UrNammu Journal of Business, Accounting and Technology Management (UJBATM)

ujbatm.urnammuacademy.org

Harnessing Artificial Intelligence for Green Innovation in the Oil Industry: The Mediating Role of Knowledge Management

Sama M.M. Thabit[1] **Hayder DH. Hussein**[2] **Mohd. Abass Bhat**[3] **Shafique Ur Rehman**[4]

[1] *College of Administration and Economics, University of Mosul, Mosul, Iraq.*

[2] *College of Administration and Economics, University of Al-Hamdaniya, Al-Hamdaniya, Iraq.*

[3] *College of Economics and Business Administration, University of Technology and Applied Sciences, Muscat, Oman.*

[4] *College of Management, Shenzhen University, China.*

Article information

Article history:
Received 15 February, 2025
Accepted 17 May, 2025
Published online 1 June, 2025

Keywords:
Artificial Intelligence
Green Innovation
Knowledge Management
Oil Industry
PLS-SEM

UrNammu Journal of Business, Accounting and Technology Management, *Vol. 1, No. 1, 2025, 30-62.*
ISSN:

Abstract

In light of growing environmental concerns and sustainability imperatives, green innovation (GI) has become a strategic priority for industries worldwide. This study investigates the role of artificial intelligence (AI) in enhancing green innovation—both proactive (PGI) and reactive (RGI)—through the mediating mechanisms of knowledge management (KM) processes, namely knowledge generation (Kg), knowledge storage and sharing (KSS), and knowledge application (Ka). Grounded in knowledge-based and resource-based theories, the study examines data collected from 572 engineers working across Iraq's three largest state-owned oil companies. Using Partial Least Squares Structural Equation Modelling (PLS-SEM), the results confirm that AI significantly enhances both PGI and RGI. Furthermore, KM processes mediate the relationship between AI and GI, with knowledge application showing the strongest mediating effect. The findings provide robust empirical support for the integrative role of KM in translating AI capabilities into environmentally sustainable innovation. Within the context of the Iraqi oil sector—a resource-dependent and environmentally sensitive industry operating in a developing economy—the study highlights how digital transformation, if strategically managed through KM practices, can foster sustainability without compromising operational performance. Theoretically, this research extends the understanding of AI-GI linkages by embedding KM as a central mediating mechanism. Practically, it offers actionable insights for energy sector leaders and policymakers in developing countries on how to leverage AI not only for efficiency gains but also for advancing environmental objectives through effective knowledge mobilisation.

DOI: ,
CA: *Sama M.M. Thabit, sama.mohammed@uomosul.edu.iq*.

1. Introduction

In an era increasingly defined by escalating environmental crises—ranging from climate change and biodiversity loss to resource depletion—organisations are under mounting pressure to strike a sustainable balance between environmental stewardship and economic performance (Rehman et al., 2021). In this context, green innovation (GI) has emerged as a critical pathway to organisational resilience and competitiveness. It has garnered widespread attention across both scholarly and industrial domains (Mothe et al., 2017). It defined as the development and application of environmentally sound products, processes, and practices, GI encompasses both proactive and reactive dimensions. Proactive green innovation (PGI) involves anticipatory strategies to pre-empt environmental challenges, whereas reactive green innovation (RGI) focuses on adaptive responses to external ecological demands (Alkaraan et al., 2024; Bai et al., 2022). However, the implementation of GI, particularly in resource-intensive sectors such as oil and gas, requires more than policy compliance or technological adoption—it demands robust systems of knowledge acquisition, integration, and utilisation.

Among the transformative technologies enabling this shift, artificial intelligence (AI) stands at the forefront. AI encompasses a suite of computational techniques—including machine learning, deep learning, neural networks, natural language processing, and computer vision—that enable systems to learn from data, predict outcomes, and enhance decision-making (Kaplan, 2023; Taha & Abbas, 2023). Within the industrial sector, particularly oil and gas, AI has demonstrated substantial potential in predictive maintenance, emissions monitoring, resource optimisation, and anomaly detection (Eloranta et al., 2021; Holmström, 2022). However, the value derived from AI hinges not solely on its technological features but on an organisation's capacity to absorb and apply AI-generated knowledge. This is particularly true in developing economies where technological modernisation often encounters institutional and human capital barriers.

This brings to the fore the critical role of knowledge management (KM). As a strategic organisational capability, KM encompasses a range of processes such as knowledge generation (Kg), storage and sharing (KSS), and application (Ka) that facilitate the conversion of data into actionable insights (Acharya et al., 2022; Al Shraah et al., 2021). These KM processes are essential for translating AI-generated data into environmental innovations that align with sustainability goals. For instance, the generation of eco-specific knowledge enhances innovation design, while sharing that knowledge across departments supports cross-functional collaboration. Ultimately, the application of such knowledge leads to tangible outcomes in green product development, resource-efficient processes, and regulatory compliance (Benabdellah et al., 2021; Mothe et al., 2017).

While scholarly attention to AI, KM, and green innovation is growing, significant theoretical and empirical gaps persist. Firstly, much of the existing literature examines AI and innovation in isolation, neglecting the integrative role of KM (Mariani et al., 2023; Sahoo et al., 2022). Secondly, the dual nature of GI—proactive and reactive—has been underexplored in relation to AI technologies, especially in developing country contexts where institutional readiness and digital capabilities are heterogeneous (Sudirjo, 2023). Thirdly, there is a paucity of empirical studies within the oil sector, which is both knowledge-intensive and environmentally sensitive, and thus an ideal setting for examining AI-KM-GI linkages. Existing studies have examined AI's potential in operational efficiency (Khelifi et al., 2020) or KM's role in innovation (Daradkeh, 2023), but rarely within a unified conceptual framework that captures the mediating function of KM in the AI–GI nexus.

This research is particularly salient for Iraq, a country whose economy is deeply entrenched in the oil sector, which contributes over 90% of government revenues. Iraq's state-owned oil companies operate in an environment of high environmental vulnerability, antiquated infrastructure, and increasing international pressure to decarbonise (Abdulmuhsin, Alkhwaldi, et al., 2025). Despite possessing vast reserves and a skilled engineering workforce, many Iraqi oil enterprises lag in digital integration and environmental innovation due to bureaucratic inertia, weak regulatory enforcement, and underdeveloped knowledge systems. The integration of AI into these companies—particularly when coupled with strong KM practices—presents a promising avenue to overcome structural inefficiencies and facilitate the transition to greener operations. For instance, AI can assist in leak detection, emissions tracking, and reservoir modelling, while KM processes can ensure these insights are institutionalised and leveraged across operational units.

While prior research has examined AI in manufacturing and KM in service industries, few studies have explored their synergistic effects on green innovation in oil-dependent developing countries (Abdulmuhsin et al., 2024; Abdulmuhsin, Hussein, et al., 2025). This constitutes a notable gap in the literature, both conceptually and contextually. Existing studies tend to isolate the roles of AI and KM or focus exclusively on reactive compliance rather than strategic sustainability. Moreover, empirical studies in the Middle East and North Africa (MENA) region often neglect the nuanced organisational dynamics within state-owned enterprises operating under political and economic constraints.

Accordingly, the current study seeks to address these gaps by examining the impact of AI on both proactive and reactive forms of green innovation, mediated by KM processes, within the Iraqi oil sector. By focusing on engineers within the country's three largest oil companies, the study contributes new empirical insights into how digital technologies and organisational knowledge capabilities intersect to drive environmental performance in a high-stakes industrial setting.

The primary objective of this research is to develop and empirically test a conceptual model that elucidates the relationships between AI, KM processes, and GI outcomes. In doing so, it offers both theoretical enrichment—by integrating digital transformation with knowledge-based and innovation management theories—and practical guidance for policymakers, environmental managers, and oil-sector executives in Iraq and other resource-rich developing nations facing similar sustainability challenges. This paper is organised in seven main sections, introduction, theoretical background and hypothesis development, methodology, results, discussion, conclusion and implications, and finally the future works.

2. Theoretical Background and Hypothesis Development

2.1 Green Innovation

Green innovation (GI) represents a natural evolution of the broader innovation paradigm, arising in response to heightened environmental awareness and the urgent need to mitigate the adverse impacts of economic activities on the natural environment. The term "green innovation" first gained traction in the mid-20th century, describing innovations aimed at reducing or eliminating environmental harm (Franceschini et al., 2016). The general concept of innovation can be traced back to Schumpeter in 1934, who characterised it as the industrial or commercial application of something novel (Datta et al., 2019; Ziemnowicz, 2013). Over time, the concept has expanded to encompass organisational, managerial, and technological changes that enhance a firm's environmental performance (Spena et al., 2016). Green innovation has thus emerged as a multidimensional construct serving environmental, economic, and social objectives.

It is broadly defined as the development or implementation of new products, processes, or organisational methods that improve a firm's environmental performance while conserving natural resources (Laihonen & Kokko, 2020). The accelerating pace of environmental degradation and the intensification of global challenges, such as climate change, have compelled organisations to adopt green innovation as a strategic necessity (Cosgrove & Loucks, 2015). This form of innovation has become closely linked to contemporary business models that seek to enhance competitiveness by reducing environmental costs and strengthening corporate image (Chen et al., 2006). Empirical evidence also suggests that green innovation transcends technological tools; it encompasses a cultural orientation within organisations that promotes learning, collaboration, and co-creation among employees (Muñoz-Pascual et al., 2019).

A core objective of green innovation is to develop products and services that minimise waste and emissions while advancing the use of renewable energy sources (Pata & Balsalobre-Lorente, 2022). As such, green innovation is increasingly recognised as a critical enabler of the United Nations

Sustainable Development Goals (SDGs) (S. J. Khan et al., 2021), positioning it as a strategic imperative in addressing global environmental challenges (Rajkhowa & Sarma, 2021).

The significance of green innovation lies in its ability to reconcile environmental and economic goals. It contributes to improved productivity, cost-efficiency over the long term, and enhances employee satisfaction and organisational commitment (Asadi et al., 2020). Furthermore, it confers a competitive advantage in green markets through the delivery of environmentally friendly and value-added products (Song et al., 2020). Stakeholders—including consumers, suppliers, and regulatory bodies—are increasingly incentivising organisations to adopt green practices, thereby making green innovation a vital determinant of corporate reputation and stakeholder loyalty (El Baz & Laguir, 2017). Additionally, green innovation facilitates regulatory compliance and enables organisations to meet environmental standards, serving as an effective mechanism to ensure organisational survival and sustainability amid growing ecological pressures (Bask et al., 2018). In light of these benefits, it is recommended that organisations prioritise green innovation as a strategic pillar, acting as a bridge between economic advancement and environmental stewardship.

2.2 Green Innovation: Characteristics and Types

Green innovation is distinguished by five fundamental characteristics that render it a potent strategic tool in the governance of modern organisations. First, *strategic orientation*—green innovation enables organisations to design and implement sustainable practices that minimise resource consumption and reduce emissions. This, in turn, enhances organisational performance and fosters long-term competitive advantage (El-Kassar & Singh, 2019; Wu & Sekiguchi, 2023). Second, *cost efficiency*—green innovation facilitates cost reduction by improving operational efficiency and mitigating financial and environmental risks (Zhang & Vigne, 2021). Third, *environmental protection*—this dimension places ecological benefits at the forefront of organisational goals, enabling firms to respond constructively to environmental challenges, particularly in pollution-intensive sectors such as manufacturing (Fang et al., 2020; Rennings, 2000). Fourth, *competitive advantage*—green innovation supports early market entry and the delivery of environmentally friendly, innovative solutions, which foster clear differentiation and enhance market value (Aziz & Samad, 2016; Cillo et al., 2019). Fifth, *sustainability*—green innovation is a cornerstone of both internal and external sustainable development, encouraging individuals and institutions to adopt positive environmental behaviours and practices (Guoyou et al., 2011; Singh & El-Kassar, 2019).

Green innovation is typically categorised into two principal dimensions: Proactive Green Innovation (PGI) and Reactive Green Innovation (RGI) (Chen et al., 2012). Proactive green innovation entails a voluntary and forward-looking approach, where organisations pre-empt environmental threats by developing novel eco-friendly products and practices. This dimension reflects an entrepreneurial market orientation aimed at cost reduction, environmental distinction, and stakeholder trust (Aragón-Correa & Sharma, 2003; Hart, 1995). Its benefits are often realised over the long term, promoting green creativity and enabling radical innovation (Bianchi et al., 1997). Conversely, reactive green innovation represents an organisation's response to external environmental pressures and regulatory mandates, rather than a self-initiated commitment to innovation. It is predominantly compliance-driven, focusing on meeting existing environmental standards rather than shaping them (Yol Lee & Rhee, 2007). While often viewed as less progressive, reactive strategies may nonetheless yield incremental environmental improvements that meet beneficiary expectations and enhance environmental performance (Chen et al., 2006). The key distinction between the two lies in orientation: while proactive green innovation drives the market through innovation, reactive green innovation follows the market through adaptation.

2.3 Artificial Intelligence

The theoretical foundations of artificial intelligence (AI) can be traced back to the mid-twentieth century, particularly through the seminal work of Alan Turing, who laid the groundwork for conceptualising how machines could emulate human thought processes (Ali et al., 2023). However, the formal inception of the field is widely recognised as the 1956 Dartmouth College Conference, where foundational research questions were proposed, shaping the trajectory of future AI development (Glauner, 2020). The term "artificial intelligence" was coined by John McCarthy, who defined it as a scientific domain concerned with developing systems capable of performing cognitive tasks akin to those carried out by humans, such as speech and image recognition, natural language processing, and decision-making (Yablonsky, 2019).

Over time, AI research has evolved into two major streams: expert systems based on rule-driven logic, and machine learning, which relies on data analysis and pattern recognition (Strickland, 2021). With the rapid advancement of digital technologies, the scope of AI has broadened to include areas such as deep learning, computer vision, and natural language processing (Mich, 2020). These technologies have significantly enhanced capabilities in data analytics and decision-making, particularly in an era increasingly shaped by big data (Apell & Eriksson, 2021).

Contemporary definitions underscore AI's multidimensional nature: it is seen as an interdisciplinary scientific field (Bobrow & Stefik, 1986), a problem-solving and decision-making tool that mimics human reasoning (Ross, 2008), and a set of systems capable of learning, adapting, and engaging in complex interactions (Budhwar et al., 2023; Popenici & Kerr, 2017). This diversity of perspectives has catalysed the adoption of AI across a wide range of sectors.

AI's value lies in several intrinsic advantages. Notably, automation and efficiency—AI systems can perform repetitive tasks with high speed and accuracy, thereby boosting productivity (Kunduru, 2023). Data analysis and insights—AI can process vast volumes of data, identify patterns, and derive actionable insights for decision-making (Polonsky & Rotman, 2023). Innovation and creativity—AI technologies can generate novel solutions and designs across various disciplines (Vartiainen & Tedre, 2023).

Furthermore, AI plays a central role in personalised services by analysing user behaviour to deliver tailored recommendations, as exemplified in streaming platforms and e-commerce (Vijayan et al., 2023). In healthcare, AI supports diagnostics, medical imaging analysis, and drug development (Iqbal et al., 2023). Applications such as digital assistants leverage natural language processing to improve human-machine interaction (Domini et al., 2023). AI is also instrumental in cybersecurity, where it detects threats and analyses data to identify anomalies (Raza et al., 2023).

Additionally, AI is embedded in autonomous systems, including vehicles and drones (Bratu, 2023). It contributes to reducing operational costs through automation and resource optimisation (Banga & Peddireddy, 2023) and supports global economic growth and job creation (Jermsittiparsert et al., 2019). From an environmental perspective, AI fosters positive sustainability outcomes—enhancing energy efficiency and reducing emissions (Ahmad et al., 2021). It also aids in tackling complex challenges in climate, transport, and energy systems, positioning AI as a vital driver of innovation and future development (M. I. Khan et al., 2021).

2.4 The Application of Artificial Intelligence in the Oil Sector

Oil remains one of the most vital sources of energy globally, accounting for approximately one-third of total energy consumption. It is a fundamental component of daily human life, underpinning transportation, electricity generation, and petrochemical products (Zhiznin et al., 2023). Amid rising global demand for fossil fuels, there is an urgent need to adopt innovative approaches to enhance the efficiency of the oil and gas industry. In this context, AI has emerged as a strategic enabler for improving operational processes, enhancing safety, and supporting data-driven decision-making with greater precision (Choubey & Karmakar, 2020).

AI technologies are employed across various facets of the oil industry, beginning with geological exploration. Here, AI algorithms play a key role in analysing seismic data and accurately predicting the location of potential oil and gas reservoirs (Kuang et al., 2021). Machine learning techniques further assist in interpreting well logs and sedimentary environments, helping reduce risk and improve the understanding of reservoir characteristics (Iraji et al., 2023).

In drilling operations, AI-powered smart drilling systems optimise drilling parameters in real time, significantly reducing downtime and enhancing overall efficiency (Guo et al., 2023). Predictive maintenance is another critical application, where sensor data are analysed to anticipate equipment failures before they occur, thus lowering operational costs and minimising system outages (Rahman et al., 2023).

Within the production and supply chain context, AI systems help detect patterns and anomalies in production processes, allowing companies to improve performance and identify bottlenecks in advance (Md et al., 2022). Historical data can also be leveraged to forecast material and equipment requirements, thereby improving inventory management efficiency and reducing waste (Albayrak Ünal et al., 2023; Kehayov et al., 2022).

From a safety and environmental perspective, AI enhances the monitoring of industrial facilities through the deployment of drones and smart sensors, which are used to detect safety breaches, monitor compliance, and identify leaks or system failures at an early stage (Kuru et al., 2023). Intelligent robotics play a vital role in inspecting and maintaining pipelines, which are often buried underground or submerged. These pipelines are susceptible to issues such as corrosion or cracking, posing significant risks to both the economy and environment in the event of a spill (Elankavi, 2020; Shukla & Karki, 2013). Given the dangers of manual maintenance under extreme conditions involving high pressure and temperature, robotic systems offer an efficient and safe alternative, making them a critical asset in oil infrastructure management (Lin et al., 2021).

Therefore, artificial intelligence is proving instrumental in transforming the oil and gas sector by improving operational efficiency, reducing costs, enhancing safety, and advancing environmental sustainability in an industry facing growing ecological and technological challenges.

2.5 Artificial Intelligence and Green Innovation

The rapid advancement of information technologies has fundamentally reshaped business models, positioning AI as a powerful catalyst for innovation—particularly within the domain of green innovation, which seeks to foster sustainable development while minimising the environmental impact of industrial activities. In this regard, AI is considered a versatile general-purpose technology that enhances productivity, supports informed decision-making, and stimulates environmental innovation across both proactive and reactive dimensions (Agrawal et al., 2019; Brynjolfsson & Mitchell, 2017).

The relationship between AI and green innovation is grounded in several key pillars. Foremost among these is the integration of big data and the Internet of Things (IoT), which together generate vast volumes of real-time data that AI algorithms can analyse to drive ecological innovation (Filiou et al., 2023). Predictive technologies are employed to forecast environmental demand, allocate resources efficiently, optimise supply chains, and reduce waste and emissions (Rahman et al., 2023).

With respect to proactive green innovation, AI provides robust tools for developing environmentally sustainable solutions that anticipate regulatory changes or market needs. This is achieved through the analysis of future trends and early responses to climate and environmental fluctuations (Chen et al., 2006; Keicher et al., 2022). Such capabilities support the design of sustainable products and the cultivation of competitive advantage. Furthermore, AI strengthens institutional innovation by facilitating collaborative creativity, evaluating external ideas, and integrating them effectively (Arias-Pérez & Huynh, 2023).

In the context of reactive green innovation, AI enables the analysis of large-scale environmental data to support regulatory compliance, respond to consumer and stakeholder demands, and adapt existing processes in line with sustainability requirements (Liao et al., 2023). It contributes to more efficient resource allocation, emissions reduction, and the implementation of environmentally friendly solutions across production and logistics operations (Slimani et al., 2024).

In the oil sector in particular, AI has become a critical enabler of environmental transformation. It is employed in a wide array of functions, including exploration, seismic analysis, drilling optimisation, predictive maintenance, inventory management, and emissions monitoring through drones and intelligent robotics (Guo et al., 2023; Kuang et al., 2021). These applications not only reduce environmental costs but also enhance safety and operational efficiency. Additionally, AI-related technologies—such as machine learning, deep learning, and IoT—support environmental sustainability by enabling greater energy control, reducing resource consumption, and improving industrial and environmental planning (Panda et al., 2024).

This convergence of technological and environmental innovation has given rise to new paradigms such as "sustainable intelligence" and "green smart manufacturing", underscoring the synergy between technological advancement and ecological transition (Abdulmuhsin, Hussein, et al., 2025). Accordingly, AI, with its analytical and predictive capabilities, emerges as a central driver in advancing environmental innovation and fulfilling strategic sustainability goals. Based on the above, the following hypotheses are proposed:

H1: Artificial intelligence has a positive impact on green innovation, with the following sub-hypotheses:

H1-1: Artificial intelligence positively influences proactive green innovation.

H1-2: Artificial intelligence positively influences reactive green innovation.

2.6 The Mediating Role of Knowledge Management

The contemporary era is witnessing a growing convergence between AI and knowledge management (KM), with AI technologies emerging as pivotal enablers in the advancement of organisational knowledge practices. AI empowers organisations to leverage both *explicit knowledge*—that which is codified and structured—and *tacit knowledge*—which is rooted in personal experience—through intelligent tools that facilitate the generation, storage, sharing, and application of knowledge in more efficient and adaptive ways (Ferreira et al., 2024; Nakash & Bouhnik, 2021).

AI enhances knowledge generation by processing and analysing large-scale data to uncover new knowledge patterns. This process includes not only the development of novel ideas but also the recombination of existing knowledge into practical solutions (Bhatt, 2001; Kumbure et al., 2024). Technologies such as artificial neural networks, natural language processing (NLP), and genetic algorithms are employed to extract textual information, analyse context, and generate new knowledge from both internal and external sources (Abdulmuhsin et al., 2024; Goel et al., 2022).

In terms of knowledge storage and dissemination, AI can construct intelligent organisational memory systems that systematically track, store, and organise knowledge in digital repositories (Alavi & Leidner, 2001; Otioma, 2022). Intelligent assistants and virtual agents streamline knowledge retrieval processes and enhance user experience by interpreting natural language inputs, ensuring timely and accessible information delivery (Abdulmuhsin, Hussein, et al., 2025). Semantic classification tools and content analysis algorithms are further used to structure knowledge assets, ensuring both accuracy and rapid accessibility (DeBellis & Neches, 2023).

Regarding knowledge application, AI supports the effective deployment of retrieved knowledge by informing decision-making and offering contextualised insights and recommendations (El Asri et al., 2021). Recommendation systems identify the most relevant knowledge to be applied, while AI-driven tools automate routine procedures and facilitate more effective knowledge transfer to employees (Maedche et al., 2019; Taherdoost & Madanchian, 2023). Moreover, AI enhances human–machine collaboration within the workplace, promoting cooperative learning and the contextual transfer of knowledge (Siwach & Li, 2024).

Practical cases, such as Repsol's implementation of AI in its oil drilling operations, demonstrate these benefits vividly. The company achieved a 40%–50% reduction in non-productive time by using AI to simulate and assess millions of scenarios, enabling engineers to evaluate outcomes rapidly (Majumder & Dey, 2024). Such examples underscore AI's capacity to serve as a core driver of knowledge activation in modern organisations through intelligent tools that foster innovation, operational efficiency, and sustainability. Through these capabilities, AI significantly supports all phases of the knowledge management cycle—from creation and acquisition to storage, dissemination, and application. Based on this understanding, the following overarching hypothesis and sub-hypotheses are proposed:

H2: Artificial intelligence positively influences knowledge management. with the following sub-hypotheses:

H2-1: Artificial intelligence positively influences knowledge generation.

H2-2: Artificial intelligence positively influences knowledge storage and sharing.

H2-3: Artificial intelligence positively influences knowledge application.

In light of rapid environmental transformations and the growing imperative for resource sustainability, KM has become a strategic pillar in fostering green innovation. As knowledge constitutes a foundational organisational resource, aligning it with environmentally friendly practices directly enhances organisational performance across economic, ecological, and social dimensions (Kaur, 2022; Wang et al., 2024).

Knowledge generation represents the initial step in advancing green innovation. This is facilitated through interpersonal interaction, experience sharing, and the development of novel ideas concerning environmental practices and green technologies (Chamba-Rueda et al., 2021; Gauthier & Zhang, 2020). Newly generated knowledge enables organisations to understand their internal strengths and weaknesses while proactively anticipating environmental challenges (Alkaraan et al., 2024). Embedding an environmental culture within the organisation also encourages the creation of innovative environmental concepts and motivates employees to respond effectively to ecological changes (Asiaei et al., 2022). This process contributes to both proactive green innovation—by designing forward-looking environmental solutions—and reactive green innovation—through stakeholder engagement and the mobilisation of collective intelligence (Bachtiar et al., 2024; Bai et al., 2022).

Knowledge storage systems serve as the backbone for documenting and transferring environmental ideas and sustainable technologies. When green knowledge is centralised, it becomes readily accessible for continuous development and cross-functional utilisation (Mukhtar et al., 2023). Knowledge sharing further facilitates cognitive interaction among researchers, practitioners, and communities, thereby expanding the potential for environmental innovation (Abu-AlSondos, 2023; Allioui & Mourdi, 2023). Knowledge storage and dissemination act as key drivers of both proactive green innovation—by enabling the transfer and documentation of successful environmental experiences—and reactive green innovation—by supporting collaborative efforts to address ongoing ecological challenges (Sestino et al., 2023; Tabuenca et al., 2024).

Knowledge application refers to the integration of knowledge into practical activities aimed at developing green products and services (Mothe et al., 2017). This is reflected in an organisation's ability to convert environmental insights into actionable solutions, thereby enhancing its responsiveness to environmental and competitive pressures (Barão et al., 2017; Ben Arfi et al., 2018). In the case of proactive innovation, knowledge application helps forecast environmental crises and formulate pre-emptive solutions (Fosu et al., 2024; Maheshwari et al., 2024). In the reactive context, participatory knowledge application enables improved environmental responses based on continuous feedback from stakeholders (Feng et al., 2022; Valujeva et al., 2023).

Thus, knowledge management—encompassing the generation, storage, and application of knowledge—plays a decisive role in advancing both proactive and reactive forms of green innovation. It constitutes the cognitive foundation upon which future environmental solutions are constructed. Accordingly, the following hypotheses are proposed:

H3: Knowledge management positively influences green innovation, with the following sub-hypotheses:

H3-1: Knowledge management positively influences proactive green innovation.

H3-2: Knowledge management positively influences reactive green innovation.

H4: Knowledge management positively moderates the relationship between artificial intelligence and green innovation, with the following sub-hypotheses:

H4-1: Knowledge management positively moderates the relationship between artificial intelligence and proactive green innovation.

H4-2: Knowledge management positively moderates the relationship between artificial intelligence and reactive green innovation.

3. Methodology

3.1 Data Collection and Sampling

The present study adopted a deductive research approach, which aligns closely with the positivist paradigm (Abdulmuhsin, Valeri, et al., 2025). This philosophical orientation facilitated the formulation and analytical testing of hypotheses within a probabilistic framework of expected outcomes. To ensure representative coverage of major state-owned oil companies in Iraq, the study employed random sampling techniques from databases comprising over 7,000 engineers employed in these companies across the northern, central, and southern regions. This sampling strategy ensured neutral and representative cross-sectional selection of participants from the Iraqi state-owned oil sector.

Data were collected using a two-part structured questionnaire. The first section gathered demographic information, including gender, age, educational background, and work experience. The second section contained 47 items related to the latent constructs under investigation. Given that the majority of the targeted participants were native Arabic speakers, the questionnaire was translated into Arabic to maintain linguistic and conceptual accuracy with the original measurement items (Abdulmuhsin, Owain, Dbesan, Alkhwaldi, et al., 2025).

The survey was designed using Google Forms and distributed via email through company-specific databases. To maximise the response rate, multiple engagement strategies were employed, including polite reminder emails and the use of professional intranet networks (Abdulmuhsin, Owain, Dbesan, Bhat, et al., 2025). The study also verified that all respondents possessed sufficient domain-specific knowledge relevant to their professional roles. The research targeted the three largest state-owned oil companies in Iraq. A random sample of engineers was surveyed between May and December 2024. From an initial pool of 700 randomly selected engineers (selected at a ratio of 1 in 10 based on their order in the database), a total of 572 valid responses were received and deemed suitable for analysis, resulting in a response rate of 81.71%. *Table 1* presents the demographic characteristics of the participants.

Table 1. Respondents' demographics.

Categories	*Details*	#	%
Gender	*Male*	475	83.0
	Female	97	17.0
Education	*PhD*	56	9.8
	MSc	191	33.4
	Bachelor	325	56.8
Age (#years)	*Less than 33*	193	33.7
	33 – 42	222	38.8
	43 – 52	103	18.0
	More than 52	54	9.4
Job Experience (#years)	*Less than 11*	140	24.5
	11 – 20	193	33.7
	21 – 30	159	27.8
	More than 30	80	14.0

Notes: *N=572*
Source: *Authors' own work*

3.2 Measurement of Constructs

This study examined three principal variables. The construct of artificial intelligence (AI) was measured using 13 items, adapted from prior studies including Al Mansoori et al. (2021), Al-Sharafi et al. (2022), and El Bhilat et al. (2024). The knowledge management (KM) construct was assessed using 26 items, adapted from studies such as Al Yami et al. (2021), Botega and da Silva (2020), and Raudeliuniene et al. (2020). Specifically, the KM scale comprised: 8 items for *knowledge generation*, 12 items for *knowledge storage and sharing*, 6 items for *knowledge application*. The green innovation (GI) construct was measured using 8 items, evenly distributed between *proactive green innovation* and *reactive green innovation*. These items were drawn from established sources, including Chen et al. (2006), Chen et al. (2012), and Trivedi and Srivastava (2023). All items were rated on a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.3 Data Analysis Strategy

Data analysis for this study was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) with the support of SmartPLS version 3.2.9. PLS-SEM is a robust statistical tool particularly suited for examining complex theoretical relationships between observed and latent variables (Rehman et al., 2025). This technique is especially valuable in management research, where many constructs are inherently abstract and cannot be directly measured (Abed et al., 2021). The decision to employ PLS-SEM was based on three key considerations. First, the complex structure of the study's constructs aligns well with the multivariate analytical capabilities of PLS-SEM (Hair Jr et al., 2017). Second, the method's ability to assess both direct and indirect relationships among variables enables a comprehensive approach to model development and evaluation (Hair Jr et al., 2011). Third, the sample size exceeded the minimum threshold of 100 observations recommended by Churi et al. (2021), thereby establishing a statistically sound basis for the use of PLS-SEM in this research.

4. Results

4.1 Measurement Model Assessment

The evaluation of the measurement model was conducted to establish the reliability and validity of the latent constructs, which are AI, KM, and GI. Reliability was assessed using Cronbach's alpha (α) and Composite Reliability (CR). As shown in *Table 2*, all constructs exceeded the recommended threshold of 0.70 (Hair Jr et al., 2011), with Cronbach's alpha values ranging from 0.895 to 0.960, and CR values from 0.916 to 0.963, indicating strong internal consistency.

Convergent validity was established through Average Variance Extracted (AVE), with all constructs exceeding the minimum recommended value of 0.50. The AVE values were 0.661 (AI), 0.598 (KM), and 0.577 (GI), suggesting that the items significantly reflect their respective constructs. Discriminant validity was assessed using the Fornell–Larcker criterion and HTMT (Heterotrait–Monotrait) ratio. As presented in *Table 3*, the square roots of the AVE (bold diagonal values) for each construct were greater than their correlations with other constructs, satisfying the Fornell–Larcker criterion. HTMT values (italicised) were also below the conservative threshold of 0.85, confirming discriminant validity (Alshaher et al., 2022).

Table 2. Correlation analysis.

Constructs	M (SD)	Kurtosis (Skewness)	1	2	3
1. AI	3.489 0.621	-0.219 (-0.082)	1		
2. KM	3.963 0.715	-0.247 (-0.030)	0.687	1	
3. GI	4.005 0.679	-0.129 (-0.084)	0.638	0.766	1
Cronbach's alpha (α)			0.957	0.960	0.895
Composite Reliability (CR)			0.962	0.963	0.916
Average Variance Extracted (AVE)			0.661	0.598	0.577

***Notes**: N=572, **P<0.001, M=Mean, SD=Standard Deviation.*
***Source:** Authors' own work*

Table 3. Constructs' Discriminant validity.

Constructs	AI	KM	GI
AI	**0.813**	*0.717*	*0.689*
KM	0.687	**0.706**	*0.827*
GI	0.638	0.766	**0.760**

***Notes: Bold number= √AVE,** Italic number=HTMT*
***Source:** Authors' own work*

4.2 Structural Model Assessment

The structural model was evaluated to test the hypothesised relationships among AI, KM, and GI, including their subdimensions—proactive green innovation (PGI), reactive green innovation (RGI), and the three KM processes (knowledge generation, storage and sharing, application). The path coefficients (β), t-statistics, p-values, effect sizes (f^2), and R^2 values are reported in *Table 4*. The direct effect of AI on GI was significant ($\beta = 0.211$, $t = 9.683$, $p < 0.001$), supporting H1. Furthermore, both dimensions of GI—PGI and RGI—were significantly influenced by AI, supporting H1-1 ($\beta = 0.184$, $p < 0.001$) and H1-2 ($\beta = 0.186$, $p < 0.001$).

AI also had a substantial positive impact on KM (H2, $\beta = 0.687$, $t = 55.586$, $p < 0.001$), with significant effects observed across all KM subdimensions: Knowledge Generation (H2-1, $\beta = 0.578$, $p < 0.001$), Knowledge Storage & Sharing (H2-2, $\beta = 0.622$, $p < 0.001$), and AI → Knowledge Application (H2-3, $\beta = 0.542$, $p < 0.001$). KM also significantly influenced GI (H3, $\beta = 0.622$, $p < 0.001$), including both PGI (H3-1, $\beta = 0.543$, $p < 0.001$) and RGI (H3-2, $\beta = 0.548$, $p < 0.001$).

Table 3. The path analysis of the study model

Relationships	*β*	*SD*	*T Statistics*	*P Values*	F^2	R^2	*Results?*
H1: AI → GI	0.211	0.022	9.683	0.000	0.060	0.611	*Accept*
H1-1: AI → GI → PGI	0.184	0.019	9.717	0.000	0.060	0.764	*Accept*
H1-2: AI → GI → RGI	0.186	0.019	9.640	0.000	0.060	0.777	*Accept*
H2: AI → KM	0.687	0.012	55.586	0.000	0.894	0.472	*Accept*
H2-1: AI → KM → Kg	0.578	0.012	46.236	0.000	0.894	0.707	*Accept*
H2-2: AI → KM → KSS	0.622	0.012	50.825	0.000	0.894	0.819	*Accept*
H2-3: AI → KM → Ka	0.542	0.014	40.147	0.000	0.894	0.623	*Accept*
H3: KM → GI	0.622	0.020	31.493	0.000	0.524	0.611	*Accept*
H3-1: KM → GI → PGI	0.543	0.018	29.699	0.000	0.524	0.764	*Accept*
H3-2: KM → GI → RGI	0.548	0.018	30.526	0.000	0.524	0.777	*Accept*
H4: AI → KM → GI	0.427	0.016	26.674	0.000	0.060	0.611	*Accept*
H4-1: AI → KM → GI → PGI	0.373	0.015	25.072	0.000	0.060	0.764	*Accept*
H4-2: AI → KM → GI → RGI	0.376	0.015	25.594	0.000	0.060	0.777	*Accept*

Note: *β = Standard regression, SD = Standard Deviation.*
NFI = 0.919, SRMR = 0.042
Source: *Authors' own work*

The mediation role of KM was also confirmed. AI's indirect effect on GI through KM was statistically significant (H4, β = 0.427, $p < 0.001$), as were its effects on PGI (H4-1, β = 0.373, $p < 0.001$) and RGI (H4-2, β = 0.376, $p < 0.001$). Effect sizes (f^2) ranged from 0.060 (small) to 0.894 (large), particularly for the paths from AI to KM subdimensions, indicating substantial predictive relevance. The R^2 values were moderate to substantial: GI (0.611), PGI (0.764), RGI (0.777), KM (0.472), Kg (0.707), KSS (0.819), and Ka (0.623), confirming the model's strong explanatory power.

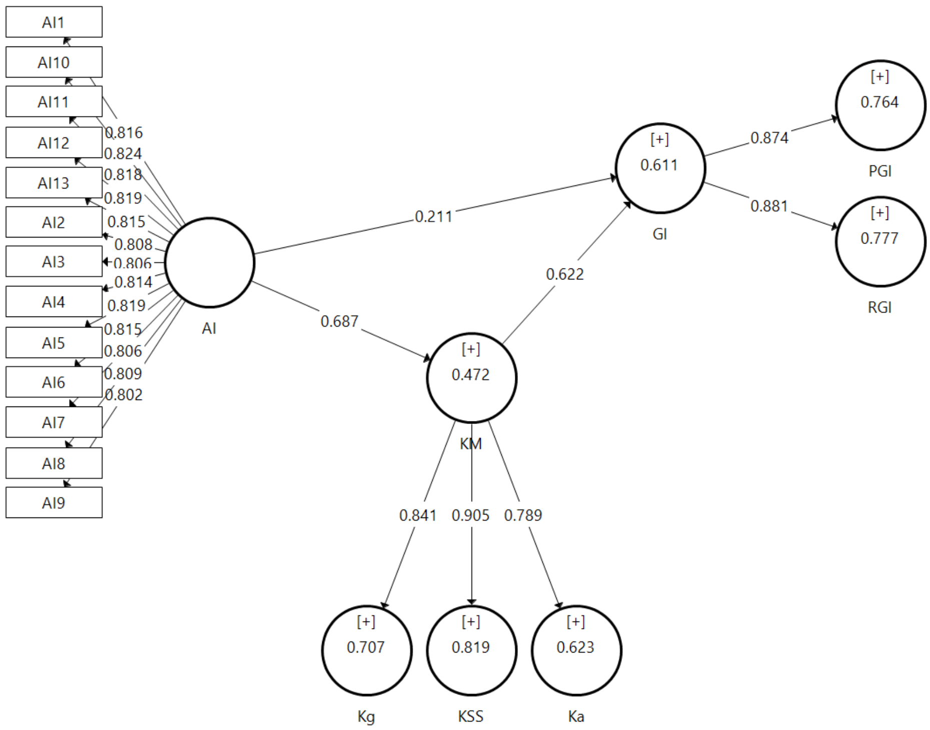
4.3 Model Fit Indices

Model fit was evaluated using Standardised Root Mean Square Residual (SRMR) and Normed Fit Index (NFI). The model exhibited an SRMR of 0.042 and an NFI of 0.919, both within acceptable thresholds (SRMR < 0.08, NFI > 0.90), indicating an excellent model fit (Alkhwaldi et al., 2025; Bhat et al., 2025). The structural model is illustrated in *Figure 1*, highlighting the significant pathways between AI, KM, and GI and their respective subdimensions, with standardised loadings supporting construct validity.

5. Discussion

This study provides compelling empirical evidence underscoring the pivotal role of AI in fostering GI within the Iraqi oil industry. By integrating AI capabilities with KM processes, the research unveils a complex, yet coherent, pathway through which organisations can strategically respond to sustainability imperatives. The findings contribute to an emerging body of scholarship situated at the intersection of digital transformation and environmental sustainability (Brynjolfsson & Mitchell, 2017; Budhwar et al., 2023).

Figure 1. The structural model of the study



Source: *Authors' own work*

The direct positive relationship between AI and green innovation ($\beta = 0.211$, $p < 0.001$) validates H1 and aligns with previous research asserting that AI technologies can enhance eco-innovative outcomes (Chen et al., 2006; Panda et al., 2024). Specifically, AI exhibited significant influence on both proactive GI (H1-1: $\beta = 0.184$) and reactive GI (H1-2: $\beta = 0.186$), supporting the notion that AI not only anticipates environmental trends but also enables firms to adapt to evolving regulatory and stakeholder demands. These findings reflect the dual function of AI: as a strategic foresight tool and as a tactical problem-solving mechanism (Filiou et al., 2023). In proactive terms, AI enables predictive modelling of environmental risks and emissions, allowing oil firms to develop technologies and strategies ahead of regulatory enforcement. This is crucial in countries like Iraq, where environmental regulations are still evolving and often inconsistently enforced. On the reactive side, AI-driven systems help organisations swiftly respond to stakeholder pressures, such as international reporting requirements, ESG metrics, and investor demands for decarbonisation (Kuang et al., 2021; Panda et al., 2024). These outcomes reinforce AI's potential to redefine environmental governance in the oil industry, transitioning it from compliance-focused to innovation-driven. In regions where environmental management has historically been underprioritised, AI offers an automated and data-rich alternative to traditional, manual, and often inefficient monitoring systems.

AI demonstrated a strong predictive effect on KM (H2: $\beta = 0.687$, $p < 0.001$), affirming the argument that intelligent systems facilitate organisational learning by optimising knowledge flows (Nakash & Bouhnik, 2021). This relationship extended across all three KM subdimensions—knowledge generation (H2-1: $\beta = 0.578$), storage and sharing (H2-2: $\beta = 0.622$), and application (H2-3: $\beta = 0.542$)—thereby reinforcing AI's capacity to support organisational memory, learning, and decision-making capabilities (Bhatt, 2001; Ferreira et al., 2024). These outcomes suggest that AI is instrumental not only in gathering environmental knowledge but also in operationalising it to support innovation and sustainability initiatives. The relationship between AI and KM is particularly salient for oil companies in developing countries, where tacit knowledge is often concentrated among a small cadre of senior engineers and technical experts (Abdulmuhsin et al., 2024). AI systems can codify, scale, and operationalise this knowledge, thereby reducing knowledge silos and addressing succession planning issues. The positive effects across all KM subprocesses—knowledge generation, storage and sharing, and application—demonstrate that AI fosters an intelligent organisational memory and supports evidence-based decision-making even in volatile contexts (Bhatt, 2001; Nakash & Bouhnik, 2021). For Iraqi oil firms operating under infrastructural constraints and international scrutiny, such a digitally enabled KM system ensures operational continuity, minimises human error, and facilitates cross-generational knowledge transfer—especially important given the demographic gap between experienced workers and digitally literate younger engineers.

Confirming H3, KM exhibited a significant positive impact on green innovation ($\beta = 0.622$), with strong effects on both proactive (H3-1: $\beta = 0.543$) and reactive (H3-2: $\beta = 0.548$) GI. These results align with the knowledge-based view (KBV) of the firm, which posits that organisations derive competitive advantage by leveraging and mobilising internal knowledge assets (Serenko, 2021). Notably, KM enables the translation of environmental insights into concrete green practices, thereby linking intellectual capital to sustainability outcomes (Asiaei et al., 2022; Barão et al., 2017). The results strongly confirm that KM enhances green innovation, particularly through proactive and reactive pathways. In the oil context, where environmental degradation and resource depletion are acute, embedding environmental knowledge into routine operations is not just a competitive advantage but a socio-political necessity (Abdulmuhsin et al., 2024). KM allows firms to develop eco-centric competencies by capturing field-level innovations—such as leak detection, emission control, and equipment efficiency—and scaling them across departments and geographies. In resource-constrained environments, formalising these knowledge assets helps reduce dependence on external consultants and costly imported technologies. Furthermore, the dissemination of context-specific green practices among oil engineers and technicians enhances organisational resilience and long-term ecological performance (Allioui & Mourdi, 2023; Asiaei et al., 2022).

The indirect effects of AI on GI via KM (H4: $\beta = 0.427$, $p < 0.001$) further elucidate the central thesis of this study: that KM processes serve as critical mediators in the digital-green nexus. This mediation holds for both proactive (H4-1: $\beta = 0.373$) and reactive (H4-2: $\beta = 0.376$) dimensions of GI. The significance of these indirect paths underscores that AI's environmental benefits are contingent upon the organisation's ability to institutionalise knowledge practices (Alavi & Leidner, 2001; Goel et al., 2022). In effect, KM amplifies the transformative power of AI by ensuring that insights generated by intelligent systems are shared, contextualised, and applied effectively within the organisation. The mediating role of KM in the AI-GI relationship adds theoretical nuance and practical depth to our understanding of innovation systems in developing countries. AI alone is insufficient unless its analytical outputs are internalised, shared, and actioned within the firm. KM processes serve as the 'absorptive capacity' that converts AI-derived insights into operational change, product redesign, or process optimisation (Alavi & Leidner, 2001; Goel et al., 2022). In Iraqi NOCs, where bureaucratic inertia and hierarchical decision-making often hinder innovation, KM systems offer a structured mechanism for diffusing AI-enhanced environmental intelligence throughout the organisation (Abdulmuhsin et al., 2024). The significance of the indirect effects on both proactive and reactive GI further suggests that in developing-country contexts, environmental innovation must be underpinned by both technological capabilities and internal knowledge infrastructures. The dual emphasis on people (KM) and platforms (AI) aligns with socio-technical systems theory, reinforcing the importance of harmonising technological tools with organisational routines and human expertise.

The structural model demonstrates strong explanatory power (R^2 up to 0.819) and satisfactory model fit indices (SRMR = 0.042; NFI = 0.919), validating the reliability of the relationships tested. The high Composite Reliability (CR) and Cronbach's Alpha ($\alpha > 0.89$) for all constructs confirm the internal consistency of the measures used. These indicators are particularly notable given the study's context—a developing economy with unique institutional and environmental complexities—which attests to the model's robustness and cross-contextual relevance.

6. Conclusion

This study investigated the interrelationships between AI, KM, and GI, with a particular focus on proactive and reactive innovation practices in Iraq's oil sector. By employing a robust PLS-SEM approach on a sample of 572 oil engineers from state-owned petroleum companies, the findings establish a comprehensive and empirically supported model in which AI serves as a significant enabler of green innovation, both directly and indirectly through KM processes. Specifically, AI positively influences knowledge generation, storage and sharing, and application—subsequently promoting green innovation initiatives that are either anticipatory of or responsive to environmental demands.

In resource-rich yet institutionally constrained contexts such as Iraq, where oil firms are under growing pressure to align with international sustainability norms, the convergence of AI and KM emerges as a pivotal strategy. This integration not only drives technological modernisation but also enhances environmental responsiveness and innovation agility. The study thereby contributes a novel framework that addresses critical gaps in the environmental innovation literature, particularly in the under-explored domain of digital transformation within the oil industry in developing economies.

6.1 Theoretical Implications

This research contributes to theoretical development in several meaningful ways. *First*, it enriches the literature on green innovation by dissecting its dual dimensions—proactive and reactive—thus offering a more granular understanding of how environmental innovation manifests across strategic and operational levels. *Second*, it extends the discourse on the role of AI in sustainability by demonstrating that AI does not act in isolation but requires strong internal knowledge infrastructures to maximise its innovation potential. This highlights KM as a critical mediating mechanism, a conceptual "bridge" that operationalises the value of AI insights. *Third*, the study contributes to organisational knowledge theory by empirically validating the three-stage KM framework—generation, storage/sharing, and application—as key antecedents to innovation in environmentally complex and data-intensive sectors such as oil and gas. This aligns with and extends Nonaka (1994)'s SECI model and Alavi and Leidner (2001)'s framework into the digital sustainability domain. *Finally*, by focusing on oil companies in a developing country, the study contextualises these relationships within an environment characterised by institutional fragility, limited regulatory enforcement, and human capital asymmetries—thereby enriching the boundary conditions of current innovation and KM theories.

6.2 Practical and Managerial Implications

The findings of this study offer strategic and actionable insights for managers, policymakers, and technology strategists in the oil and energy sectors of developing countries. Managers in state-owned oil companies should integrate AI tools not only for operational efficiency but also for fostering environmental innovation. Predictive analytics, sensor networks, and intelligent automation can serve as catalysts for both regulatory compliance and competitive green positioning. To fully capitalise on AI capabilities, organisations must build robust KM systems that institutionalise knowledge flows. This includes investing in digital repositories, incentivising knowledge sharing among field engineers, and formalising feedback loops from green project outcomes. Rather than treating AI and KM as discrete functions, oil companies should develop integrated AI-KM platforms that allow real-time knowledge capture, contextual analysis, and application in field operations. Smart dashboards, digital twins, and AI-enhanced training systems are examples of such integrations. Given the unique socio-political and infrastructural constraints in developing countries, green innovation strategies must be contextually embedded. This means aligning AI investments with local capacity-building, environmental challenges (e.g. gas flaring, water use), and indigenous knowledge. Governmental bodies and regulatory agencies in developing economies should support the digital transformation of public oil companies by mandating ESG disclosures and incentivising AI-driven green initiatives through subsidies or technology transfer programmes. Thus, the study affirms that for oil companies in developing economies to transition toward sustainable operations, they must treat AI and KM not as auxiliary functions but as core enablers of strategic environmental innovation.

7. Limitations and Future Research Directions

Despite its valuable contributions, this study is subject to several limitations that offer pathways for future research. Firstly, the study's cross-sectional design limits the ability to draw causal inferences. Although PLS-SEM is a powerful method for testing theoretical models, future research should consider longitudinal approaches to assess how the relationships among AI, KM, and green innovation evolve over time, particularly as digital maturity progresses in the oil sector. Secondly, the study is contextually bound to state-owned oil companies in Iraq—a developing country with distinct institutional, cultural, and regulatory characteristics. While this specificity enriches the contextual relevance of the findings, it may limit generalisability to other industries or countries. Future research could undertake comparative studies between public and private oil firms, or between firms in high-income versus low-income contexts, to test the external validity of the proposed model. Thirdly, this study focused on engineers' perceptions and organisational-level innovation practices, without incorporating external stakeholder views such as suppliers, regulators, or communities. Given the systemic nature of green innovation, future studies should adopt multi-stakeholder perspectives to capture broader environmental, social, and governance (ESG) dynamics. Moreover, although the model captured three core KM processes, it did not explore how organisational culture, leadership styles, or absorptive capacity might moderate or mediate these relationships. Integrating such constructs could yield a richer understanding of the socio-technical ecosystem surrounding green innovation in resource-intensive sectors. Finally, while AI was treated as a multidimensional construct, this study did not distinguish between different types of AI (e.g., machine learning, expert systems, NLP). Future research could explore how specific AI technologies differentially affect knowledge processes and innovation outcomes, thereby offering more granular managerial guidance.

Acknowledgements

The authors extend their heartfelt gratitude to the universities and institutions—including the University of Mosul and Dakota State University —for their invaluable support and encouragement throughout the course of this study. Additionally, we deeply appreciate the invaluable insights and expertise provided by our colleagues in our respective departments, which greatly contributed to the successful completion of our research.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

Authors' contributions

All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published this version of the manuscript.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability

The datasets analysed during the current study are available from the corresponding author on reasonable request.

Appendix A. Study Questionnaire Items

Artificial Intelligence (AI), *Adapted from El Bhilat et al. (2024); Al Mansoori et al. (2021); Al-Sharafi et al. (2022)*

"Our organisation uses AI tools to improve decision-making efficiency. AI is used to analyse environmental data to support green strategies. We utilise AI for forecasting and predictive analytics in operations. AI helps identify risks related to environmental management. AI systems assist in real-time monitoring of performance indicators. Our organisation integrates AI with existing business processes. Employees are trained to work with AI applications. AI contributes to process automation

in our organisation. We use AI to support R&D activities. AI applications enhance supply chain and logistics operations. AI supports strategic planning through data-driven insights. Our company allocates investment in AI to promote innovation. We apply AI to optimise resource usage and reduce waste."

Knowledge Management (KM), *Adapted from Al Yami et al. (2021); Raudeliuniene et al. (2020); Botega & da Silva (2020)*

Knowledge Generation (8 items)

"Our organisation encourages the development of new ideas. AI tools support the generation of novel knowledge. We actively explore innovative ways to improve environmental practices. Employees contribute their insights to knowledge creation. Cross-functional teams collaborate to generate solutions. Environmental challenges are used to stimulate idea generation. Learning from past projects is promoted. We adapt external knowledge to improve our operations."

Knowledge Storage and Sharing (12 items)

"Knowledge is systematically documented for future use. Environmental best practices are stored in digital repositories. AI is used to index and retrieve stored knowledge. Our employees have easy access to stored knowledge. There is a culture of knowledge sharing in the organisation. Employees are encouraged to share knowledge informally. Our systems support sharing knowledge across departments. Environmental data and experiences are shared regularly. Knowledge from past projects is reused in new initiatives. Knowledge repositories are kept up to date. Our knowledge systems help avoid repeating mistakes. Experts contribute actively to knowledge-sharing platforms."

Knowledge Application (6 items)

" We apply previously acquired knowledge to solve new problems. Knowledge is used to improve environmental decision-making. AI recommendations are implemented in operational processes. Employees utilise organisational knowledge to meet sustainability goals. Environmental knowledge is embedded in routine tasks. We customise knowledge application based on project needs."

Green Innovation (GI), *Adapted from Y.-S. Chen et al. (2016b); Y. S. Chen et al. (2012); Trivedi & Srivastava (2023)*

Proactive Green Innovation (4 items)

"We develop green products or processes before being required by regulation. Our organisation invests in eco-innovation to gain competitive advantage. We proactively identify opportunities for environmental improvement. We innovate to reduce environmental impact beyond compliance."

Reactive Green Innovation (4 items)

"We modify existing products or operations in response to environmental regulations. Customer demands for green solutions drive our innovation. We react to competitors' environmental practices by adapting our own. Environmental innovation is often triggered by external pressures."

References

Abdulmuhsin, A. A., Alkhwaldi, A. F., Dbesan, A. H., & Tarhini, A. (2025). Empirical insights on organisational sustainability: exploring the influence of communities of practice and associated technologies. *Sustainability Accounting, Management and Policy Journal*. https://doi.org/10.1108/sampj-02-2024-0155

Abdulmuhsin, A. A., Hussein, H. D., Al-Abrrow, H., Masa'deh, R. e., & Alkhwaldi, A. F. (2024). Impact of artificial intelligence and knowledge management on proactive green innovation: the moderating role of trust and sustainability. *Asia-Pacific Journal of Business Administration*, *17*(3), 765-795. https://doi.org/10.1108/apjba-05-2024-0301

Abdulmuhsin, A. A., Hussein, H. D. H., Ramo, R. M., Masa'deh, R. e., & Alkhwaldi, A. F. (2025). Artificial Intelligence and Green Innovation. In *Generative AI in Creative Industries* (pp. 593-604). https://doi.org/10.1007/978-3-031-89175-5_37

Abdulmuhsin, A. A., Owain, H. O., Dbesan, A. H., Alkhwaldi, A. F., & Tarhini, A. (2025). Knowledge management in metaverse: does knowledge storage matter as a factor affecting adoption and acceptance? *International Journal of Organizational Analysis*. https://doi.org/10.1108/ijoa-02-2024-4287

Abdulmuhsin, A. A., Owain, H. O., Dbesan, A. H., Bhat, M. A., Rehman, S. U., & Alkhwaldi, A. F. (2025). Acceptance of KM-driven metaverse technology in higher education institutions: are educators ready to be immersed? *Information Discovery and Delivery*. https://doi.org/10.1108/idd-11-2024-0188

Abdulmuhsin, A. A., Valeri, M., Al-Taie, A. A. A., & Dbesan, A. H. (2025). Understanding the Academic Personality of Workplace Friendship and Knowledge Management: Insights from Higher Education. In *Organisational Behaviour and Design* (pp. 43-61). https://doi.org/10.1007/978-3-031-80422-9_3

Abed, S. N., Abdulmuhsin, A. A., & Alkhwaldi, A. F. (2021). The factors influencing the innovative performance of leaders in nurses' professional: a developing country perspective. *Leadersh Health Serv (Bradf Engl)*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/LHS-06-2021-0054

Abu-AlSondos, I. A. (2023). An empirical study of critical success factors in implementing knowledge management systems (KMS): The moderating role of culture. *Uncertain Supply Chain Management*, *11*(4), 1527-1538. https://doi.org/10.5267/j.uscm.2023.7.016

Acharya, C., Ojha, D., Gokhale, R., & Patel, P. C. (2022). Managing information for innovation using knowledge integration capability: The role of boundary spanning objects. *International Journal of Information Management*, *62*. https://doi.org/10.1016/j.ijinfomgt.2021.102438

Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. *Journal of Economic Perspectives*, *33*(2), 31-50. https://doi.org/10.1257/jep.33.2.31

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2021). Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. *Journal of Cleaner Production*, *289*, 1-65. https://doi.org/10.1016/j.jclepro.2021.125834

Al-Sharafi, M. A., Al-Emran, M., Iranmanesh, M., Al-Qaysi, N., Iahad, N. A., & Arpaci, I. (2022). Understanding the impact of knowledge management factors on the sustainable use of AI-based chatbots for educational purposes using a hybrid SEM-ANN approach. *Interactive Learning Environments*, *31*(10), 7491-7510. https://doi.org/10.1080/10494820.2022.2075014

Al Mansoori, S., Salloum, S. A., & Shaalan, K. (2021). The Impact of Artificial Intelligence and Information Technologies on the Efficiency of Knowledge Management at Modern Organizations: A Systematic Review. In *Recent Advances in Intelligent Systems and Smart Applications* (pp. 163-182). https://doi.org/10.1007/978-3-030-47411-9_9

Al Shraah, A., Abu-Rumman, A., Al Madi, F., Alhammad, F. A. F., & AlJboor, A. A. (2021). The impact of quality management practices on knowledge management processes: a study of a social security corporation in Jordan. *The TQM Journal*, *34*(4), 605-626. https://doi.org/10.1108/tqm-08-2020-0183

Al Yami, M., Ajmal, M. M., & Balasubramanian, S. (2021). Does size matter? The effects of public sector organizational size' on knowledge management processes and operational efficiency. *VINE Journal of Information and Knowledge Management Systems*, *52*(5), 670-700. https://doi.org/10.1108/vjikms-07-2020-0123

Alavi, M., & Leidner, D. E. (2001). Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. *MIS Quarterly*, *25*(1), 107-139. https://doi.org/10.2307/3250961

Albayrak Ünal, Ö., Erkayman, B., & Usanmaz, B. (2023). Applications of Artificial Intelligence in Inventory Management: A Systematic Review of the Literature. *Archives of Computational Methods in Engineering*, *30*(4), 2605-2625. https://doi.org/10.1007/s11831-022-09879-5

Ali, S. M., Dick, S., Dillon, S., Jones, M. L., Penn, J., & Staley, R. (2023). Histories of artificial intelligence: a genealogy of power. *BJHS Themes*, *8*, 1-18. https://doi.org/10.1017/bjt.2023.15

Alkaraan, F., Elmarzouky, M., Hussainey, K., Venkatesh, V. G., Shi, Y., & Gulko, N. (2024). Reinforcing green business strategies with Industry 4.0 and governance towards sustainability: Natural-resource-based view and dynamic capability. *Business Strategy and the Environment*, 1-19. https://doi.org/10.1002/bse.3665

Alkhwaldi, A. F., Abdulmuhsin, A. A., Masa'deh, R. e., & Abu-AlSondos, I. A. (2025). Business intelligence adoption in higher education: the role of data-driven decision-making culture and UTAUT. *Journal of International Education in Business*. https://doi.org/10.1108/jieb-08-2024-0110

Allioui, H., & Mourdi, Y. (2023). Exploring the Full Potentials of IoT for Better Financial Growth and Stability: A Comprehensive Survey. *Sensors (Basel)*, *23*(19), 1-68. https://doi.org/10.3390/s23198015

Alshaher, A., Hasan, M. M. H., & Abdulmuhsin, A. A. (2022). A multi-dimensional approach for accepting and using e-learning cloud: a developing country's perspective. *International Journal of Knowledge Management Studies*, *13*(2). https://doi.org/10.1504/ijkms.2022.121925

Apell, P., & Eriksson, H. (2021). Artificial intelligence (AI) healthcare technology innovations: the current state and challenges from a life science industry perspective. *Technology Analysis & Strategic Management*, *35*(2), 179-193. https://doi.org/10.1080/09537325.2021.1971188

Aragón-Correa, J. A., & Sharma, S. (2003). A Contingent Resource-Based View of Proactive Corporate Environmental Strategy. *Academy of Management Review*, *28*(1), 71-88. https://doi.org/10.5465/amr.2003.8925233

Arias-Pérez, J., & Huynh, T. (2023). Flipping the odds of AI-driven open innovation: The effectiveness of partner trustworthiness in counteracting interorganizational knowledge hiding. *Industrial Marketing Management*, *111*, 30-40. https://doi.org/10.1016/j.indmarman.2023.03.005

Asadi, S., OmSalameh Pourhashemi, S., Nilashi, M., Abdullah, R., Samad, S., Yadegaridehkordi, E.,…Razali, N. S. (2020). Investigating influence of green innovation on sustainability performance: A case on Malaysian hotel industry. *Journal of Cleaner Production*, *258*, 1-34. https://doi.org/10.1016/j.jclepro.2020.120860

Asiaei, K., O'Connor, N. G., Barani, O., & Joshi, M. (2022). Green intellectual capital and ambidextrous green innovation: The impact on environmental performance. *Business Strategy and the Environment*, *32*(1), 369-386. https://doi.org/10.1002/bse.3136

Aziz, N. N. A., & Samad, S. (2016). Innovation and Competitive Advantage: Moderating Effects of Firm Age in Foods Manufacturing SMEs in Malaysia. *Procedia Economics and Finance*, *35*, 256-266. https://doi.org/10.1016/s2212-5671(16)00032-0

Bachtiar, M., Panji, K. A. R., Sufa, S. A., Amani, S. Z., & Mayangsari, A. (2024). Lifestyle Dynamics and Purchasing Pattern Transformation: Significant Shifts in Indonesian Society Post-Pandemic. *Journal of Business Management and Economic Development*, *2*(02), 553-567. https://doi.org/10.59653/jbmed.v2i02.621

Bai, J., Cao, L., Mosbach, S., Akroyd, J., Lapkin, A. A., & Kraft, M. (2022). From Platform to Knowledge Graph: Evolution of Laboratory Automation. *JACS Au*, *2*(2), 292-309. https://doi.org/10.1021/jacsau.1c00438

Banga, D., & Peddireddy, K. (2023). Artificial Intelligence for Customer Complaint Management. *International Journal of Computer Trends and Technology*, *71*(3), 1-6. https://doi.org/10.14445/22312803/ijctt-v71i3p101

Barão, A., de Vasconcelos, J. B., Rocha, Á., & Pereira, R. (2017). A knowledge management approach to capture organizational learning networks. *International Journal of Information Management*, *37*(6), 735-740. https://doi.org/10.1016/j.ijinfomgt.2017.07.013

Bask, A., Rajahonka, M., Laari, S., Solakivi, T., Töyli, J., & Ojala, L. (2018). Environmental sustainability in shipper-LSP relationships. *Journal of Cleaner Production*, *172*, 2986-2998. https://doi.org/10.1016/j.jclepro.2017.11.112

Ben Arfi, W., Hikkerova, L., & Sahut, J.-M. (2018). External knowledge sources, green innovation and performance. *Technological Forecasting and Social Change*, *129*, 210-220. https://doi.org/10.1016/j.techfore.2017.09.017

Benabdellah, A. C., Zekhnini, K., Cherrafi, A., Garza-Reyes, J. A., & Kumar, A. (2021). Design for the environment: An ontology-based knowledge management model for green product development. *Business Strategy and the Environment*, *30*(8), 4037-4053. https://doi.org/10.1002/bse.2855

Bhat, M. A., Khan, S. T., Alkhwaldi, A. F., & Abdulmuhsin, A. A. (2025). Unlocking the potential: exploring the drivers behind blockchain and its influence on SMEs performance within TOE framework. *The TQM Journal*. https://doi.org/10.1108/tqm-07-2024-0232

Bhatt, G. D. (2001). Knowledge management in organizations: examining the interaction between technologies, techniques, and people. *Journal of Knowledge Management*, *5*(1), 68-75. https://doi.org/10.1108/13673270110384419

Bianchi, R., Noci, G., Pozzi, C., & Priano, A. (1997). Analysing basic patterns of environmental innovation within value chains. Proceedings of the 4th International Product Development Management Conference,(Stockholm, 1997),

Bobrow, D. G., & Stefik, M. J. (1986). Perspectives on artificial intelligence programming. *Science*, *231*(4741), 951-957. https://doi.org/10.1126/science.231.4741.951

Botega, L. F. d. C., & da Silva, J. C. (2020). An artificial intelligence approach to support knowledge management on the selection of creativity and innovation techniques. *Journal of Knowledge Management*, *24*(5), 1107-1130. https://doi.org/10.1108/jkm-10-2019-0559

Bratu, I. (2023). A first critical analysis of the European approach to damage caused by artificial intelligence enabled by global navigation satellite systems. A bridge to nowhere or a cloud with a silver lining? *International Review of Law, Computers & Technology*, *37*(2), 147-165. https://doi.org/10.1080/13600869.2023.2192567

Brynjolfsson, E., & Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science*, *358*(6370), 1530-1534. https://doi.org/10.1126/science.aap8062

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R.,…Varma, A. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal*, *33*(3), 606-659. https://doi.org/10.1111/1748-8583.12524

Chamba-Rueda, L. M., Dávila, G. A., & Pardo-Cueva, M. (2021). Quality Management, Knowledge Creation, and Innovation Performance: Insights from Ecuador. *Latin American Business Review*, *24*(1), 31-58. https://doi.org/10.1080/10978526.2021.1997144

Chen, Y.-S., Lai, S.-B., & Wen, C.-T. (2006). The Influence of Green Innovation Performance on Corporate Advantage in Taiwan. *Journal of Business Ethics*, *67*(4), 331-339. https://doi.org/10.1007/s10551-006-9025-5

Chen, Y. S., Chang, C. H., & Wu, F. S. (2012). Origins of green innovations: the differences between proactive and reactive green innovations. *Management Decision*, *50*(3), 368-398. https://doi.org/10.1108/00251741211216197

Choubey, S., & Karmakar, G. P. (2020). Artificial intelligence techniques and their application in oil and gas industry. *Artificial Intelligence Review*, *54*(5), 3665-3683. https://doi.org/10.1007/s10462-020-09935-1

Churi, P., Pawar, A. V., & Abdulmuhsin, A. A. (2021). Perception of privacy issues and awareness in health-care knowledge management systems: empirical study in Indian health-care context. *International Journal of Organizational Analysis*, *30*(5), 1100-1119. https://doi.org/10.1108/ijoa-11-2020-2486

Cillo, V., Petruzzelli, A. M., Ardito, L., & Del Giudice, M. (2019). Understanding sustainable innovation: A systematic literature review. *Corporate Social Responsibility and Environmental Management*, *26*(5), 1012-1025. https://doi.org/10.1002/csr.1783

Cosgrove, W. J., & Loucks, D. P. (2015). Water management: Current and future challenges and research directions. *Water Resources Research*, *51*(6), 4823-4839. https://doi.org/10.1002/2014wr016869

Daradkeh, M. (2023). Exploring the influence of risk management on the performance of industry–university collaborative projects: the moderating role of knowledge management capabilities. *Journal of Organizational Effectiveness: People and Performance*. https://doi.org/10.1108/joepp-03-2023-0098

Datta, S., Jha, A., & Kulchania, M. (2019). On accounting's twenty-first century challenge: evidence on the relation between intangible assets and audit fees. *Review of Quantitative Finance and Accounting*, *55*(1), 123-162. https://doi.org/10.1007/s11156-019-00839-y

DeBellis, M., & Neches, R. (2023). Knowledge Representation and The Semantic Web: An Historical

Overview of Influences on Emerging Tools. *Recent Advances in Computer Science and Communications*, *16*(6). https://doi.org/10.2174/2666255815666220527145610

Domini, B., Dewi, A. S., & Cesna, G. P. (2023). The Effects of Artificial Intelligence (AI) on Company Performance Including the Value of AI-based Business Transformation Initiatives. *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, *5*(1), 24-38. https://doi.org/10.34306/itsdi.v5i1.606

El-Kassar, A.-N., & Singh, S. K. (2019). Green innovation and organizational performance: The influence of big data and the moderating role of management commitment and HR practices. *Technological Forecasting and Social Change*, *144*, 483-498. https://doi.org/10.1016/j.techfore.2017.12.016

El Asri, H., Benhlima, L., & Agnaou, A. (2021). Integrating Artificial Intelligence in Knowledge Management: A Primer. In *Advances in Integrated Design and Production* (pp. 516-526). https://doi.org/10.1007/978-3-030-62199-5_45

El Baz, J., & Laguir, I. (2017). Third-party logistics providers (TPLs) and environmental sustainability practices in developing countries. *International Journal of Operations & Production Management*, *37*(10), 1451-1474. https://doi.org/10.1108/ijopm-07-2015-0405

El Bhilat, E. M., El Jaouhari, A., & Hamidi, L. S. (2024). Assessing the influence of artificial intelligence on agri-food supply chain performance: the mediating effect of distribution network efficiency. *Technological Forecasting and Social Change*, *200*. https://doi.org/10.1016/j.techfore.2023.123149

Elankavi, R. S. (2020). Developments in Inpipe Inspectionrobot: A Review. *Journal of Mechanics of Continua and Mathematical Sciences*, *15*(5), 238-248. https://doi.org/10.26782/jmcms.2020.05.00022

Eloranta, V., Ardolino, M., & Saccani, N. (2021). A complexity management approach to servitization: the role of digital platforms. *International Journal of Operations & Production Management*, *41*(5), 622-644. https://doi.org/10.1108/ijopm-08-2020-0582

Fang, J., Tang, X., Xie, R., & Han, F. (2020). The effect of manufacturing agglomerations on smog pollution. *Structural Change and Economic Dynamics*, *54*, 92-101. https://doi.org/10.1016/j.strueco.2020.04.003

Feng, H., Wang, F., Song, G., & Liu, L. (2022). Digital Transformation on Enterprise Green Innovation: Effect and Transmission Mechanism. *Int J Environ Res Public Health*, *19*(17), 1-31. https://doi.org/10.3390/ijerph191710614

Ferreira, J. J. M., Fernandes, C. I., & Veiga, P. M. (2024). The effects of knowledge spillovers, digital capabilities, and innovation on firm performance: A moderated mediation model. *Technological Forecasting and Social Change*, *200*, 1-10. https://doi.org/10.1016/j.techfore.2023.123086

Filiou, D., Kesidou, E., & Wu, L. (2023). Are smart cities green? The role of environmental and digital policies for Eco-innovation in China. *World Development*, *165*, 1-13. https://doi.org/10.1016/j.worlddev.2023.106212

Fosu, E., Fosu, F., Akyina, N., & Asiedu, D. (2024). Do environmental CSR practices promote corporate social performance? The mediating role of green innovation and corporate image. *Cleaner and Responsible Consumption*, *12*, 1-10. https://doi.org/10.1016/j.clrc.2023.100155

Franceschini, S., Faria, L. G. D., & Jurowetzki, R. (2016). Unveiling scientific communities about sustainability and innovation. A bibliometric journey around sustainable terms. *Journal of Cleaner Production*, *127*, 72-83. https://doi.org/10.1016/j.jclepro.2016.03.142

Gauthier, J., & Zhang, Z. (2020). Green knowledge management and strategic renewal: a discursive perspective on corporate sustainability. *International Journal of Productivity and Performance Management*, *69*(8), 1797-1811. https://doi.org/10.1108/ijppm-10-2019-0489

Glauner, P. (2020). Unlocking the Power of Artificial Intelligence for Your Business. In *Innovative Technologies for Market Leadership* (pp. 45-59). https://doi.org/10.1007/978-3-030-41309-5_5

Goel, A., Goel, A. K., & Kumar, A. (2022). The role of artificial neural network and machine learning in utilizing spatial information. *Spatial Information Research*, *31*(3), 275-285. https://doi.org/10.1007/s41324-022-00494-x

Guo, J., Wan, J.-L., Yang, Y., Dai, L., Tang, A., Huang, B.,…Li, H. (2023). A deep feature learning method for remaining useful life prediction of drilling pumps. *Energy*, *282*, 1-30. https://doi.org/10.1016/j.energy.2023.128442

Guoyou, Q., Saixing, Z., Chiming, T., Haitao, Y., & Hailiang, Z. (2011). Stakeholders' Influences on Corporate Green Innovation Strategy: A Case Study of Manufacturing Firms in China. *Corporate Social Responsibility and Environmental Management*, *20*(1), 1-14. https://doi.org/10.1002/csr.283

Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107-123. https://doi.org/10.1504/ijmda.2017.087624

Hair Jr, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2011). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*(3), 414-433. https://doi.org/10.1007/s11747-011-0261-6

Hart, S. L. (1995). A Natural-Resource-Based View of the Firm. *Academy of Management Review*, *20*(4), 986-1014. https://doi.org/10.2307/258963

Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. *Business Horizons*, *65*(3), 329-339. https://doi.org/10.1016/j.bushor.2021.03.006

Iqbal, J., Cortes Jaimes, D. C., Makineni, P., Subramani, S., Hemaida, S., Thugu, T. R.,…Arain, M. (2023). Reimagining Healthcare: Unleashing the Power of Artificial Intelligence in Medicine. *Cureus*, *15*(9), 1-14. https://doi.org/10.7759/cureus.44658

Iraji, S., Soltanmohammadi, R., Matheus, G. F., Basso, M., & Vidal, A. C. (2023). Application of unsupervised learning and deep learning for rock type prediction and petrophysical characterization using multi-scale data. *Geoenergy Science and Engineering*, *230*, 1-48. https://doi.org/10.1016/j.geoen.2023.212241

Jermsittiparsert, K., Gill, A. R., Mihardjo, L. W. W., Sasmoko, & Haseeb, M. (2019). Economic Impact of Artificial Intelligence: New Look for the Macroeconomic Assessment in Asia-Pacific Region. *International Journal of Computational Intelligence Systems*, *12*(2), 1295-1310. https://doi.org/10.2991/ijcis.d.191025.001

Kaplan, A. (2023). Innovation in Artificial Intelligence: Illustrations in Academia, Apparel, and the Arts. In *Oxford Research Encyclopedia of Business and Management* (pp. 1195-1209). https://doi.org/10.1093/acrefore/9780190224851.013.421

Kaur, V. (2022). Knowledge-based dynamic capabilities: a scientometric analysis of marriage between knowledge management and dynamic capabilities. *Journal of Knowledge Management*, *27*(4), 919-952. https://doi.org/10.1108/jkm-02-2022-0112

Kehayov, M., Holder, L., & Koch, V. (2022). Application of artificial intelligence technology in the manufacturing process and purchasing and supply management. *Procedia Computer Science*, *200*, 1209-1217. https://doi.org/10.1016/j.procs.2022.01.321

Keicher, L., Ardilio, A., & Nawroth, G. (2022). *Boosting Innovation by Artificial Intelligence (AI): Effects and Potentials of AI in the Process of Innovating* 2022 Portland International Conference on Management of Engineering and Technology (PICMET), Portland, OR, USA.

Khan, M. I., Khan, S., Khan, U., & Haleem, A. (2021). Modeling the Big Data challenges in context of smart cities – an integrated fuzzy ISM-DEMATEL approach. *International Journal of Building Pathology and Adaptation*, *41*(2), 422-453. https://doi.org/10.1108/ijbpa-02-2021-0027

Khan, S. J., Dhir, A., Parida, V., & Papa, A. (2021). Past, present, and future of green product innovation. *Business Strategy and the Environment*, *30*(8), 4081-4106. https://doi.org/10.1002/bse.2858

Khelifi, H., Luo, S., Nour, B., Moungla, H., Ahmed, S. H., & Guizani, M. (2020). A blockchain-based architecture for secure vehicular Named Data Networks. *Computers & Electrical Engineering*, *86*. https://doi.org/10.1016/j.compeleceng.2020.106715

Kuang, L., Liu, H., Ren, Y., Luo, K., Shi, M., Su, J., & Li, X. (2021). Application and development trend of artificial intelligence in petroleum exploration and development. *Petroleum Exploration and Development*, *48*(1), 1-14. https://doi.org/10.1016/s1876-3804(21)60001-0

Kumbure, M. M., Tarkiainen, A., Stoklasa, J., Luukka, P., & Jantunen, A. (2024). Causal maps in the analysis and unsupervised assessment of the development of expert knowledge: Quantification of the learning effects for knowledge management purposes. *Expert Systems with Applications*, *236*, 1-22. https://doi.org/10.1016/j.eswa.2023.121232

Kunduru, A. R. (2023). Cloud BPM Application (Appian) Robotic Process Automation Capabilities. *Asian Journal of Research in Computer Science*, *16*(3), 267-280. https://doi.org/10.9734/ajrcos/2023/v16i3361

Kuru, K., Pinder, J. M., Watkinson, B. J., Ansell, D., Vinning, K., Moore, L.,…Jones, D. (2023). Toward Mid-Air Collision-Free Trajectory for Autonomous and Pilot-Controlled Unmanned

Aerial Vehicles. *IEEE Access*, *11*, 100323-100342. https://doi.org/10.1109/access.2023.3314504
Laihonen, H., & Kokko, P. (2020). Knowledge management and hybridity of institutional logics in public sector. *Knowledge Management Research & Practice*, *21*(1), 14-28. https://doi.org/10.1080/14778238.2020.1788429
Liao, H.-T., Pan, C.-L., & Zhang, Y. (2023). Smart digital platforms for carbon neutral management and services: Business models based on ITU standards for green digital transformation. *Frontiers in Ecology and Evolution*, *11*, 1-10. https://doi.org/10.3389/fevo.2023.1134381
Lin, P., Li, X., Long, Z., Ma, P., Zhu, G., Wei, J., & Fan, Z. (2021). *Pipeline Leak Detection, Location and Repair* 2021 IEEE 11th Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER), Jiaxing, China.
Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T.,…Söllner, M. (2019). AI-Based Digital Assistants. *Business & Information Systems Engineering*, *61*(4), 535-544. https://doi.org/10.1007/s12599-019-00600-8
Maheshwari, S., Kaur, A., & Renwick, D. W. S. (2024). Green Human Resource Management and Green Culture: An Integrative Sustainable Competing Values Framework and Future Research Directions. *Organization & Environment*, 1-25. https://doi.org/10.1177/10860266231217280
Majumder, S., & Dey, N. (2024). Artificial Intelligence: The Future of People Management. In *The Vogue of Managing People in Workplace* (pp. 83-102). https://doi.org/10.1007/978-981-99-6070-5_5
Mariani, M. M., Machado, I., & Nambisan, S. (2023). Types of innovation and artificial intelligence: A systematic quantitative literature review and research agenda. *Journal of Business Research*, *155*, 1-14. https://doi.org/10.1016/j.jbusres.2022.113364
Md, A. Q., Jha, K., Haneef, S., Sivaraman, A. K., & Tee, K. F. (2022). A Review on Data-Driven Quality Prediction in the Production Process with Machine Learning for Industry 4.0. *Processes*, *10*(10), 1-29. https://doi.org/10.3390/pr10101966
Mich, L. (2020). Artificial Intelligence and Machine Learning. In *Handbook of e-Tourism* (pp. 1-21). Springer, Cham. https://doi.org/10.1007/978-3-030-05324-6_25-1
Mothe, C., Nguyen-Thi, U. T., & Triguero, Á. (2017). Innovative products and services with environmental benefits: design of search strategies for external knowledge and absorptive capacity. *Journal of Environmental Planning and Management*, *61*(11), 1934-1954. https://doi.org/10.1080/09640568.2017.1372275
Mukhtar, B., Shad, M. K., Lai, F.-W., & Waqas, A. (2023). Empirical analysis of ESG-driven green innovation: the moderating role of innovation orientation. *Management & Sustainability: An Arab Review*, 1-24. https://doi.org/10.1108/msar-08-2023-0043
Muñoz-Pascual, L., Galende, J., & Curado, C. (2019). Human Resource Management Contributions to Knowledge Sharing for a Sustainability-Oriented Performance: A Mixed Methods Approach. *Sustainability*, *12*(1). https://doi.org/10.3390/su12010161
Nakash, M., & Bouhnik, D. (2021). Should knowledge management in organizations be rebranded? *VINE Journal of Information and Knowledge Management Systems*, *54*(2), 242-255. https://doi.org/10.1108/vjikms-09-2021-0193
Nonaka, I. (1994). A Dynamic Theory of Organizational Knowledge Creation. *Organization Science*, *5*(1), 14-37. https://doi.org/10.1287/orsc.5.1.14
Otioma, C. (2022). IT Capability, Organisational Learning and Innovation Performance of Firms in Kenya. *Journal of the Knowledge Economy*, *14*(3), 3489-3517. https://doi.org/10.1007/s13132-021-00886-8
Panda, J., Das, S., Panda, M., & Pattnaik, D. (2024). Sustainable Intelligence. In *Sustainable Science and Intelligent Technologies for Societal Development* (pp. 464-474). https://doi.org/10.4018/979-8-3693-1186-8.ch025

Pata, U. K., & Balsalobre-Lorente, D. (2022). Exploring the impact of tourism and energy consumption on the load capacity factor in Turkey: a novel dynamic ARDL approach. *Environ Sci Pollut Res Int*, *29*(9), 13491-13503. https://doi.org/10.1007/s11356-021-16675-4

Polonsky, M. J., & Rotman, J. D. (2023). Should Artificial Intelligent Agents be Your Co-author? Arguments in Favour, Informed by ChatGPT. *Australasian Marketing Journal*, *31*(2), 91-96. https://doi.org/10.1177/14413582231167882

Popenici, S. A. D., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Res Pract Technol Enhanc Learn*, *12*(1), 1-22. https://doi.org/10.1186/s41039-017-0062-8

Rahman, N. H. A., Hasikin, K., Razak, N. A. A., Al-Ani, A. K., Anni, D. J. S., & Mohandas, P. (2023). Medical Device Failure Predictions Through AI-Driven Analysis of Multimodal Maintenance Records. *IEEE Access*, *11*, 93160-93179. https://doi.org/10.1109/access.2023.3309671

Rajkhowa, S., & Sarma, J. (2021). Climate change and flood risk, global climate change. In *Global Climate Change* (pp. 321-339). https://doi.org/10.1016/b978-0-12-822928-6.00012-5

Raudeliuniene, J., Albats, E., & Kordab, M. (2020). Impact of information technologies and social networks on knowledge management processes in Middle Eastern audit and consulting companies. *Journal of Knowledge Management*, *25*(4), 871-898. https://doi.org/10.1108/jkm-03-2020-0168

Raza, A., Munir, K., Almutairi, M. S., & Sehar, R. (2023). Novel Class Probability Features for Optimizing Network Attack Detection With Machine Learning. *IEEE Access*, *11*, 98685-98694. https://doi.org/10.1109/access.2023.3313596

Rehman, S. U., Bresciani, S., Ashfaq, K., & Alam, G. M. (2021). Intellectual capital, knowledge management and competitive advantage: a resource orchestration perspective. *Journal of Knowledge Management*, *26*(7), 1705-1731. https://doi.org/10.1108/jkm-06-2021-0453

Rehman, S. U., Bresciani, S., Giordino, D., & Abdulmuhsin, A. A. (2025). Exploring the role of knowledge management and organizational agility in an emerging market. *Journal of Innovation & Knowledge*, *10*(5). https://doi.org/10.1016/j.jik.2025.100761

Rennings, K. (2000). Redefining innovation — eco-innovation research and the contribution from ecological economics. *Ecological Economics*, *32*(2), 319-332. https://doi.org/10.1016/s0921-8009(99)00112-3

Ross, P. (2008). Intelligent tutoring systems. *Journal of Computer Assisted Learning*, *3*(4), 194-203. https://doi.org/10.1111/j.1365-2729.1987.tb00331.x

Sahoo, S., Kumar, A., & Upadhyay, A. (2022). How do green knowledge management and green technology innovation impact corporate environmental performance? Understanding the role of green knowledge acquisition. *Business Strategy and the Environment*, *32*(1), 551-569. https://doi.org/10.1002/bse.3160

Serenko, A. (2021). A structured literature review of scientometric research of the knowledge management discipline: a 2021 update. *Journal of Knowledge Management*, *25*(8), 1889-1925. https://doi.org/10.1108/jkm-09-2020-0730

Sestino, A., Kahlawi, A., & De Mauro, A. (2023). Decoding the data economy: a literature review of its impact on business, society and digital transformation. *European Journal of Innovation Management*, 1-26. https://doi.org/10.1108/ejim-01-2023-0078

Shukla, A., & Karki, H. (2013). *A review of robotics in onshore oil-gas industry* 2013 IEEE International Conference on Mechatronics and Automation, Takamatsu, Japan.

Singh, S. K., & El-Kassar, A.-N. (2019). Role of big data analytics in developing sustainable capabilities. *Journal of Cleaner Production*, *213*, 1264-1273. https://doi.org/10.1016/j.jclepro.2018.12.199

Siwach, G., & Li, C. (2024). *Unveiling the Potential of Natural Language Processing in Collaborative Robots (Cobots): A Comprehensive Survey* 2024 IEEE International Conference on Consumer Electronics (ICCE), Slimani, K., Hussein, A. H. A., Jabbar, K. A., Mohammed, A., Jasim, L., Gerasymov, O., & Kerkeb, M. L. (2024). Harvesting the Future: AI and IoT in Agriculture. *E3S Web of Conferences*, *477*, 1-7. https://doi.org/10.1051/e3sconf/202447700090

Song, W., Yu, H., & Xu, H. (2020). Effects of green human resource management and managerial environmental concern on green innovation. *European Journal of Innovation Management*, *24*(3), 951-967. https://doi.org/10.1108/ejim-11-2019-0315

Spena, P. R., Holzner, P., Rauch, E., Vidoni, R., & Matt, D. T. (2016). Requirements for the Design of Flexible and Changeable Manufacturing and Assembly Systems: A SME-survey. *Procedia CIRP*, *41*, 207-212. https://doi.org/10.1016/j.procir.2016.01.018

Strickland, E. (2021). The Turbulent Past and Uncertain Future of AI: Is there a way out of AI's boom-and-bust cycle? *IEEE Spectrum*, *58*(10), 26-31. https://doi.org/10.1109/mspec.2021.9563956

Sudirjo, F. (2023). Marketing Strategy in Improving Product Competitiveness in the Global Market. *Journal of Contemporary Administration and Management (ADMAN)*, *1*(2), 63-69. https://doi.org/10.61100/adman.v1i2.24

Tabuenca, B., Uche-Soria, M., Greller, W., Hernández-Leo, D., Balcells-Falgueras, P., Gloor, P., & Garbajosa, J. (2024). Greening smart learning environments with Artificial Intelligence of Things. *Internet of Things*, *25*, 1-17. https://doi.org/10.1016/j.iot.2023.101051

Taha, I. M., & Abbas, A. A. (2023). The Role of Environmental Monitoring in Promoting Green Creativity. *Economics and Business*, *37*(1), 15-36. https://doi.org/10.2478/eb-2023-0002

Taherdoost, H., & Madanchian, M. (2023). Artificial Intelligence and Knowledge Management: Impacts, Benefits, and Implementation. *Computers*, *12*(4), 72-87. https://doi.org/10.3390/computers12040072

Trivedi, K., & Srivastava, K. B. L. (2023). The impact of intellectual capital-enhancing HR practices and culture on innovativeness—mediating role of knowledge management processes. *Journal of Organizational Effectiveness: People and Performance*, *11*(3), 573-593. https://doi.org/10.1108/joepp-05-2023-0174

Valujeva, K., Freed, E. K., Nipers, A., Jauhiainen, J., & Schulte, R. P. O. (2023). Pathways for governance opportunities: Social network analysis to create targeted and effective policies for agricultural and environmental development. *J Environ Manage*, *325*(Pt B), 1-10. https://doi.org/10.1016/j.jenvman.2022.116563

Vartiainen, H., & Tedre, M. (2023). Using artificial intelligence in craft education: crafting with text-to-image generative models. *Digital Creativity*, *34*(1), 1-21. https://doi.org/10.1080/14626268.2023.2174557

Vijayan, V., Singh, P., Verma, A., Vij, S., Thakur, J., & Senthil Kumar, T. S. (2023). Implications & Impact of Artificial Intelligence in Digital Media: With Special Focus on Social Media Marketing. *E3S Web of Conferences*, *399*, 1-13. https://doi.org/10.1051/e3sconf/202339907006

Wang, G., Niu, Y., Mansor, Z. D., Leong, Y. C., & Yan, Z. (2024). Unlocking digital potential: Exploring the drivers of employee dynamic capability on employee digital performance in Chinese SMEs-moderation effect of competitive climate. *Heliyon*, *10*(4), 1-21. https://doi.org/10.1016/j.heliyon.2024.e25583

Wu, J., & Sekiguchi, T. (2023). Understanding Organizational Performance in Dynamic Environments: An Integrative Framework of Activity-System Maps and the NK Model. *Academy of Management Learning & Education*, *22*(2), 239-256. https://doi.org/10.5465/amle.2021.0150

Yablonsky, S. A. (2019). Multidimensional Data-Driven Artificial Intelligence Innovation. *Technology Innovation Management Review*, *9*(12), 16-28. https://doi.org/10.22215/timreview/1288

Yol Lee, S., & Rhee, S. K. (2007). The change in corporate environmental strategies: a longitudinal empirical study. *Management Decision*, *45*(2), 196-216. https://doi.org/10.1108/00251740710727241
Zhang, D., & Vigne, S. A. (2021). How does innovation efficiency contribute to green productivity? A financial constraint perspective. *Journal of Cleaner Production*, *280*, 21-42. https://doi.org/10.1016/j.jclepro.2020.124000
Zhiznin, S. Z., Shvets, N. N., Timokhov, V. M., & Gusev, A. L. (2023). Economics of hydrogen energy of green transition in the world and Russia.Part I. *International Journal of Hydrogen Energy*, *48*(57), 21544-21567. https://doi.org/10.1016/j.ijhydene.2023.03.069
Ziemnowicz, C. (2013). Joseph A. Schumpeter and Innovation. In *Encyclopedia of Creativity, Invention, Innovation and Entrepreneurship* (pp. 1171-1176). https://doi.org/10.1007/978-1-4614-3858-8_476