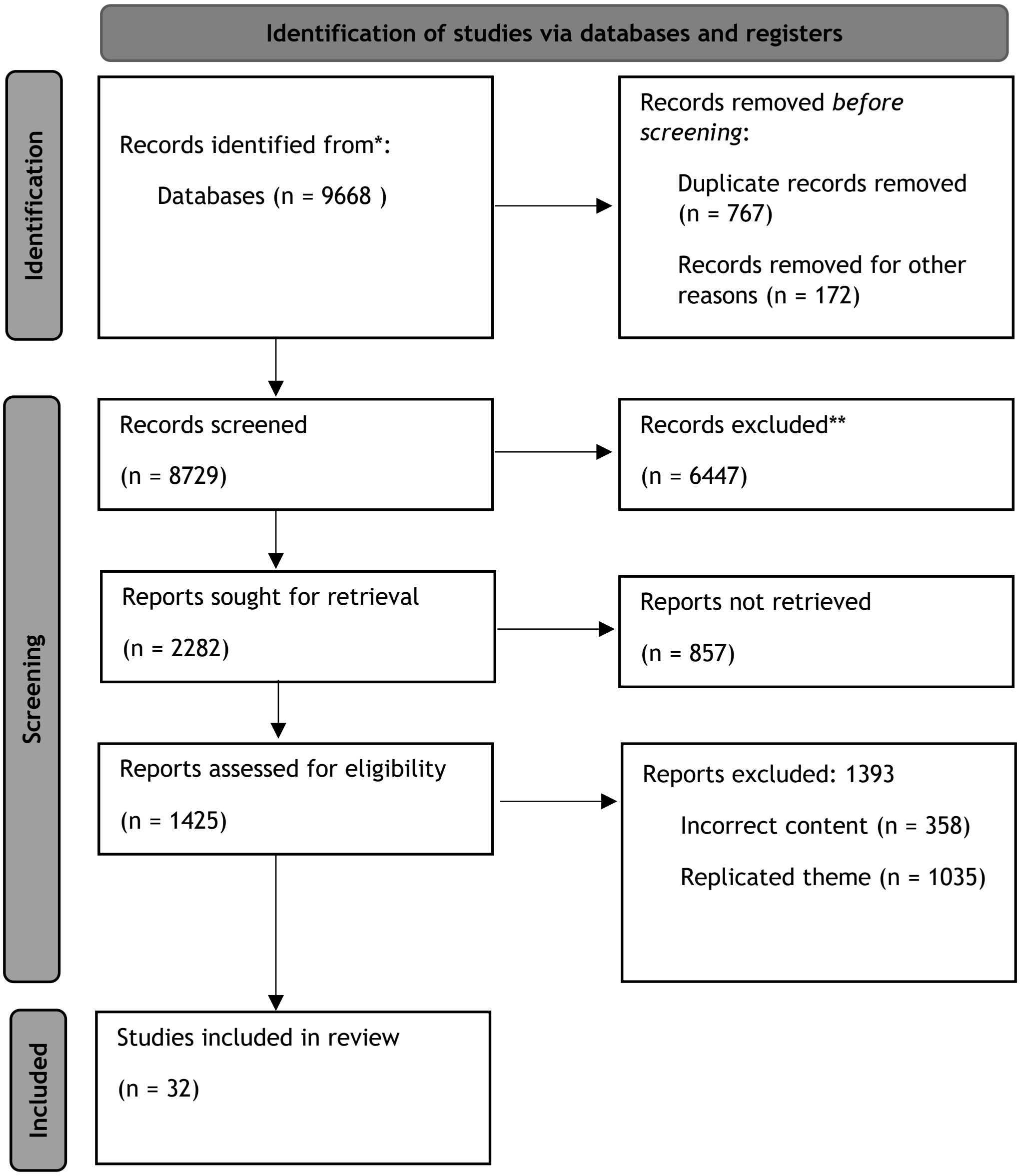

Figure 1: PRISMA statement used to narrow down literature

2.4. Data collection

Once the literature had been refined using the PRISMA statement, the qualitative data from the selected studies was extracted and presented using an author matrix. This was used to compare the primary findings and limitations across the reviewed literature to ensure thoroughness and accuracy.

Following the data extraction, a quality assessment, as summarised in Table 3, was carried out to ascertain the reliability and relevance of the literature. This quality assessment used a set of criteria from [27] and [28] to assess the quality of every study, including having a well-defined research aim, a suitable methodology, and reporting its limitations.

The quality assessment also examined each study's strengths and limitations to evaluate the credibility of the extracted data and thereby enhance the overall reliability of the findings.

Table 3: Quality assessment criteria used to measure the reliability of the literature

Question
Does the study have a well-defined research aim?
Does the study have appropriate research questions?
Does the study have a suitable methodology?
Does the study have an appropriate data collection process?
Does the collection of data in the study happen in an unbiased way?
Does the study have a suitable data analysis process?
Does the study interpret its results efficiently?
Does the study report its limitations or validity threats?
Does the collected data in the study support its results and conclusions?

2.5. Data analysis

After the data had been analysed, the author matrix was converted into a concept matrix by categorising the data into key concepts and themes. According to [29], a concept matrix allows an extensive comparative analysis of reviewed literature to be carried out by examining its similarities, differences, and emerging patterns. Furthermore, the matrix visualises the relationships between the main themes, providing essential implications for the findings.

3. LITERATURE REVIEW RESULTS

This section presents the results of the literature review, from which the literature trends and key findings concerning the integration of AI into data-driven decision-making are discussed.

3.1. Literature trends

In order to analyse the chosen articles' publication patterns and to understand our findings more clearly, we examined several trends. Initially we analysed the number of studies published per year, as seen in Figure 2, which indicates a peak in publications in 2023, followed by 2021, 2022, and 2024, proving the articles to be relevant. Second, we analysed the publication country of the studies, as seen in Figure 3, with some publications occurring in more than one country. When examining Figure 3, we observed that most of the publications were in the United States and the United Kingdom, but that none were in African countries. This trend indicates the need for more research into integrating AI into decision-making in African countries. Last, we examined the different research methodologies employed by the studies, as depicted in Figure 4, which showed the literature review to be the most common methodology used. The evidence of the literature review indicates that there is an ongoing contribution to the development of knowledge about the integration of AI into data-driven decision-making.

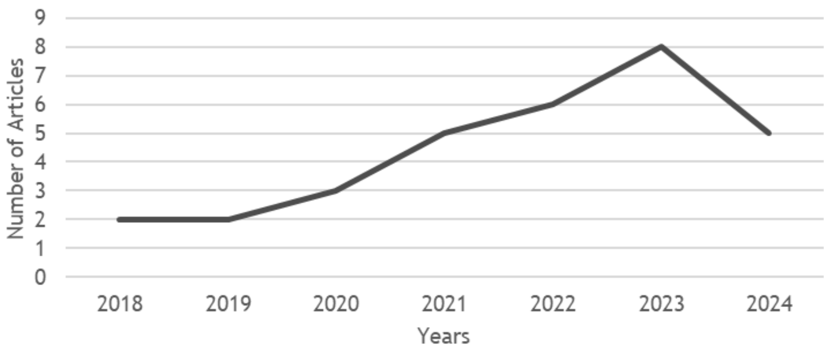

Figure 2: Document publications per year

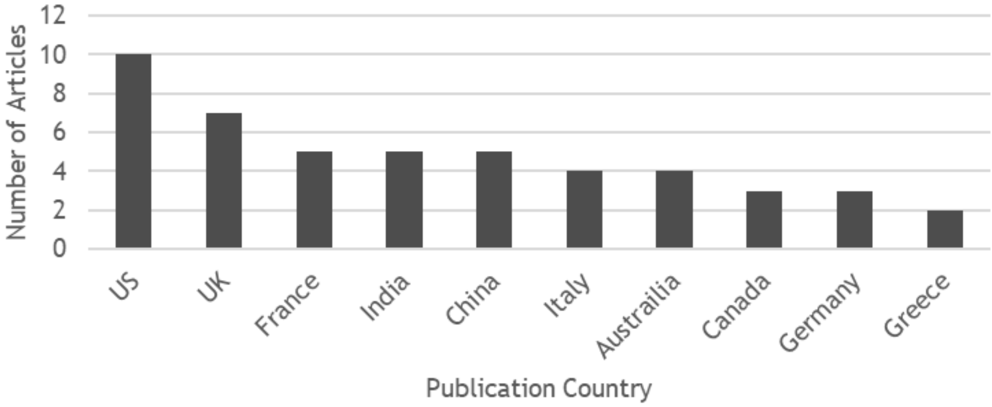

Figure 3: Document publications per country

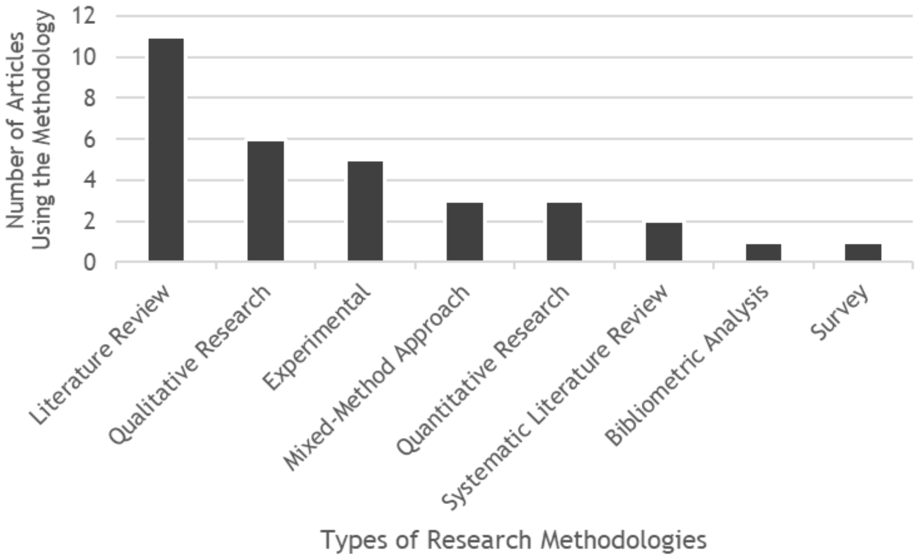

Figure 4: Research methodologies used

3.2. Main findings

The primary findings obtained during the systematic examination of the literature are discussed below. We begin with an exploration of the benefits and risks of integrating AI into decision-making, followed by an identification of the sectors using AI in decision-making, and ending with the various methods that companies use to mitigate the risks posed by AI in decision-making.

3.2.1. Advantages of using artificial intelligence for data-driven decision-making

AI for decision-making offers organisations many benefits, as depicted in Table 4, and gives companies a competitive advantage by improving their efficiency and effectiveness.

Table 4: Summary of the benefits that artificial intelligence has for decision-making

Benefits	Description	Sources
Improves business outcomes	Predictive maintenance, data science, and data analytics lead to improved processes and reduced costs, which result in better results in all sectors.	[1], [3], [4], [8], [30], [31], [32]
Reduces costs	Predictive maintenance, data science, and AI lead to reduced expenses owing to streamlined operations in all sectors.	[1], [3], [4], [32]
Improves patient care	Data science and AI applications improve decision-making, which in turn is responsible for better health care outcomes and regulation processes.	[4], [7]
Enhances operation efficiency	Advanced technologies optimise processes, promote sustainability, and improve environmental performance in various sectors.	[1], [8], [13], [30], [31], [33]
Improves customer satisfaction	AI-driven personalisation and quality product improvement enhance user satisfaction across all platforms and manufacturing sectors.	[5], [33]
Enhances adaptability and competitiveness	AI and Industry 4.0 technologies lead to adaptability and competitiveness through data-driven decision-making and innovations.	[5], [9], [12], [34], [35]
Improves time of assistance to victims	Advanced technologies such as AI and big data analytics lead to enhanced response strategies in humanitarian operations.	[12]
Improved and faster decision-making	AI, machine learning, and data analytics enable quick and informed decision-making in many industries.	[1], [4], [5], [8], [10], [13], [35],
Increased growth	Advanced technologies in the manufacturing, finance, and research sector increase growth owing to improved decision-making.	[3], [8], [13], [31], [33], [35]
Improves sustainability	AI and big data contribute to sustainability in manufacturing, urban development, and environmental governance.	[3], [8], [14], [30], [36], [37]
Improves policies and public values	Technologies and data analytics enhance evidence-based decision-making, refine policies, and strengthen societal values.	[11], [17], [36], [38],
Strengthens governance	Advanced technologies help make better and more transparent governance decisions.	[7], [9], [11], [15], [18], [33], [36], [38]
Advanced performance	Data science, artificial intelligence, and Industry 4.0 methodologies enhance decision-making and efficiency in the sectors.	[4], [6], [8], [11], [35], [42]
Increased monitoring and managing environmental challenges	Data-driven approaches and artificial intelligence enhance the monitoring and management of environmental challenges.	[8], [14], [30], [37]

3.2.2. Risks of using artificial intelligence for data-driven decision-making

Although the areas of application of artificial intelligence are numerous, they have risks, as illustrated in Table 5. As these consequences are severe, companies must ensure that they are actively managing such risks to realise the full benefits of the technologies.

Table 5: Summary of the risks that artificial intelligence brings to decision-making

Risks	Description	Sources
Bias and discrimination	The biases built into AI systems lead to unfair outcomes in the decisions made in different sectors.	[2], [16], [17], [38], [39], [40]
Privacy concerns	The application of artificial intelligence and data-driven decision-making in almost all sectors leads to privacy issues, affecting personal data security and democratic principles.	[16], [39], [40]
Environmental governance	A big challenge exists in applying advanced technologies such as artificial intelligence and big data when addressing environmental governance.	[8], [37], [41]
AI-infected viruses	The increased existence of viruses infected with artificial intelligence leads to destructive risks for computer systems that may negatively impact members of society.	[19]
Ethical concerns	The presence of biases in AI causes ethical issues such as privacy concerns and threats to democratic values.	[16], [39], [40]
Technological control	The use of AI in decision-making raises concerns about who is in control and what impact the technology has on individual autonomy.	[5]

3.2.3. Sectors using artificial intelligence for decision-making

As detailed in Table 4, various companies in many sectors use AI and its associated benefits in making data-driven decisions. Given the wide adoption of AI in multiple domains, Figure 5 depicts the frequency of the various sectors mentioned in the literature, with some literature studies affecting more than one sector. As seen in Figure 5, the sectors most dependent on AI are the manufacturing, finance, and healthcare industries, proving the importance of technology globally.

Table 6: Sectors using artificial intelligence for data-driven decision-making

Sector	How artificial intelligence assists
Manufacturing	It makes manufacturing processes more effective, predicts maintenance needs, ensures product integrity, and suggests environmentally sustainable practices.
Climate change	It helps to mitigate challenges to achieving carbon neutrality by identifying adaptation strategies, seeking improvements, and using holistic approaches.
Streaming platforms	It personalises the content and services to increase user satisfaction and engagement.
Finance	It analyses risks, detects fraud, and enhances processes by automating them.
Healthcare	It helps efficiently to dispense medicine, diagnose diseases, and personalise therapy.
Supply chain management	It helps to increase supply chain productivity and sustainability.
Governance	It suggests the moral correctness of decisions.
Disaster relief	It helps quickly to assess, coordinate, and distribute resources for providing relief.
Education	It supports customised learning, automates administrative tasks, and provides access to data analysis in education.
Innovation management	It improves decision-making processes, encourages knowledge creation, and fosters innovation management by experimenting in unknown environments.
Transportation	It enhances autonomous vehicles’ safety, environmental impact, and societal acceptance.
Higher education institutions (HEIs)	It helps in resource allocation, performance evaluation, and research enhancement.
Materials science	It accelerates research, helps in error detection, and improves structural analysis.
Cybersecurity	It helps to detect and prevent threats.

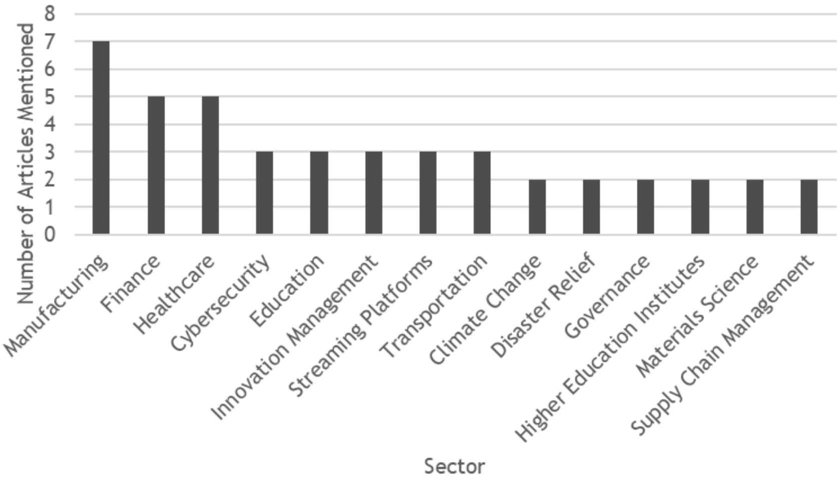

Figure 5: Frequency of sector references in analysed literature

3.2.4. Methods employed to address risks when incorporating AI-driven decision-making

Owing to the many risks involved in using AI for decision-making, firms must devise strategies to counteract these possible effects. Some approaches that companies have already taken to minimise AI's impacts are summarised in Table 7.

Table 7: Strategies used to account for risks when implementing AI-based decision-making

Strategy	Source
Implementing ethical and legal principles	[7]
Addressing biases in AI systems	[7]
Implementing training and awareness	[33]
Performing regular auditing and monitoring	[15]
prioritising fairness, accountability, and transparency in machine learning	[31]
Investing in data quality and security	[36]
Ensuring transparency and accountability	[15]
Implementing human oversight	[33]

4. DISCUSSION

4.1. Principal findings

This section discusses the implication of integrating AI into data-driven decision-making by analysing the literature trends described in section 3.1 and examining the research questions in section 3.2.

4.1.1. Literature trend analysis

As seen in section 3.1, literature trends can provide essential insights into the findings from the obtained literature and give helpful information for further research endeavours. Initially, as seen in Figure 2, the publication years of the literature are highly relevant, proving the findings to be reliable and credible, and reflecting a rising research interest in AI-driven decision-making in various sectors. In addition, as seen in Figure 3, the lack of articles published in African countries indicates an extreme need for more research on integrating AI into data-driven decision-making in this region.

4.1.2. Discussion of research questions

RQ1: What are the benefits of using AI in data-driven decision-making?

AI has many advantages for various fields and sectors, as shown in Table 4. In maintenance planning and risk mitigation, AI uses predictive maintenance to optimise processes and to reduce costs in order to enhance business outcomes [1], [4], [8], [30]. In addition, in healthcare, AI improves patient care by improving diagnostic accuracy and operational efficiency [4], [7]; and in humanitarian efforts, it refines response strategies to ensure the rapid delivery of aid to disaster victims [12]. AI, too, enhances customer satisfaction by providing personalised services [5], [33], and it fosters competitiveness by using data-driven insights [5], [9], [34]. Moreover, AI encourages growth and sustainability and is pivotal in forming government policies [11], [36], [38] and in environmental monitoring. Hence, as a result, the technology can provide a more sustainable and efficient future across various sectors [8], [30].

RQ2: What are the risks of using AI in data-driven decision-making?

AI-driven decision-making processes have several risks for various sectors, as shown in Table 5. The outstanding issue with the technology is societal discrimination, because biased algorithms might lead to unfair outcomes owing to race or gender issues [16], [38], [39]. In using AI in health and finance, there is a risk of privacy being violated, causing ethical and autonomy problems [39], [40]. In environmental governance, AI leads to complexities in data and results in security problems that affect sustainability efforts [8], [41]. In addition, systems infected by 'AI viruses' are the most significant cybersecurity threat and threaten human and infrastructural safety [19]. Finally, human autonomy is substantially threatened by AI through its influence on consumer freedom [5]. Therefore, the risks that AI poses must be vigilance maintained to ensure that the technology will be safe to use.

RQ3: Which sectors mainly use AI for decision-making?

As AI offers many advantages, many sectors use the technology, as depicted in Table 6. The most prominent sector using technology for data-driven decision-making is the manufacturing sector, as seen in Figure 5; it uses AI to enhance the efficiency of manufacturing processes, predict the need for maintenance, ensure the quality of the products they produce, and encourage environmentally friendly practices [1], [8], [33], [35]. The second most prominent sectors using AI are the finance and healthcare sectors, which use AI in assessing risks, detecting fraud, improving medical diagnoses, and personalising treatment [3], [4], [7], [35]. The remaining sectors – supply chain management, governance, disaster relief, education, innovation management, transportation, higher education institutions, materials science, and cybersecurity – rely on AI for decision-making to address specific problems and to improve operational efficiency, as noted in Table 6.

RQ4: What strategies do organisations use to address issues when using AI for data-driven decision-making?

Since incorporating AI into data-driven decision-making risks having serious consequences, organisations must strategically manage these ethical concerns, biases, and privacy issues to enhance their competitive advantage, as detailed in Table 7. Some of the strategies are enforcing moral and legal standards [7], conducting training sessions to raise awareness among staff [33], performing regular audits and monitoring to ensure compliance, emphasising accountability in machine-learning processes [31], investing in data security to prevent privacy infringements [36], and ensuring human oversight in maintaining control [33]. These strategies empower an organisation to handle effectively the risks that AI poses so that it gains the benefits of the technology.

4.2. Implications

The implications from the key findings in section 4.1 highlight that AI is of great value to different sectors, since it provides them with an opportunity to achieve a competitive edge. The application of AI in decision-making processes in the manufacturing, finance, healthcare, and education sectors allows them to increase their efficiency and effectiveness [1], [4], [7], [15], [39], [40]. However, at the same time, the risks linked with AI call for mitigative strategies to ensure the responsible deployment of the technology. Thus there is a call to business leaders to harness the full potential of AI while addressing the risks related to privacy, fairness, and transparency [31]. Policymakers are urged to integrate AI into government frameworks to provide social benefits, ensuring that ethical considerations are taken care of [7]. Therefore, although AI has many transformative benefits, its risks must be researched through proactive strategies to ensure that it is used sustainably and responsibly in different sectors.

4.3. Strengths and limitations

The structured PRISMA protocol followed in this study offers reliability and methodological clarity. In addition, the study considers recently published and peer-reviewed articles (Figure 3) to capture the latest developments in the field, strengthening the relevance of the findings. Nevertheless, despite the thorough review process followed to ensure the quality of the identified articles, the study's results rely on published articles, and as a result, publication bias remains a limitation.

5. CONCLUSION

The integration of AI into data-driven decision-making in the manufacturing, finance, healthcare, education, and transport sectors has a number of advantages and risks. AI-driven decision-making can improve the performance, progress, and sustainability of various industries. However, its associated risks must be addressed with strategic measures to harness responsibly the technology's full potential and to gain a competitive advantage in the data-driven landscape.

AI contributes to business growth and sustainability by smoothing out operations, increasing efficiency, and fostering innovation. However, the risks related to bias, discrimination, privacy concerns, and AI-driven security threats require attention. Organisations could implement measures to respond to these challenges by employing ethical and legalistic norms, bias mitigation methods, and periodic monitoring and audit practices. These measures would provide accountability and transparency by reducing the risks and maximising the benefits of the AI-enabled decision-making process.

6. RECOMMENDATIONS

In future research efforts, researchers should study the effect of AI on additive manufacturing, as there is an increased research interest in AI-enabled decision-making in manufacturing industries. As this study has also recognised the need to identify articles from the African region, further studies may also focus on AI's effect on decision-making in the area. In addition, one way to demonstrate the impact of AI on decision-making in various sectors would be by comparing the outcomes of decisions using AI with those made without AI.

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