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Leveraging AI and ML for business and management innovation

Suliman Alazzaz[1]
[1]Assistant Professor, Business Administration Department, Saudi Electronic University, Riyadh, Saudi Arabia.
Email ID : S.alazzaz@Seu.edu.sa

ABSTRACT

This systematic review examines the role of Artificial Intelligence (AI), Machine Learning (ML), and their combined applications in promoting organizational innovations across business and management contexts. Thirty papers published between 2020 and 2025 were systematically reviewed, comprising ten papers each focused on AI, ML, and AI-ML integration respectively. The analysis reveals that these technologies, alongside emerging innovations like blockchain and Internet of Things (IoT), significantly influence organizational innovation through multiple mechanisms and contexts. AI demonstrates particular strength in innovation analytics, business model innovation, and circular economy applications, while ML excels in knowledge management, customer retention strategies, and cybersecurity innovation. Their convergence, often with complementary technologies, enables transformative innovations across diverse sectors including healthcare, manufacturing, supply chain management, and financial services. Several novel frameworks identified in the review provide valuable insights into innovation development processes and organizational value creation. However, widespread adoption faces substantial barriers including data privacy concerns, transparency and reliability issues, significant skill deficits, limited organizational capabilities, and challenging business environments. The review identifies critical gaps in empirical research and highlights the predominance of poor-quality studies lacking methodological rigor. Future research directions emphasize the need for more empirical investigations, mixed-method approaches, cross-country comparative analyses, and theoretical development to advance understanding of technology-enabled innovation..

Keywords: Artificial Intelligence, Machine Learning, organizational innovation, digital transformation, business model innovation, technology adoption barriers, systematic review

1. INTRODUCTION:

In this era of rapid technological evolution, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative forces reshaping the contours of business strategy and management practice. From predictive analytics and intelligent automation to adaptive decision-making and customer personalisation, these technologies are not merely augmenting operational efficiency, they are redefining the very foundations of organisational innovation. As firms navigate increasingly complex and volatile environments, the strategic integration of AI and ML offers unprecedented opportunities to enhance agility, foster data-driven cultures, and unlock new value propositions.

This review critically examines the diverse applications of AI and ML in driving innovation within the business and management sectors. By linking theoretical perspectives with practical case studies, the review seeks to demonstrate that AI and ML offer a detailed understanding of how these technologies can be utilised not only for operational improvements but also for strategic renewal and sustainable development.

The paper is organised as follows: this introductory section is followed by the Methodology section, which outlines the processes used for identifying, screening and selecting papers. In the Results section, the selected papers are described. This is followed by a Discussion section to integrate the findings from the review along with some numerical trends. After the Conclusion section summing up the findings, the limitations of this review and the scope for future research are outlined.

Methodology

Google Scholar was searched to identify the papers relevant to the topic. Appropriate search terms and their combinations were used to identify papers. The identified papers were screened and selected repeatedly using the inclusion and exclusion criteria listed in Table 1, using the PRISMA flow diagram.

Table 1

Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria	Remarks
Full-text journal papers and reports.	Abstracts	Abstracts may not contain all the information required.
Papers in English.	Papers in other languages	Even the best translation may distort some details.

Published 2020-2025	Published earlier	To reflect the recent trend.
	Books, chapters	Full texts are not always available.
	Dissertations	Guided research.
	Comments on other papers.	
	Reference details not available.	Citation difficulties.

Besides the above criteria, an overall quality score of 1 to 5 will be awarded depending on a clear definition of the aim, appropriateness of methodology, clear description of findings, recommendations/implications for research and/or practice and mention of limitations. An Excel file will be used to tabulate these details.

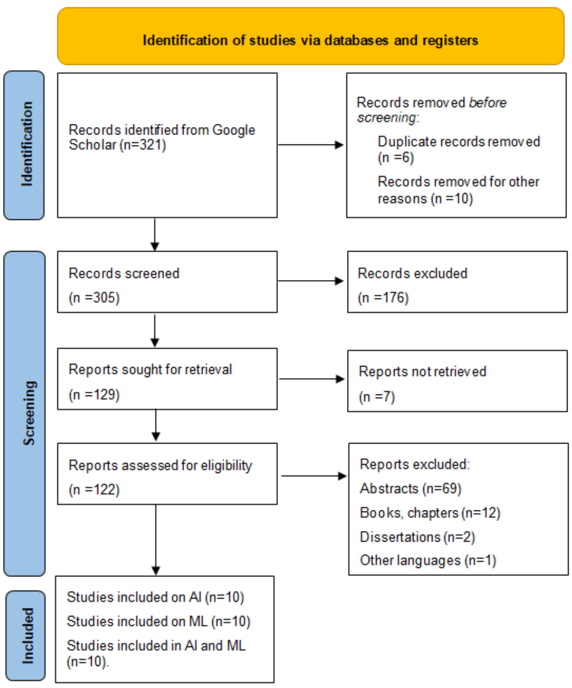
For convenience, the aim was divided into four as follows:

Leveraging AI for innovation in business and management.

Leveraging ML for innovation in business and management.

Leveraging AI and ML for innovation in business and management.

Ten papers were selected for each of these aims to provide a total of 30 papers for this review. In the following Results section, the selected 10 papers of each aim are described. The PRISMA diagram is shown below.



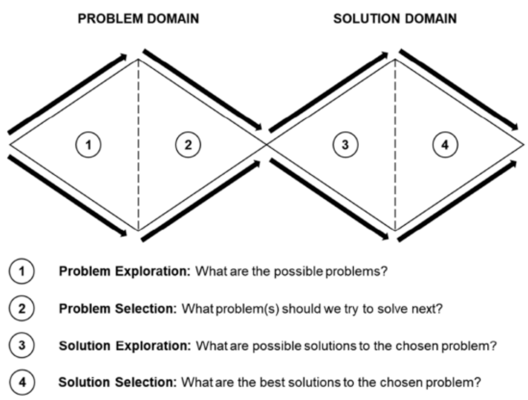
2. RESULTS

Leveraging AI for innovation in business and management

Currently, AI may not be ready to handle the more creative tasks within the innovation process. On the other hand, AI may be able to significantly support innovation managers. Kakatkar, Bilgram, and Füller (2020) performed an innovation analytics to derive computer-enabled, data-driven insights, models and visualisations within the innovation process. They observed that AI can play a key role in the innovation process by driving multiple aspects of innovation analytics. Considering the fuzzy front end of the innovation process as a double diamond (Fig.1) spanning exploration and selection of concepts in the problem and solution space, the authors discussed the aspects of innovation analytics where AI can play an important role. Four case studies of AI in action – one for each part of the innovation process – based on their previous work, demonstrated how AI-enabled innovation analytics can yield richer insights more cost-effectively. The cases were a large German manufacturer of personal care products, a leading American manufacturer of semiconductor chips, a solution exploration for crowdfunding and an American food company solving the challenges of generating new solutions for the traditional chocolate bar. The four case studies represented four phases of innovation processes: problem exploration, problem selection, solution exploration and solution selection, respectively. The authors also discussed the implications of their findings for innovation managers, considering the advantages and disadvantages of using AI in innovation. No limitation was mentioned.

Figure 1

The Double Diamond innovation process (Kakatkar, Bilgram, & Füller, 2020).



To evaluate the effects of AI on platform business model innovation (BMI), Katsamakas and Pavlov (2020) proposed a causal loop diagram (CLD). An analysis of the model showed that AI provided critical feedback loops for the business model. Managers and entrepreneurs can create, strengthen, accelerate and use such feedback loops to leverage AI for innovation. No limitation was mentioned.

Farayola, Abdul, Irabor, and Okeleke (2023) used a review of the literature aimed at dissecting the role of AI in reshaping business models, highlighting the interplay between technological innovation and business strategy.

In business models, AI enhances operational efficiency, data-driven decision-making, and customer-centric approaches. The challenges and opportunities were discussed. AI-driven business models facilitate the incorporation of AI technologies to enhance, innovate, or create new aspects of a business's operations, products, or services. These business models leverage AI for improved decision-making and operational efficiency. AI can be integrated with other advanced technologies like 5G to further accelerate this evolution, leading to more agile, efficient, and customer-centric business models.

Aiming to provide clarity on the phenomenon of business activation of AI, Sestino and De Mauro (2022) used a systematic review of the literature from 2009 to 2019. The authors used text mining methods and traditional clustering techniques to return a set of N clusters of documents, in which each cluster identifies a topic covered in literature consistent with the research objective. Then, they used the Latent Dirichlet Allocation (LDA) to analyse the content and meaning of the words. The topic modelling resulted in six topics identified from the reviewed papers. They included business implications, human implications, industrial applications, social applications, prediction methods, and recognition methods. The number of papers published on these topics increased over the years of the review. The focus areas of the six topics do not include innovation. The need to strengthen research on human implications, industrial applications and recognition methods has been stressed.

Eyo-Udo (2024) systematically reviewed the integration of Artificial Intelligence (AI) into Supply Chain Management (SCM), focusing on its impact on operational efficiency, strategic innovation, and sustainability. A content analysis was done on the selected papers from 2013 to 2023. Artificial intelligence plays a pivotal role in enhancing supply chain management by enabling more informed decision-making, lowering operational costs, and streamlining resource utilisation. Nonetheless, its adoption is shaped by key challenges, including concerns over data privacy, ethical dilemmas, and the shortage of skilled professionals. The study identifies opportunities for further investigation into innovation-driven strategies and resilience-building within supply chains. It offers strategic guidance for both practitioners and policymakers, underscoring the need to cultivate an innovation-oriented mindset, strengthen digital capabilities, and establish regulatory environments conducive to AI integration. Future research avenues include assessing the long-term effects of AI on supply chain sustainability, examining the ethical dimensions of autonomous technologies, and analysing the synergies between AI and other emerging innovations.

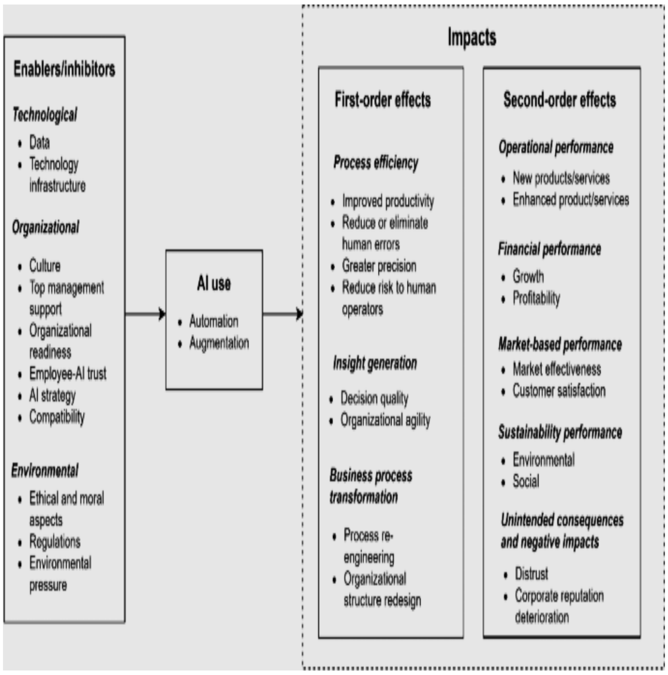
According to Truong and Papagiannidis (2022), the four stages of innovation are discovery and generation of new ideas, screening of these ideas, testing the ideas and the development of the finally selected idea for commercialisation. However, AI is now used for specific tasks in narrow domains. The ability of AI to use large volumes of data to identify trends and predict indirectly benefits innovation. These abilities can be used by managers.

Aldoseri, Al-Khalifa, and Hamouda (2024) explored the relationship between AI and innovation as foundational elements in the digital transformation framework for sustained growth and operational excellence. The study identified the key pillars to promote AI-powered innovation, including monitoring performance measurement to use the power of the present, continuous learning and innovation, data analytics and insights, predictive analytics, and innovative product development. Continuous learning, interdisciplinary collaboration, and industry partnerships are important in nurturing a thriving AI-powered innovation ecosystem. The authors used a literature review and experience-driven approach in this study.

A systematic review of 43 papers by Enholm, Papagiannidis, Mikalef, and Krogstie (2022) revealed certain technological, organisational and environmental enablers/inhibitors of AI adoption in business organisations. The impact of AI was categorised into first-order and second-order impacts. First-order impacts pertain to the changes it brings to an organisation's operational processes. These are reflected in key performance indicators (KPIs), which focus on aspects such as efficiency, effectiveness, capacity, productivity, quality, profitability, competitiveness, and overall value. AI can help in insight generation due to its ability to process large volumes of data, leading to better decision-making and innovations. The second-order impacts occur at the firm level, leading to improved operational, financial, market or sustainability performance. However, all these benefits may not be achieved in the absence of an AI governance system. The absence of a proper AI governance system can lead to unnoticed bias in the data or AI results. AI outcomes concerning gender or racial discrimination have been reported. Other negative consequences are black-box algorithms, lack of transparency and accountability, security concerns, and harm to society and the environment. Greater transparency, explainability can reduce these negative effects. The generally used theories and frameworks in AI research are contingency theory, dual-process theory, resource-based view (RBV), TOE framework, value co-destruction, organisational learning theory, network effect and theory of artificial knowledge creation. The authors identified some research gaps from this review. They include AI adoption and diffusion, AI and socio-organisational change, AI-driven value propositions, competitive value of AI (includes innovation), and AI and extended organisation. However, there are challenges of data, information, knowledge, decisions and actions in this respect. The conclusion section contains some practice recommendations. An organisational framework of AI and business value is shown in Fig.2.

Figure 2

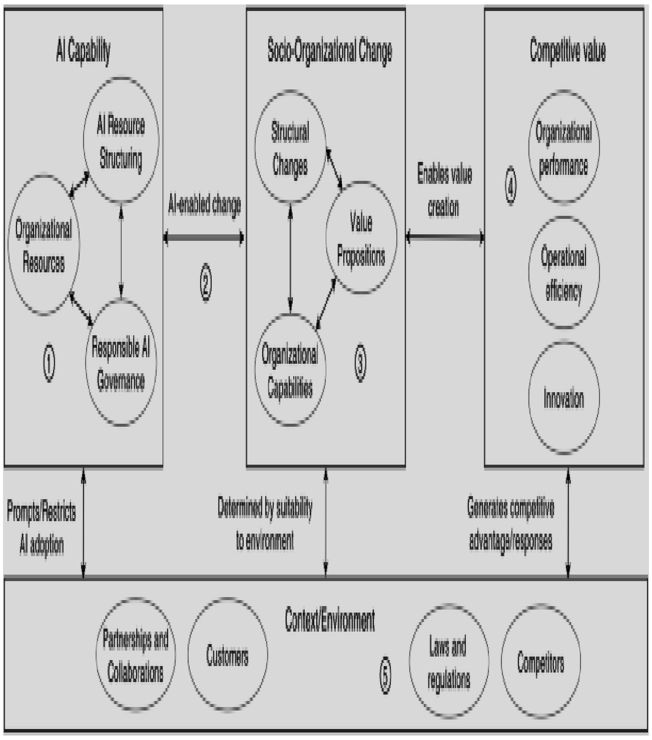
Organisational framework of AI and business value (Enholm, Papagiannidis, Mikalef, & Krogstie, 2022)



An AI and business value research framework is presented in Fig. 3.

Figure 3

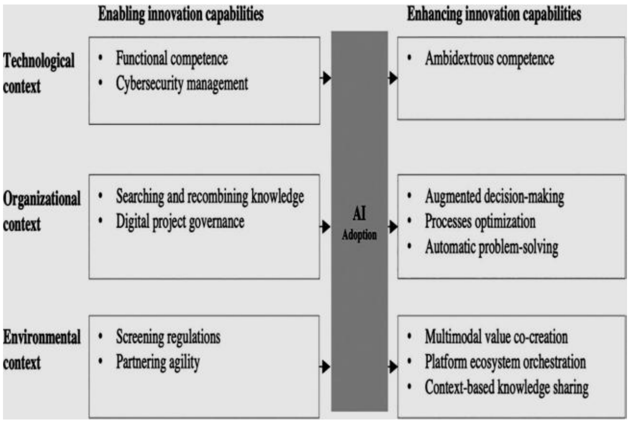
AI and business value research framework (Enholm, Papagiannidis, Mikalef, & Krogstie, 2022)



Gama and Magistretti (2025) aimed to summarise the role of AI in influencing innovation capabilities and provide a taxonomy of AI applications based on empirical studies. They used the T-O-E framework to analyse the contents of 62 papers in a systematic review. The authors discovered the dichotomous nature of AI in triggering innovation capabilities. They include enabling and enhancing capabilities. The enabling capabilities are related to AI adoption for innovation. The enhancing capabilities are related to the role of AI in creating or transforming innovation capabilities. Practically, AI is adopted to replace, reinforce or reveal. AI also develops ambidextrous (exploitative and explorative) innovation capabilities. The authors have provided some recommendations for practitioners. Some unintended ethical, legal and social consequences of using AI have been discussed. The authors mention the limitations of bias due to inclusion and exclusion criteria, limiting the study only to the T-O-E framework and the scope of rapidly evolving concepts changing the AI perspectives in innovation. The role of AI in the two innovation capacities is provided in Fig.4.

Figure 4

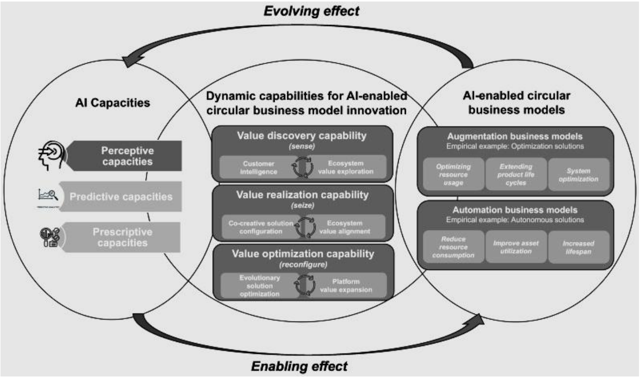
The role of AI in innovation capacities (Gama & Magistretti, 2025)



Sjödin, Parida, and Kohtamäki (2023) examined the potential of AI to facilitate circular business model innovation (CBMI) for industrial manufacturers, along with the necessary AI competencies and dynamic capabilities for their commercialisation. They analysed six leading B2B firms engaged in control systems and solutions, manufacturing, transport solutions, shipping, construction, and mining. To gather data, the authors conducted 54 in-depth interviews with knowledgeable participants from these firms. They also analysed the relevant documents available from these firms. The case studies led to the identification of AI's perceptive, predictive, and prescriptive capabilities. All three improve resource use efficiency by enhancing and automating data-driven analysis and decision-making. They also identified new dynamic capabilities related to innovating AI-enabled business models, including value discovery, value realisation, and value optimisation. These capabilities help manufacturers generate economic and sustainable value by collaborating with customers and ecosystem partners. Based on the findings, the authors proposed a framework for AI-enabled circular business model innovation (Fig. 5). Some managerial implications have been discussed. Some future research areas have been suggested. The limitations include the use of only six case studies from Scandinavia and considering only one type of CBM.

Figure 5

A framework for AI-enabled circular business model innovation (Sjödin, Parida, & Kohtamäki, 2023)



Leveraging ML for innovation in business and management

Through a comprehensive literature review, the study by Syahnur (2024) underscored the essential role of resilient technological infrastructure in advancing e-commerce performance, with particular attention to the transformative influence of emerging technologies like artificial intelligence, blockchain, and the Internet of Things. Additionally, it highlights how various forms of innovation, including product, process, business model, and organisational innovation, serve as key drivers of organisational success. The author outlined several actionable insights for e-commerce professionals and business executives, emphasising the need to prioritise digital infrastructure investments, foster an innovation-driven organisational culture, and implement customer-focused approaches to effectively respond to shifting consumer demands and expectations. Some ideas for future research have been given. Some limitations of this paper were mentioned by the author. Although the study aimed to deliver a thorough examination of e-commerce excellence, aspects like sector-specific characteristics, geographic disparities, and shifting market conditions may require deeper exploration. Furthermore, the research methodology may carry inherent limitations, including restricted sample size, potential biases in data collection, and challenges related to the broader applicability of the findings.

Innovation is essential for business success, whether through developing new products or improving existing processes. Machine learning (ML) helps accelerate product development by analysing market trends, customer feedback, and competition, making it easier to spot unmet needs and emerging opportunities. ML also enhances design and testing through simulations, reducing time to market. Leading companies like Google and Tesla are pioneers in using ML to drive innovation. In financial planning, ML improves forecasting by using historical data and current market trends to predict cash flow, optimise budgets, and evaluate investments. It also supports regulatory compliance by detecting anomalies and accounting errors. These capabilities help businesses stay resilient and financially stable, even in uncertain market conditions (Tulli, 2023).

As knowledge management (KM) fosters innovation, the factors that spark organisations' interest regarding knowledge management are globalisation, learner organisation, corporate amnesia, and technological advances. Hence, the availability of knowledge management within the organisation helps the organisation with its strategy, reduces the time spent on problem solving, and enables organisations to stay competitive in the long run. Future research stemming from this study will include a case-based analysis of implementing KM with machine learning, such as how a KM platform with machine learning can be utilised as a digital twin for patients through robo-advisory. Anshari, Syafrudin, Tan, Fitriyani, and Alas (2023) used a systematic review of 85 papers to report the above findings.

Analysis of six papers from Web of Science using SciMAT and Gioia Methodology by Jiménez-Partearroyo and Medina-López (2024) showed that business intelligence gathered from using ML for large volumes of data can enhance knowledge management and innovation. The challenges include the need for skilled personnel and adaptability to rapid technological changes. The authors presented some practical implications of their findings. The choice of only one database and the discussion of only six papers are mentioned as the limitations.

A new wave of big data analytics (BDA) firms is leveraging crowdsourced optical character recognition (OCR) data through carefully designed online experiments and sophisticated machine learning (ML) methods to predict consumer demand and assess the market viability of emerging products across various sectors. Using an in-depth qualitative analysis of a case study of a UK digital BDA firm, Mariani and Wamba (2020) developed a consumer goods company innovation (CGCI) conceptual framework. The qualitative methods consisted of in-depth interviews with nine top management of the BDA firm and 11 people from three clients of the BDA firm in two phases. Apart from the interviews, an analysis of the relevant documents was also done. The framework illustrates how digital BDA firms assist consumer goods companies in innovating and testing new products before they are launched on the market. Some theoretical and managerial implications have been discussed. The limitations are the limited number of case studies and the limited focus on the role of BDA for the clients.

The possibility of ML combined with IoT and other modern technologies in enhancing innovations in organisations was discussed by Adekunle, Chukwuma-Eke, Balogun, and Ogunsola (2021) in a PRISMA review of the literature. The aim was to explore the role of ML in automation, focusing on its applications in predictive maintenance, quality control, supply chain optimisation, and real-time monitoring. The authors discussed several practical suggestions. The challenges of data quality, transparency, and ethical aspects have been highlighted.

The role of advanced financial analytics in developing innovative financial strategies was discussed by Oyedokun, Ewim, and Oyeyemi (2024). Organisations may need to overcome the challenges of quality, privacy and security of the data, integration with the current financial systems, and shortage of skills in the required technology. The use of innovative financial strategies can lead to a competitive advantage for the organisation.

Olalekan Kehinde (2025) noted that today, ML continues to evolve, leveraging innovations such as deep learning and natural language processing to address increasingly complex challenges in healthcare. Innovative tools and practices developed by researchers are utilised in many healthcare applications by almost all healthcare organisations. These developments ensure patient-centred and evidence-based healthcare. The author has given some suggestions for research and practice.

According to Ike, et al. (2023), the potential for innovation in customer retention through ML advancements is vast. The continued development of more sophisticated algorithms can lead to even more personalised and dynamic retention strategies. In this rapidly progressing area, continuous innovation and adaptation will help to maintain a competitive edge and promote long-term customer loyalty. The authors used some real-world examples like Amazon and Netflix to illustrate their points. These case studies show how ML can be used for innovative customer retention strategies.

The increasing complexity and sophistication of cyber threats necessitate innovative approaches to cybersecurity. ML plays a transformative role in automating cybersecurity through its predictive analytical techniques. Organisations can strengthen system resilience by applying ML algorithms to uncover patterns and detect anomalies, enabling real-time threat identification and proactive risk mitigation. Predictive analytics further supports this approach by anticipating future vulnerabilities and attack pathways using historical data. Combined, these technologies facilitate a transition from reactive to proactive cybersecurity, equipping organisations with more adaptive and robust defence mechanisms in a rapidly evolving digital landscape (Karamchand, 2023).

Leveraging AI and ML for innovation in business and management

AI-driven chatbots and virtual assistants are unlocking new opportunities by boosting operational efficiency, lowering expenses, and uncovering novel revenue channels. Cutting-edge tools like demand forecasting, dynamic pricing, anomaly detection, and automated data analytics further accelerate innovation, empowering businesses to make agile, data-informed decisions in a fast-changing market environment. Ultimately, the integration of artificial intelligence, machine learning, and business intelligence marks a transformative shift for financial institutions, ushering in a new era of innovation, strategic advantage, and digital-era success. Babatunde (2024) compared the USA and Nigeria on the progress and status of AI and ML adoption and its consequences.

As organisations are facilitated by AI, ML and blockchain to embrace innovations, they gain competitive edges, optimise resource allocation, and elevate customer satisfaction in a dynamic marketplace. The three technologies together form the trinity of innovations. The synergies among the three technologies are exemplified by IBM Food Trust, HSBC and AI-powered trade finance, supply chain management in pharmaceuticals, smart grids in the energy sector and healthcare data management. The challenges of implementing them are ethical, security and regulatory. Based on these reviewed findings, Chowdhury (2024) provided some recommendations for businesses, some emerging trends and scope for future research.

A review by Iyelolu, Agu, Idemudia, and Ijomah (2024) aimed to provide a comprehensive understanding of the current state of AI in SMEs, offering insights into overcoming challenges and capitalising on future opportunities for growth and innovation. The authors used a systematic review and a critical evaluation of selected studies. SMEs need to innovate to foster economic and employment growth, enhance operational efficiency, improve market performance, develop resilience to external shocks, and thereby enhance their competitiveness. AI (and ML) have the potential to drive innovations in SMEs by overcoming the barriers to their adoption and allowing future growth opportunities. These technologies can significantly enhance operational efficiency, product development, customer engagement, and competitive advantage for SMEs. The specific barriers to adoption of these technologies by SMEs are a lack of skill, a lack of infrastructure, resistance to change and issues related to data privacy and security. To overcome these barriers, they require assistance with government incentives, public-private partnerships, training in skills, affordable models of AI as a service, a supportive ecosystem with good infrastructure, favourable regulations, and access to funds. Six case studies were discussed to demonstrate the usefulness of AI and ML for innovation in SMEs. Some future trends of research were discussed.

Pattanayak (2021) explored how generative AI (Gen AI) and machine learning (ML) could transform innovation in business consulting. Innovation managers see both promise and risk in this digital shift, particularly as technology complicates information retrieval and analysis. To overcome these challenges, managers may increasingly depend on AI and ML to identify opportunities and assess competitive advantages, balancing algorithmic insights with human intuition to enhance decision-making. The research combined a systematic review of 98 papers with a Delphi study involving interviews with ten experts and two survey rounds with 19 and 11 participants, respectively. Findings suggest that while core innovation types remain stable, the methods of innovation are evolving. GenAI's capacity to process diverse data sources enables idea generation from customer input and interdisciplinary links, fostering collaborative and hybrid innovation models. It may also reshape perceptions of creativity, challenging traditional artistic norms and redefining scientific and artistic innovation. GenAI is poised to significantly influence new product development (NPD) processes.

Akter, Michael, Uddin, McCarthy, and Rahman (2022) explored digital business transformation through four technologies: AI, blockchain, cloud computing and data analytics (ABCD). Integration, hybridisation, recombination and convergence of ABCD determine the dynamic nature of innovation. Such a digital transformation has conferred immense benefits to organisations in healthcare, manufacturing, automotive, consulting, entertainment, technology and retail sectors. The authors provided some ideas for future research.

Segun-Falade, et al. (2024) noted that modern energy management system (EMS) software harnesses AI, machine learning, and IoT to enhance energy efficiency, lower operational expenses, and reduce environmental impact. By aggregating real-time data from diverse sensors and devices, these systems offer detailed insights into consumption patterns, helping industries quickly detect inefficiencies and take corrective action. A key advancement in EMS is the creation of intuitive dashboards that simplify complex energy data for users. Case studies across sectors like manufacturing, logistics, and data centres highlight the practical benefits of adopting advanced EMS solutions. The authors advocate for ongoing research to further innovate EMS technologies.

Generative AI, along with ML, has led to many business model innovations (BMI). Kanbach, Heiduk, and Blueher (2024) conducted a scoping review with content analysis consisting of 513 data points from academic publications, company reports, and public information such as press releases, news articles, interviews, and podcasts. BMI is an attempt to create, implement, and sustain strategies to generate, deliver, and capture value. Here, innovation means modifying the architecture or configuration of a business model regarding its activities and components. Thus, BMI consists of three types of innovation: value creation, value capture, and new proposition. The authors discussed these three types of innovations using case studies from software engineering, healthcare and financial services. The authors gave three propositions on GAI's impact on innovation: GAI as an innovation initiator, determining the degree of innovation, and determining the timing of innovation. The limitations of this paper are that the findings are getting fast outdated, not all sources are research articles, non-inclusion of papers other than English, possible subjective bias in discussions and limiting the discussions to three case studies.

Joel, Oyewole, Odunaiya, and Soyombo (2024) analysed the trends, challenges, and opportunities of digital transformation in business development. The authors also explored how businesses across industries are leveraging digital technologies to transform their operations, improve customer experiences, and drive growth. They examined the challenges businesses face in implementing digital transformation initiatives and the opportunities digital transformation presents for future business development strategies. Companies are increasingly adopting digital technologies such as cloud computing, AI, ML, IoT, and big data analytics to drive innovation. Digital transformation opens up new opportunities for innovation and the development of new business models, enabling companies to stay competitive in a rapidly changing market. Digital transformation is reshaping business development strategies, driving innovation, and creating new growth opportunities. Digital transformation enables organisations to develop innovative products and services by leveraging emerging technologies. The authors used a qualitative review and two case studies to explain the above points. Some possible future trends were also presented.

In the automotive domain, artificial intelligence (AI), machine learning (ML), and generative AI (GAI) are pivotal in driving design innovation. Their convergence is instrumental in advancing autonomous vehicle technologies, enhancing safety, efficiency, and responsiveness to consumer preferences. Madhavaram, Sunkara, Kuraku, Galla, and Gollangi (2024) underscore the transformative impact of AI and ML on operational efficiency and design innovation through a qualitative literature review. In the context of rapidly evolving automotive manufacturing, innovation emerges as a critical determinant of progress. Cutting-edge technologies such as AI and ML are revolutionising production workflows and enriching product capabilities, thereby fostering greater efficiency and sustainability. For example, AI integration enables manufacturers to more precisely predict the mechanical properties of automotive materials. The study highlights how ML techniques can optimise these properties by analysing processing parameters and material characteristics, streamlining the design process and minimising costs typically incurred through conventional trial-and-error methods. As the industry undergoes digital transformation, manufacturers are increasingly equipped to adapt to dynamic consumer expectations and stringent environmental standards, reinforcing their competitiveness and long-term sustainability. Cultivating a culture of continuous innovation is therefore essential for professionals navigating the future of automotive manufacturing. The innovations discussed offer multifaceted benefits to the sector, and the authors provide insights into the prospective applications of AI and ML. Additionally, the diagrams included in the study may serve as valuable resources for automotive designers aiming to leverage these technologies for cutting-edge vehicle development.

The convergence of automation and process optimisation within AI-driven digital transformation has become a critical approach for organisations seeking to boost operational efficiency, stimulate innovation, and maintain a competitive edge. Aldoseri, Al-Khalifa, and Hamouda (2023) offered a novel contribution by presenting a structured and comprehensive roadmap that delineates the core principles essential for effectively integrating automation and refining processes in the context of emerging AI technologies. The authors introduced an integrated framework anchored in eight foundational pillars: Data-Driven Insights, Seamless Automation, Adaptive Learning and Continuous Improvement, Human-Centric Collaboration, Ethical and Responsible AI, Strategic Alignment, Scalability, and Innovation. These pillars serve as strategic touchstones for navigating the complexities of automation-led transformation initiatives. By adopting this framework, organisations are equipped to unlock the full potential of automation, drive sustained innovation, and establish themselves as frontrunners in the dynamic realm of AI-enabled business transformation.

3. DISCUSSION

Except for five empirical studies, the rest of the 30 reviewed papers were reviews with or without case studies. In the case of reviews, unique methods of analysis were used in five papers. Some other trends are discussed below.

Number of papers in different years

The number of papers published in different years is presented for each aim in Table 2.

Table 2

The number of papers in different years

Year	No.	No.	No.	
	AI	ML	AI +ML	Total
2020	2	1	0	3
2021	0	1	1	2
2022	3	0	0	3
2023	2	4	1	7
2024	2	3	8	13
2025	1	1	0	2
Total	10	10	10	30

As shown in Table 2, the highest number of papers was published in 2024 (13) and in the case of AI+ML (8). Seven papers were published in 2023. The peak number of papers published in the case of AI was three in 2022. For ML, the highest number of four papers was published in 2023.

Method

The number of papers using different methods of study for each aim is presented in Table 3.

Table 3

The number of papers using different methods of study

Method	No.	No.	No.	Total
	AI	ML	AI+ ML	
Empirical	1	2	2	5
Discussion	1	2	1	4
Discussion + Case studies	1	0	0	1
Qualitative review	0	3	1	4
Qualitative review + Case studies	0	1	4	5
Systematic review	5	2	1	8
Systematic review + Case studies	0	0	0	0
Others	2	0	1	3
	10	10	10	30

Comparatively, empirical studies were very few, with only five papers using this method. Nine papers were qualitative reviews with (5) or without case studies or real-world examples (4). There were eight systematic reviews, but none with case studies or real-world examples. The need for more empirical studies is highlighted by this analysis.

Implications

The number of papers providing implications of their findings is given in Table 4.

Table 4

The number of papers providing implications of their findings

	No.	No.	No.	Total
Implications	AI	ML	AI+ML	
Theoretical	0	1	0	1
Practical	7	7	8	22
Theoretical and practical	2	0	0	2
Research	4	3	4	11
NA	0	2	0	2
Total	13	13	12	38

The totals are more than 10 for each aim (13 each for AI and ML and 12 for AI+ML) and thus, 38 for all aims. This is due to some papers providing more than one type of implication. Practical implications dominate for all three aims (7 each for AI and ML and 8 for AI+ML) and thus for the total (22). There were 11 research papers consisting of 4 for AI, 3 for ML and 4 for AI+ML.

Mention of limitations

A good quality paper mentions limitations of the study to caution readers about the applicability of the findings. In this review, the mention of limitations showed a unique trend. The number of papers mentioning/not mentioning limitations for each aim is presented in Table 5.

Table 5

The number of papers mentioning/not mentioning limitations

	No.	No.	No.	Total
Limitations	AI	ML	AI+ML	
Not mentioned	8	7	9	24
Mentioned	2	3	1	6
Total	10	10	10	30

Out of 30 reviewed papers, only six mentioned any limitations of their studies. Out of this, eight AI-related papers, seven ML-related papers and nine AL+ML-related papers did not mention any limitations.

Quality of the reviewed papers

As was outlined in the Methodology section, the quality of the papers was assessed on a 0 to 5 scale for aim, methodology, findings, implications and mention of limitations. The observed trend in the quality of the 30 reviewed papers is given in Table 6 for each aim.

Table 6

The quality of the reviewed papers

	No.	No.	No.	Total
Quality	AI	ML	AI+ML	
2 to 3	7	7	4	18
3.5 to 4	1	0	5	6
4.5 to 5	2	3	1	6
TOTAL	10	10	10	30

Out of 30, 18 papers were of poor quality, with the scores ranging from 2 to 3. Six papers each were of medium (3.5 to 4) and high (4.5 to 5) quality. Thus, the general trend was poor quality trending towards medium and high qualities.

Integration of findings

Components of innovation analytics of AI could promote innovation (Kakatkar et al., 2020) with critical feedback if necessary (Katsamakas & Pavlov, 2020). Similarly, financial analytics can promote innovative financial strategies (Oyedokun, 2024)

According to Farayola et al. (2023), AI can create, enhance or innovate new products or services. Innovative ways of supply chain management were identified by Eyo-Udo (2024). Truong and Papagiannidis (2022) observed that most organisations do not use AI in all stages of the innovation process. Aldoseri et al. (2024) identified the requirements to promote the four AI-enabled innovation pillars. Enholm et al.(2022) identified technological-organisational-environmental factors affecting AI adoption for innovation. AI can help in innovations either by directly causing it or by creating ambidextrous innovation capabilities (Gama & Magistretti, 2025). Sjödin et al. (2023) identified new dynamic capabilities related to innovating AI-enabled business models, including value discovery, value realisation, and value optimisation.

Various forms of innovation, like product, process, services, and business model, are promoted by a resilient technology like ML (Syahnur, 2024). Tulli (2023) noted that ML accelerates product development by analysing market trends, customer feedback, and competition, making it easier to spot unmet needs and emerging opportunities. The essentiality of promoting knowledge management for innovations through ML was stressed by Anshari et al. (2023). According to Jiménez-Partearroyo and Medina-López (2024), business intelligence gathered from using ML for large volumes of data can enhance knowledge management and innovation. A framework to show how digital BDA firms assist consumer goods companies in innovating and testing new products before they are launched on the market was proposed by Mariani and Wamba (2020). ML can promote innovations if combined with IoT (Adekunle et al., 2021). According to Olalekan Kehinde (2025), ML continues to evolve, leveraging innovations such as deep learning and natural language processing to address increasingly complex challenges. There is great potential for innovation for customer retention using ML (Ike et al., 2023). ML can be useful to devise innovative approaches for cybersecurity (Karamchand, 2023).

The combination of AI, ML, Blockchain, IoT and Generative AI can enhance innovation through their effects on different types, stages, components and aspects of the innovation process (Babatunde, 2024; Chowdhury, 2024; Pattanayak, 2021; Jain et al., 2024; Segun-Falade et al., 2024; Kanbach et al., 2024; Joel et al., 2024; Madhavaran et al., 2024). This is true for SMEs also (Iyelolu et al., 2024). AL and ML serve strategic innovations through the eight pillars of an integrated framework (Aldoseri et al., 2023).

4. CONCLUSIONS

This systematic review of 30 papers aimed to examine the role of AI, ML or AI and ML in promoting innovations in organisations. All three technologies, along with others like blockchain and IoT, were found to influence innovations in different ways and in various organisational contexts. New frameworks suggested in a few reviews help to examine how innovations develop and benefit organisations. However, there are many barriers to the large-scale adoption of these technologies for innovations. These barriers include data privacy, transparency, and reliability, skill deficits, organisational capabilities and the business environment.

Limitations of this review

Use of only Google Scholar might have missed numerous papers obtainable from databases. Selecting only the papers in English might have missed important papers published in other languages. The target of 10 papers each for three aims might have limited the scope for selecting more important papers.

By default, 17 out of 30 papers were reviews of various types. The selection of more empirical studies might have led to more useful results. Out of 30, 18 papers were of poor quality. The selection of good-quality papers might have altered the results.

Scope for future research

Although the trends obtained from 30 papers cannot be generalised, the lack of adequate empirical studies needs to be addressed by more empirical research in this area. The papers need to be of better quality and must mention their limitations.

Mixed research approaches were rare among the reviewed papers. There should be greater use of mixed methods in empirical research in future.

There is a lack of theoretical adequacy for the concepts highlighted in some papers. More theoretical studies are warranted.

Comparisons between best practices in using AI, etc, for innovations in different countries may be useful.

Some studies should deal with demographic characteristics of organisational leadership in determining innovations driven by technologies.

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