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# AI capability and green innovation impact on sustainable performance: Moderating role of big data and knowledge management

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ABSTRACT

This study addresses the environmental impact of industries by focusing on increased resource consumption and waste generation that lead to ecosystem degradation. It advocates sustainable practices and a circular economy (CE) as strategies to mitigate these effects. Thus, the study examines how Artificial Intelligence (AI) capabilities directly affect green innovations and their subsequent influence on sustainable performance and CE. In addition, it introduces two key moderating factors—big data analytics and knowledge management systems—in the relationship between AI capabilities and green innovation. We validate the model using multi-sectoral population data from various Qatari industries and employ structural equation modeling (SEM) and artificial neural networks (ANN) as analytical approaches. The results indicate the significant impact of AI capability on green innovation, with these innovations critically linked to sustainable performance and CE. Remarkably, interactions with big data analytics and knowledge management systems enhance the positive impact of AI capabilities. Hence, this study emphasizes AI's noteworthy implications for green innovation, shaping sustainable performance, and CE. Identifying big data analytics and knowledge management systems as vital moderators adds complexity. The findings guide industries to integrate AI, big data analytics, and knowledge management systems for practical applications, stressing a holistic approach to promoting environmentally responsible practices across sectors.

## 1. Introduction

Human activities, including industrial processes, contribute to climate change, technological innovation, economic integration, and disruption (Allal-Chérif et al., 2023). While these activities fulfill society's basic needs, they concurrently release a significant amount of pollutants into the environment, leading to loss of raw materials, health hazards, increased mortality rates, crop damage, and overall environmental degradation (Gerassimidou et al., 2021; Dwivedi et al., 2022). This poses a formidable challenge and requires organizations to prioritize local and global ecological concerns (Dwivedi et al., 2022; Lengyel, 2023). Furthermore, the necessity to pursue sustainability is influenced by crises, financial collapses, and external demands from various stakeholders, including the public and government entities (Khan et al., 2019; Struckell et al., 2022). Hence, achieving sustainability poses a genuine challenge for society and businesses amid the escalating impacts of climate change, as emphasized by Rehman et al. (2021). Consequently, the achievement of environmentally sustainable growth has become a pivotal challenge.

Although there have been notable strides toward achieving sustainable development goals, manufacturing continues to present obstacles to achieving sustainable performance. This is exacerbated by the fact that economic growth often hinges on high-energy, carbon-producing manufacturing methods and the proliferation of environmentally harmful industries (Hizarci-Payne et al., 2021). In a sustainable market, states strive for excellence in a dynamic environment, which leads to increased energy demand. Rapid development and motorization further complicate environmental sustainability (Karaşan et al., 2024). Consequently, global issues such as pollution, resource constraints, and environmental concerns raise alarms about organizational

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sustainability. These challenges compelled organizations to adopt environmentally friendly practices that offered diverse values. Integrating social, economic, ecological, and corporate sustainable practices gives rise to a novel concept known as sustainable organizational performance (Yang et al., 2022; Paul et al., 2021). To thrive and endure, organizations face the challenge of reducing pollution and achieving sustained sustainability, prompting top management to explore sustainable methods for enhanced profitability (Gerassimidou et al., 2021). Hence, organizations must prioritize environmental sustainability, implement eco-friendly practices, and integrate resources for sustainable capabilities and enduring performance (Borah et al., 2022).

Despite business efforts to minimize environmental impacts, substantial resource extraction and increased waste production have resulted in ecosystem degradation. In response, the circular economy (CE) concept has acquired prominence, which offers solutions to break the repeated material and resource flow cycle through various phases (Santa-Maria et al., 2022). Practitioners and academics have strongly supported the adoption of a circular economy over the past decade (Chowdhury et al., 2022). A circular economy involves a firm or manufacturing process that emulates a natural resource system aligned with the United Nations Sustainable Development Goals (SDGs) (Shahzad et al., 2020; Bag et al., 2021). These practices are becoming increasingly crucial globally, as they promote sustainable consumption, influence green economics and procurement in emerging and established economies, and promote economic growth. In a circular economy, the focus shifts from the end-of-life concept to alternative energy sources and minimizing the use of hazardous materials in industrial processes (Khan et al., 2021; Bag et al., 2021). Consequently, a circular economy revolutionizes production and consumption processes by recovering valuable elements from waste. This approach underscores critical principles, including sustainable funding, responsible sourcing, and the restoration of natural ecosystems, as highlighted by Santa-Maria et al. (2022).

Enhancing sustainable performance and CE and leveraging new technologies, particularly artificial intelligence (AI) applications, is a significant opportunity. The widespread adoption of AI is important for organizations, driven by the accessibility of big data and progress in methods and infrastructure (Mikalef and Gupta, 2021). Gartner reports revealed a substantial growth of 270 % in organizations implementing AI since 2015, tripling in 2018 (Rowell-Jones and Howard, 2019). Despite the enthusiasm surrounding AI's potential business value, organizations that adopt AI solutions encounter challenges that hinder performance gains (Zhang et al., 2021). Previous studies point to a productivity paradox with AI technologies, emphasizing the need for organizations to focus on fully capitalizing on their AI investments (Mikalef and Gupta, 2021). Hence, the delayed achievement of anticipated outcomes from AI can be attributed to setbacks in implementation and restructuring, while organizations are prompted to allocate more resources to effectively harness the potential of AI. Understanding and implementing these complementary resources is crucial for unlocking the performance gains from AI (Mikalef and Gupta, 2021). This necessitates a focus on building AI capabilities to address the disruptions caused by human activities, considering local and global environments, including climate change, sustainability, technological innovations, and economic integration. Such concerns are integral to improving green innovation, sustainable performance, and CE (Chowdhury et al., 2022).

Ensuring environmental stability and adopting green practices have become imperative for the long-term survival of organizations. This shift has given rise to new research areas, such as green innovation studies and sustainability within operations management (de Medeiros et al., 2022; Shahzad et al., 2020). Establishing technological infrastructure is essential in this context, prompting businesses to transition their operations from traditional to green and initiate processes of green innovation (Fang et al., 2022). With escalating pollution and diminishing natural resources, there is an increasing emphasis on innovation, focusing on ecofriendly aspects. It is widely believed that adopting innovative programs is tied to better outcomes that can be consistently achieved over time (Rehman et al., 2021). Technological innovations geared toward the environmentally friendly production of goods and services are directly linked to sustainable performance (Kim and Moon, 2021). Consequently, green innovation is crucial for consistently maintaining performance and CE (Razzaq et al., 2021). Nevertheless, comprehensive studies are needed to ascertain the extent to which green innovation contributes to sustainable performance and CE (Suchek et al., 2021).

Big data has assumed significance in initiating AI capabilities and green innovation. Beyond enhancing organizational efficiency, big data has both environmental and social effects on innovation, making it instrumental in AI and green innovation processes (Dong et al., 2022). AI aids informed decision-making and facilitates seamless work processes by utilizing cloud computing and other technological tools. Additionally, big data helps analyze and use large amounts of data, further supporting technology and green innovation (Dai et al., 2022). Knowledge Management Systems (KMS) for the Internet of Things (IoT) play a crucial role in organizing and using a company's collective knowledge for sustainability, fostering innovativeness, and enhancing responsiveness to environmental changes (de Bem Machado et al., 2022; Di Vaio et al., 2021). Nevertheless, as Santoro et al. (2018) noted, there are still research gaps in comprehending the design, utilization, and effectiveness of ICTs and systems that aid in managing knowledge. Bridging this divide is crucial, as organizations increasingly deploy KMS to support development, exchange, and storage. As the Internet of Things (IoT) has escalated, organizations can gain competitive advantage by establishing digital ecosystems using ICT tools, infrastructure, experimental technology platforms, and software applications (Israilidis et al., 2021). This study introduces big data analytics and KMS as pivotal factors in the interaction between AI capability and green innovation, bolstering efforts toward sustainable performance and CE initiatives.

The primary objective of this study is to investigate the direct influence of AI capability on green innovation and subsequently analyze the impact of green innovations on sustainable performance and CE. Additionally, this study aims to introduce and explore two crucial moderating factors, namely, big data analytics and KMS, in the interaction between AI capability and green innovation. This study hypothesizes that these moderating elements influence the interactions between AI capability and green innovations, consequently shaping a firm's sustainable performance and circular economy (CE) outcomes. The outlined research objectives form the basis for comprehensively understanding the dynamics between AI capability, green innovations, and the pivotal role of moderating factors in achieving sustainable practices and CE initiatives within organizations. Based on the above-mentioned objectives, the research objectives of this study are outlined below.

- RQ1: How does AI capability impact green innovation within organizational contexts?
- RQ2: How do green innovations contribute to sustainable performance and a circular economy?
- RQ3: How does big data analytics moderate the relationship between AI capabilities and green innovation?
- RQ4: To what extent do knowledge management systems moderate the relationship between AI capabilities and green innovation?

This study investigates how AI can drive green innovation in Qatar, contribute to sustainable performance, and promote CE. It evaluates the direct impact of AI on fostering green innovation and its role in sustainability and CE practices in the region. Additionally, this study explores how big data analytics and KMS can enhance the interaction between AI capabilities and green innovation. This study highlights the potential impact of AI on sustainable development and the CE in Qatar by using advanced technologies and data-driven strategies tailored to local contexts.

The remainder of the paper is organized as follows. Sections 2 and 3 reviews the relevant theories and literature related to AI capability, green innovations, and sustainability. Section 4 details the research design, variables, and measures used. Section 5 presents the data analysis and highlights the key findings. Finally, Section 6 explores the wider reach of the findings on theory, practice, and future research directions.

## 2. Literature review

Global concerns such as pollution, resource limitations, and environmental issues have highlighted the sustainability challenges faced by organizations (Passmore and Woodward, 2023). Exploring sustainable methods and emphasizing environmentally friendly practices that address these concerns and generate economic value are all considerations for organizations facing these challenges (Shao et al., 2023). Integrating sustainable practices across social, economic, environmental, and organizational dimensions has contributed to the contemporary notion of sustainable organizational performance (de Oliveira et al., 2023; El-Kassar and Singh, 2019; Paul et al., 2021). This emerging concept reflects a more inclusive way of acknowledging the interconnectedness of environmental, social, and economic factors that foster sustainable practices within organizational frameworks.

Within the context of the CE, a circular model focuses on driving technological advancements in waste recycling and recovery, both during the production process and at the end of a product's lifecycle (Gnekpe and Plantec, 2023; Coenen et al., 2020). Technological advancements in recycling and waste treatment processes play a crucial role in adopting circular strategies and reducing the effects of cross-border material and resource transfer (Zhang et al., 2023; Chen et al., 2024). Investments in innovations related to waste recycling and recovery act as intangible assets, demonstrating a company's ability to adhere to circular model principles. Patents, recognized as valid indicators of innovation by several authors, are used as proxy indicators to measure recycling and secondary raw material innovation (Aldieri et al., 2019).

Earlier research has used patent data to investigate different waste management and recovery solutions derived through research and development (Aldieri et al., 2019; Chen and Rau, 2023). These intangible assets, represented by patents, provide insights into the shift toward a CE by tracking waste conversion into sustainable materials within a specific geographical area (Malinauskaite and Jouhara, 2019). However, CE brings about a unified approach to enhance the sustainable and adaptive use of environmental and human resources. This framework supports a significant shift toward more efficient recycling and reuse of products and goods, and promotes the prudent utilization of existing resources without waste (Islam et al., 2024; Singh et al., 2018; Pigosso and McAloone, 2021; Garcia and Cayzer, 2019). The CE fulfils a dual role: it aids businesses by reducing expenses, energy use, and greenhouse gas emissions, while simultaneously supporting environmental conservation and the advancement of sustainable practices (Singh et al., 2018; Momete, 2020; Kolade and Owoseni, 2022).

## 3. Theoretical foundation and conceptual model

In line with the above discussion, and as reported regarding the main objective, this study proposes a conceptual model that addresses the causal relationship between AI capability and green innovation. It also analyzes the direct impact of green innovation on sustainable performance and CE. Furthermore, the current conceptual model explores the crucial moderating roles of big data analytics and KMS in the interaction between AI capability and green innovation. By incorporating these moderating factors, this study seeks to offer a more comprehensive understanding of how technological and knowledge-based resources can strengthen AI's effectiveness in driving green innovation (Fig. 1).

This study adds to the current understanding by addressing the gaps in how AI, sustainability practices, and organizational performance interact within the context of CE. Specifically, this study provides valuable insights into how organizations in diverse sectors, particularly within the Qatari context, can leverage AI capabilities to foster green innovations, thereby improving their sustainable performance and contributing to CE. This context-specific contribution is vital, as it offers practical advice for Qatar's policymakers and business leaders, helping them strategically implement AI and KMS to achieve sustainability goals. Further justification of the main research hypotheses reflecting these causal associations and moderating interactions and are presented below.

### 3.1. AI capability toward green innovations

Despite being a subject of interest for many decades, a universally accepted definition of AI still needs to be established in the literature. The current study adopts the definition proposed by Mikalef and Gupta (2021) AI is the capability of a system to analyze and understand data, draw conclusions, and learn from it to reach specific organizational and

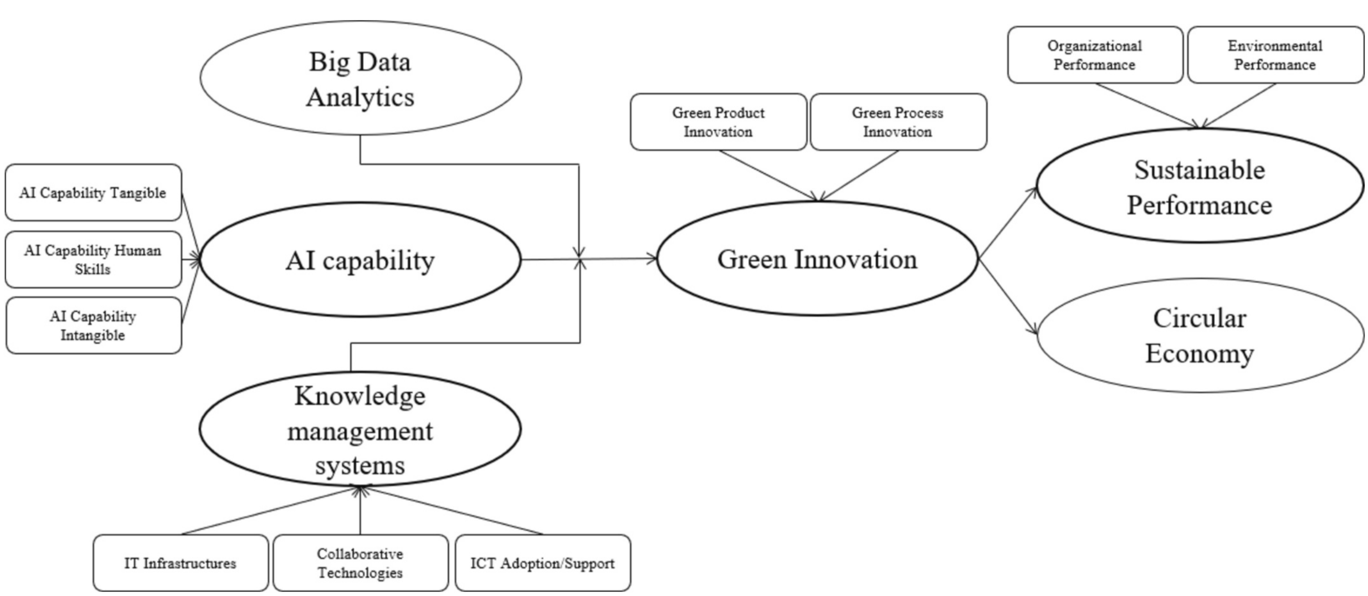


**Fig. 1.** Research model.

societal objectives. Accordingly, AI capability refers to a firm's capacity to choose, coordinate, and manage resources, specifically for AI applications.

Therefore, an AI application is conceptualized as any manufacturing system capable of autonomously generating insights or acting to achieve predetermined objectives that are directly or indirectly aligned with organizational and societal goals. Unlike human capabilities, most AI applications employed in corporate settings exhibit characteristics complementary to human capabilities, as noted in previous studies (Dwivedi et al., 2021). However, research investigating the organized implementation of AI and its impact on key performance metrics is limited, leaving a gap in our understanding. Moreover, discussions abound regarding how AI can catalyze innovation within organizations (e.g., Yu et al., 2023). The rationale behind these claims lies in the potential of AI to automate manual tasks, thereby allowing humans more time to engage in innovative activities. Additionally, AI applications can augment human capabilities by utilizing large datasets to assist professionals in innovation tasks across various domains (Lee and Lim, 2021; Mikalef et al., 2023). This study posits that AI capability enhances the green innovation process by formulating the following hypothesis:

**Hypothesis 1**. AI significantly affects green innovation.

### 3.2. Green innovations toward sustainable performance and CE

Chen et al. (2006) refer to green product innovation as something that encompasses product development performance, focusing on environmental factors, including energy efficiency, pollution control, waste recycling, non-toxicity, and eco-friendly product design. Such innovation is a pivotal tool for minimizing or preventing ecological harm. Green innovations offer companies dual advantages: economic benefits derived from producing environmentally friendly products, and financial benefits that enhance overall productivity (Chen et al., 2006; Seman et al., 2019). Given the increasing global demand for eco-friendly products and services, strategic positions in green innovation are critical for companies to meet customer expectations without compromising the ecosystem (Liu et al., 2020; Dong et al., 2022). Green innovations encompass developing and implementing novel products, processes, or practices and are increasingly recognized as critical drivers of green and sustainable business performance (Asadi et al., 2020; Aftab et al., 2022). These novel concepts offer more efficient and effective mechanisms for reducing environmental impacts, such as carbon footprint and waste, and for promoting sustainability (Koseoglu et al., 2022). By integrating green innovations, businesses can significantly enhance their operational efficiency, meet regulatory requirements, and respond to the growing demand for environmentally responsible practices (Kumar et al., 2021). Thus, this study postulates that green innovation is integral to achieving sustainable performance and proposes the following hypothesis:

Integrating green innovation is crucial for companies that aim to maintain their competitive advantage. Successful implementation requires firms to cultivate capabilities for reuse, recycling, remanufacturing, and disposal, thereby securing sustainable environmental practices and financial performance. Specifically, green core competencies encompass technical skills, knowledge, values, and attitudes within the workforce, supporting sustainable outcomes across social, economic, and environmental dimensions in organizations, industry, and communities (Wang et al., 2020; Al Halbusi et al., 2023a). This study posits that green innovation is integral to advancing the circular economy and proposes the following hypotheses:

**Hypothesis 2**. Green innovation significantly affects sustainable performance.

**Hypothesis 3**. Green innovation significantly affects CE.

### 3.3. Moderating the role of big data analytics

Big data are an extensive collection of datasets that exceed the processing capacities of conventional data systems in terms of accessibility, acquisition, analysis, and utilization within a practical timeframe (Agrawal et al., 2022; Lutfi et al., 2023). The extensive utilization of technology in an organization's operations is significant and actively reshapes the contemporary business landscape (Hamilton and Sodeman, 2020; Shah, 2022). Dealing with Big Data involves three stages: acceptance, utilization, and assimilation (Gunasekaran et al., 2017; Ashaari et al., 2021). The use of big data measures stakeholders' understanding of the importance of technology, whereas its routinization signifies an organization's governance system that enables technology integration. Finally, extensive data integration evaluates how widely technology spreads across an organization to maximize benefits (Bag et al., 2023). This comprehensive approach underscores the transformative impact of Big Data on modern business landscapes.

Recently, there has been a societal transition from conventional to information-technology-driven systems, marked by a notable surge in the demand for and utilization of big data (Teng and Khong, 2021). In the contemporary knowledge-based economy, big data play a crucial role, giving rise to popular concepts such as green innovation and sustainability (Choi and Park, 2022). Recent research points to big data as a catalyst for green innovation (El-Kassar and Singh, 2019), promoting organizational efficiency, and contributing to environmentally friendly practices. The role of big data in preventing blind decision making and supporting flawless work is important for green innovation (Ashaari et al., 2021). The analysis and application of large datasets are strengthened by facilitating efficient decision-making, addressing environmental challenges, such as pollution resource constraints, and fostering economic growth (Hamilton and Sodeman, 2020), including sustainable performance and CE. Given the relatively recent nature of this concept, in-depth exploration is warranted to provide the following proposition.

**Hypothesis 4**. Big data analytics moderates the interaction between AI and green innovations; this relationship is more robust when big data analytics is higher, influencing sustainable performance and CE.

### 3.4. Moderating the role of KMS

KMS are designed to manage organizational knowledge and facilitate the activities involved in generating, storing, sharing, and using knowledge (Jarrahi et al., 2023). From a knowledge-based perspective, KMS assist knowledge management by capturing the expertise and insights of individuals, thereby enabling a broader organization to leverage and benefit from its dissemination (Di Vaio et al., 2021). Recognized as a vital process, KMS are critical for maintaining and enhancing competitive advantages in a knowledge-based global economy. However, current studies in this field have mostly focused on internal knowledge (Lichtenthaler and Lichtenthaler, 2009; de Bem Machado et al., 2022), with limited attention paid to a comprehensive view that includes both internal and external knowledge (Audretsch and Belitski, 2023). From the viewpoint of dynamic capabilities, Teece (2007) posits that businesses can augment their capacity to navigate dynamic environments by amalgamating their internal and external knowledge. Consequently, the following hypothesis is developed:

**Hypothesis 5**. KMS moderate the relationship between AI and green innovation. This relationship is more robust when knowledge management systems are higher, influencing sustainable performance and CE.

## 4. Research methodology

### 4.1. Constructs measurements

As indicated in Table 1, a construct measurement section is required

**Table 1**
Constructs measurement including dimensions, items and sources.

| Constructs | Dimensions/ Indicators | Numbers of Items | Sources |
|---|---|---|---|
| AI Capability Tangible | Data<br>Technology<br>Basic Resources | 16 items | Mikalef and Gupta (2021) |
| AI Capability Human Skills | Technical Skills<br>Business Skills | 14 items | Mikalef and Gupta (2021) |
| AI Capability Intangible | Inter-Departmental Coordination<br>Organizational Change Capacity<br>Risk Proclivity | 16 items | Mikalef and Gupta (2021) |
| AI capability was assessed through three dimensions to capture its comprehensive impact. Tangibles (e.g., data, technology, and essential resources) were measured using items to ensure a thorough evaluation of physical and technical assets. Human skills (e.g., technical and business skills) were assessed reflecting the importance of skilled personnel in leveraging AI. Intangibles (e.g., inter-departmental coordination, organizational change capacity, and risk bias) were evaluated to capture non-physical elements crucial for AI integration. Overall, AI capability was measured using indicators and items ensuring a robust and validated approach. | | | |
| Green Innovation | Green Product Innovation<br>Green Process Innovation | 8 items | Chen et al. (2006) and Al Halbusi et al. (2023b) |
| Green innovation was assessed using multiple dimensions to capture product and process innovations. These items were used to evaluate green product innovation and green process innovation. This comprehensive measurement approach ensures a detailed evaluation of green innovation efforts within firms. | | | |
| Knowledge Management Systems | IT Infrastructures<br>Collaborative Technologies<br>ICT Adoption/ Support | 15 items | Santoro et al. (2018) |
| This variable involves three dimensions to capture the full scope of knowledge management within organizations. IT infrastructures, collaborative technologies, and ICT adoption items. This approach ensures a detailed assessment of the systems supporting knowledge management. | | | |
| Big Data Analytics | | 10 items | Bag et al. (2021) |
| Big data analytics was evaluated using the mentioned items. This measurement captures various aspects of big data analytics, ensuring a thorough understanding of how firms utilize big data for decision-making and innovation. | | | |
| Sustainable Performance | Organizational Performance<br>Environmental Performance | 10 items | Lin et al. (2013) and Imran et al. (2021) |
| Sustainable performance was evaluated using ten items, categorized into two dimensions: organizational performance and environmental performance. This ensures a comprehensive evaluation of both economic and environmental aspects of sustainability. | | | |
| Circular Economy | | 10 items | Zeng et al. (2017) and Al Halbusi et al. (2024) |
| The circular economy is recognized as a crucial element of sustainable development. CE was measured using items to capture various aspects of CE practices and their impact on sustainability. | | | |

to ensure the reliability and validity of the variables. It details how variables are quantified and provides clarity and consistency in data collection. Using items drawn from the existing literature and assessed with a seven-point Likert scale, this study ensures that the concepts of AI capability, green innovations, sustainable performance, and CE outcomes are accurately captured. This standardization allowed for meaningful comparisons and robust analyses, supporting the study's overall findings and conclusions. The measurement issues are outlined as follows:

***AI capability***: The AI capability was assessed using three dimensions involving tangibles (data, technology, and essential resources). A total of 16-items measured the tangible aspects. Human skills, also known as soft skills (e.g., problem-solving and business skills), were assessed using 14 items. Intangibles such as interdepartmental coordination, organizational change capacity, and risk bias were assessed using a 16-item evaluation. Thus, the AI capability was measured using 46-items adapted from Mikalef and Gupta (2021). Regarding ***green innovation,*** this variable was assessed using multiple dimensions such as green products and process innovation. Thus, green product innovation was measured using four 4-items, and green process innovation was similar (Chen et al., 2006; Al Halbusi et al., 2023b). For ***Big Data Analytics,*** big data were evaluated through multiple items as measured with 10-items adapted from Bag et al. (2021). Concerning ***KMS,*** this variable involves three dimensions (IT infrastructure, Collaborative Technologies, and ICT adoption). IT infrastructure was measured using four 4 items, collaborative technologies were assessed using 5 items, and ICT adoption was evaluated using 6 items. These items were obtained from Santoro et al. (2018). ***Sustainable performance*** was evaluated using 10 items, categorized into two categories, a 4-item organizational performance and a 6-item environmental performance measure. These dimensions were adapted from previous studies (Lin et al., 2013; Imran et al., 2021). ***CE:*** CE is recognized as an important element for sustainable development and is measured by 10-items, these items adapted from the existing literature (Zeng et al., 2017; Al Halbusi et al., 2024).

Using well-established items from previous studies, this study ensures the reliability and validity of the constructs, offering a strong basis for analyzing the connections between AI capability, green innovation, sustainable performance, and CE outcomes.

### 4.2. Sample and data process

This model was verified using a multi-sectoral population in Qatar (i.e., financial institutions, manufacturing firms, technology companies, healthcare, and tourism). The target population for this study includes CEOs, chairpersons, environmental managers, IT managers, operations managers, and environmental managers.

This study utilizes a multi-sectoral population in Qatar to provide comprehensive insights into AI capabilities, green innovations, sustainable performance, and CE practices. Key economic sectors, including manufacturing, services, construction, energy, and finance, were chosen based on their contributions to the national GDP and sustainability potential. The sample included organizations that captured the influence of organizational size. Preference was given to organizations actively engaged in sustainability initiatives and those adopting advanced technologies, such as AI and big data analytics. Surveys were distributed online and in-person, with follow-ups to ensure broad participation, and initial data validation checks confirmed accurate sector and organizational representation. This approach ensures a robust and representative sample, providing a solid foundation for analyzing AI capabilities, green innovations, sustainable performance, and CE outcomes in Qatar.

Nevertheless, this study adopted a purposive sampling technique to ensure that the participants possessed the necessary expertise to provide accurate and meaningful insights into the investigated variables (e.g., Hulland et al., 2018). CEOs and chairpersons were selected because they comprehensively understand organizational strategy, resource allocation, and long-term sustainability planning, which enables them to assess how AI capability influences broader strategic goals. Their role in decision making gives them a unique perspective on aligning AI technologies with green innovation initiatives at a high level.

Environmental managers were selected because of their direct involvement in sustainability practices and green innovations, which were the core components of this study. Their specialized knowledge allows them to evaluate the effectiveness of these initiatives and how AI can support environmental goals. With their in-depth understanding of AI technologies and big data analytics, IT managers are critical for providing technical insights into AI capabilities. Their expertise ensures that the study accurately captures the potential of AI systems to drive innovation and sustainability within organizations.

Operations managers were included because of their hands-on roles in implementing AI and sustainability strategies in everyday business processes. Their practical experience ensured that the strategic and technological aspects, operational feasibility, and challenges of adopting AI and green innovation were evaluated.

By deliberately selecting individuals from these critical roles, this study ensures a well-rounded, expert-driven analysis of the interplay between AI capability, green innovation, sustainable performance, and CE outcomes. This targeted approach increases the reliability and depth of the findings as participants are positioned to offer insights based on both strategic oversight and operational execution.

Therefore, permission was sought from each firm's senior human resource officers before commencing the survey. The researchers contacted the CEOs, chairpersons, environmental managers, IT managers, operations managers, and other relevant personnel from 500 firms via email and in-person interactions.

### 4.3. Common method variance (CMV)

Common method variance (CMV) can introduce a significant source of bias in behavioral research, particularly when surveys rely on a single source of information. Hence, various measures were implemented before data collection to mitigate potential biases. Participants were assured that there were no correct or incorrect answers, and that their responses would remain anonymous (Podsakoff et al., 2012; Podsakoff et al., 2023). Importantly, the data were collected from various sources at different times. In the first stage, IT and operations managers rated the AI capability, big data analytics, KMS, and green innovation. One month later, the chairpersons and environmental managers assessed IT, operations managers, and CE in the second stage. Of the 500 firms approached, 350 responses were received from the CEOs, operations managers, environmental managers, and IT managers. The interval between the two stages was established to minimize the potential influence on the contextual condition scores, or vice versa. Of 500 questionnaires, 467 responses were returned. Of the 467 responses, 458 were valid, with a response rate of 94 %. Thus, excluding irregularities in questionnaires is essential to maintain data quality. The identified irregularities encompassed incomplete or inconsistent responses and random or careless answering patterns. These irregularities were detected through thorough data validation procedures such as checking for missing values, verifying response consistency, and scrutinizing response patterns for anomalies, thereby guaranteeing the reliability and validity of the study outcomes.

## 5. Data analysis

Structural Equation Modeling (SEM) is a statistical technique used across various disciplines to explore the intricate relationships among variables within a predefined theoretical framework. Within SEM, Partial Least Squares (PLS) has emerged as a suitable method, particularly in scenarios where prediction is the primary objective. PLS-SEM differs from other SEM approaches in that it adopts a component-based modeling strategy, prioritizing the maximization of explained variance in endogenous latent variables. Its predictive focus makes PLS-SEM advantageous for forecasting and understanding variance in observed variables (Hair et al., 2017). Collectively, PLS-SEM's adaptability, robustness, and predictive capabilities make it a valuable tool for researchers aiming to model and analyze complex relationships in their data.

### 5.1. Bias test

A *t*-test was used to assess the differences in features between sample firms that returned their surveys and those that did not. There were no statistically significant differences in fundamental characteristics among firms, including operational tenure, employee count, and asset size. Consequently, non-response bias was deemed minute (Armstrong and Overton, 1977).

### 5.2. Validity and reliability

With the measures of reflection and item reliability (as indicated by loadings), our results demonstrate that all items exceed the recommended threshold of 0.707, as outlined by Hair et al. (2017, 2019) (Table 2). To assess the internal consistency of the constructs, we computed composite reliability, which exceeded the 0.70 cutoff (Hair et al., 2017). Moreover, concerning convergent validity, the average variance extracted (AVE) for the constructs aligns with the recommended threshold of 0.5 (Hair et al., 2017, 2019). A summary of these findings is provided in Table 2.

Regarding the formative measures, Table 3 presents supportive evidence for using formative indicators. The results demonstrate minimal collinearity, with variance inflation factors (VIF) consistently falling well below the commonly accepted limit of five, as advised by Hair et al. (2017, 2019). Consequently, collinearity is not a cause for concern for any formative construct. Additionally, an assessment of the significance and relevance of the formative constructs revealed that all formative indicators were significant based on outer weights, *t*-values, and *p*-values, as outlined in Table 3 (Hair et al., 2017, 2019). Therefore, we confidently assert the successful establishment of a formative measurement model.

The Fornell-Larcker method for assessing discriminant validity revealed no concerns. Specifically, the AVE for each construct exceeded the amount of variance shared by the construct with other latent variables, as shown in Table 4 (Hair et al., 2017). When evaluating discriminant validity, the Heterotrait–Monotrait (HTMT) ratio did not raise any issues. This is evident from the HTMT values being below the 0.85 threshold, as indicated in Table 4. Consequently, the discriminant validity for each pair of constructs was validated following the set criteria (Henseler et al., 2015).

### 5.3. Structural model: hypotheses tests

Table 5 and Fig. 2 present the results for the hypotheses. Supporting H-1, the results demonstrate that AI capability significantly and positively influenced green innovation (*$\beta = 0.411$, t-value, 3.484 $p < .000$;* Table 4, Fig. 2). In addition, in line with the predictions of H-2, the findings indicate that green innovation significantly influences sustainable performance (*$\beta = 0.322$, t-value, 3.115 $p < .000$;* Table 5, Fig. 2). For H-3, which examines the interaction between green innovation and the CE, the findings reveal significance (*$\beta = 0.386$, t-value = 6.467, $p < .000$*; Table 5, Fig. 2). Consequently, the direct effect of H1–H3 is confirmed.

The initial interaction involving AI capability and big data analytics on green innovation revealed a noteworthy interaction effect (*$\beta = 0.268$, t-value, 2.85, $p < .000$*), thereby supporting H-4. Similarly, the second interaction concerning AI capability and KMS on CE displayed a significant interaction effect (*$\beta = 0.187$, t-value, 2.23, $p < .000$*), confirming the acceptance of H-5 (see Table 5 and Fig. 2).

Following Dawson's (2014) recommendation to enhance understanding, interaction plots were generated to illustrate how interactions differed visually under high and low conditions. Fig. 3 depicts the strong connection between AI capabilities and green innovation, which is even more significant when big data analytics is higher, as evidenced by the steeper slope. Hence, AI capabilities and green innovation interactions are supported by robust big data analytics, enhanced resource optimization, efficiency, and proactive environmental management. This correlation is strengthened with increased levels of big data analytics, emphasizing its role in promoting eco-friendly solutions and sustainable practices. This integration demonstrates how advanced technologies can

**Table 2**
Measurement model first-order constructs: item loading, construct reliability and convergent validity.

| Constructs | Code | Scale | Standardized factor loadings | Composite reliability | Average variance extracted |
|---|---|---|---|---|---|
| AI Capability Tangible (Data) | ACTD-1 | Reflective | 0.788 | 0.815 | 0.621 |
| | ACTD-2 | | 0.776 | | |
| | ACTD-3 | | 0.858 | | |
| | ACTD-4 | | 0.763 | | |
| | ACTD-5 | | 0.812 | | |
| | ACTD-6 | | 0.866 | | |
| AI Capability Tangible (Technology) | ACTT-1 | Reflective | 0.871 | 0.847 | 0.578 |
| | ACTT-2 | | 0.728 | | |
| | ACTT-3 | | 0.877 | | |
| | ACTT-4 | | 0.762 | | |
| | ACTT-5 | | 0.841 | | |
| | ACTT-6 | | 0.812 | | |
| | ACTT-7 | | 0.796 | | |
| AI Capability Tangible (Basic Resources) | ACBR-1 | Reflective | 0.787 | 0.852 | 0.701 |
| | ACBR-2 | | 0.784 | | |
| | ACBR-3 | | 0.863 | | |
| AI Capability Human Skills (Technical Skills) | ACTS-1 | Reflective | 0.817 | 0.874 | 0.614 |
| | ACTS-2 | | 0.854 | | |
| | ACTS-3 | | 0.778 | | |
| | ACTS-4 | | 0.844 | | |
| | ACTS-5 | | 0.771 | | |
| | ACTS-6 | | 0.822 | | |
| | ACTS-7 | | 0.864 | | |
| AI Capability Human Skills (Business Skills) | ACBS-1 | Reflective | 0.789 | 0.789 | 0.652 |
| | ACBS-2 | | 0.884 | | |
| | ACBS-3 | | 0.832 | | |
| | ACBS-4 | | 0.852 | | |
| | ACBS-5 | | 0.795 | | |
| | ACBS-6 | | 0.841 | | |
| | ACBS-7 | | 0.833 | | |
| AI Capability Intangible (Inter-Departmental Coordination) | ACIC-1 | Reflective | 0.881 | 0.864 | 0.584 |
| | ACIC-2 | | 0.874 | | |
| | ACIC-3 | | 0.795 | | |
| | ACIC-4 | | 0.834 | | |
| | ACIC-5 | | 0.782 | | |
| | ACIC-6 | | 0.799 | | |
| | ACIC-7 | | 0.815 | | |
| AI Capability Intangible (Organizational Change Capacity) | AOCC-1 | Reflective | 0.818 | 0.818 | 0.643 |
| | AOCC-2 | | 0.833 | | |
| | AOCC-3 | | 0.831 | | |
| | AOCC-4 | | 0.844 | | |
| | AOCC-5 | | 0.757 | | |
| | AOCC-6 | | 0.874 | | |
| AI Capability Intangible (Risk Proclivity) | ACRP-1 | Reflective | 0.841 | 0.811 | 0.671 |
| | ACRP-2 | | 0.762 | | |
| | ACRP-3 | | 0.866 | | |
| Green Product Innovation | GPI-1 | Reflective | 0.837 | 0.825 | 0.587 |
| | GPI-2 | | 0.813 | | |
| | GPI-3 | | 0.756 | | |
| | GPI-4 | | 0.826 | | |
| Green Process Innovation | GPRI-1 | Reflective | 0.799 | 0.847 | 0.665 |
| | GPRI-2 | | 0.891 | | |
| | GPRI-3 | | 0.787 | | |
| | GPRI-4 | | 0.783 | | |
| Big Data Analytics (BDA) | BDA-1 | Reflective | 0.753 | 0.878 | 0.587 |
| | BDA-2 | | 0.871 | | |
| | BDA-3 | | 0.794 | | |
| | BDA-4 | | 0.766 | | |
| | BDA-5 | | 0.882 | | |
| | BDA-6 | | 0.876 | | |
| | BDA-7 | | 0.789 | | |
| | BDA-8 | | 0.755 | | |
| | BDA-9 | | 0.876 | | |
| | BDA-10 | | 0.789 | | |
| IT infrastructures | ITI-1 | Reflective | 0.794 | 0.894 | 0.614 |
| | ITI-2 | | 0.863 | | |
| | ITI-3 | | 0.779 | | |
| | ITI-4 | | 0.819 | | |
| Collaborative Technologies | CT-1 | Reflective | 0.758 | 0.875 | 0.598 |
| | CT-2 | | 0.844 | | |
| | CT-3 | | 0.743 | | |
| | CT-4 | | 0.841 | | |
| | CT-5 | | 0.844 | | |
| ICT adoption/support | ICT-1 | | 0.837 | 0.841 | 0.611 |

(continued on next page)

**Table 2** (*continued*)

| Constructs | Code | Scale | Standardized factor loadings | Composite reliability | Average variance extracted |
|---|---|---|---|---|---|
| | ICT-2 | | 0.813 | | |
| | ICT-3 | | 0.756 | | |
| | ICT-4 | | 0.826 | | |
| | ICT-5 | | 0.726 | | |
| | ICT-6 | | 0.748 | | |
| Organizational Performance | OP-1 | | 0.897 | 0.819 | 0.587 |
| | OP-2 | | 0.694 | | |
| | OP-3 | | 0.881 | | |
| | OP-4 | | 0.775 | | |
| Environmental Performance | ENP-1 | | 0.823 | 0.885 | 0.632 |
| | ENP-2 | | 0.746 | | |
| | ENP-3 | | 0.812 | | |
| | ENP-4 | | 0.786 | | |
| | ENP-5 | | 0.836 | | |
| | ENP-6 | | 0.822 | | |
| Circular Economy | CE-1 | | 0.862 | 0.853 | 0.693 |
| | CE-2 | | 0.756 | | |
| | CE-3 | | 0.762 | | |
| | CE-4 | | 0.843 | | |
| | CE-5 | | 0.830 | | |
| | CE-6 | | 0.802 | | |
| | CE-7 | | 0.814 | | |
| | CE-8 | | 0.777 | | |
| | CE-9 | | 0.833 | | |
| | CE-10 | | 0.856 | | |

**Table 3**
Measurement model second-order constructs: weight, VIF, t-value and p-value.

| Constructs | Indicators | Scale | Weight | VIF | t-value | p-value |
|---|---|---|---|---|---|---|
| AI Capability Tangible | Data | Formative | 0.334 | 1.46 | 3.49 | 0.000 |
| | Technology | | 0.322 | 2.21 | 3.89 | 0.000 |
| | Basic Resources | | 0.311 | 1.361 | 2.98 | 0.000 |
| AI Capability Human Skills | Technical Skills | Formative | 0.313 | 2.86 | 3.41 | 0.000 |
| | Business Skills | | 0.341 | 2.37 | 3.76 | 0.000 |
| AI Capability Intangible | Inter-Departmental Coordination | Formative | 0.217 | 1.37 | 3.14 | 0.001 |
| | Organizational Change Capacity | | 0.311 | 1.58 | 3.63 | 0.000 |
| | Risk Proclivity | | 0.482 | 3.11 | 4.53 | 0.000 |
| Green Innovation | Green Product Innovation | Formative | 0.334 | 1.46 | 4.41 | 0.000 |
| | Green Process Innovation | | 0.327 | 1.78 | 3.86 | 0.000 |
| Knowledge Management Systems | IT Infrastructures | Formative | 0.322 | 1.486 | 3.896 | 0.002 |
| | Collaborative Technologies | | 0.321 | 1.264 | 4.200 | 0.000 |
| | ICT Adoption/Support | | 0.320 | 1.491 | 2.175 | 0.001 |
| Sustainable Performance | Organizational Performance | Formative | 0.314 | 1.491 | 2.175 | 0.000 |
| | Environmental Performance | | 0.234 | 1.315 | 2.574 | 0.002 |

Note (s): VIF = Variance Inflation Factor.

**Table 4**
Descriptive statistics, correlation matrix, and discriminant validity (AVE and HTMT).

| Constructs | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|
| 1. AI capability | 4.41 | 0.560 | **0.54** | *0.627* *[0.537; 0.719]* | *0.653* *[0.561; 0.739]* | *0.439* *[0.333; 0.537]* | *0.605* *[0.486; 0.710]* | *0.100* *[0.089; 0.183]* |
| 2. Green Innovation | 3.65 | 0.441 | 0.55 | **0.66** | *0.739* *[0.667; 0.854]* | *0.508* *[0.434; 0.602]* | *0.702* *[0.643; 0.771]* | *0.215* *[0.162; 0.323]* |
| 3. Big Data Analytics | 3.61 | 0.709 | 0.57 | 0.78 | **0.45** | *0.482* *[0.403; 0.584]* | *0.732* *[0.657; 0.805]* | *0.137* *[0.106; 0.259]* |
| 4. Knowledge management systems | 4.34 | 0.521 | 0.26 | 0.18 | 0.17 | **0.60** | *0.593* *[0.510; 0.683]* | *0.131* *[0.109; 0.241]* |
| 5. Sustainable Performance | 4.14 | 0.521 | 0.55 | 0.63 | 0.61 | 0.14 | **0.51** | *0.211* *[0.137; 0.332]* |
| 6. Circular Economy | 3.86 | 0.521 | 0.41 | 0.36 | 0.10 | 0.01 | 0.20 | **0.67** |

Note (s): S.D. = Standard Deviation.
Bold values on the diagonal in the correlation matrix are square roots of AVE (variance shared between the constructs and their respective measures).

drive transformative impacts on environmental stewardship. Similarly, Fig. 4 illustrates that the positive association between AI capability and green innovation becomes more prominent with a steeper slope when KMS are higher. Thus, effective KMS boost the connection between AI capabilities and green innovation, enabling organizations to optimize AI for sustainable practices. This correlation was evident in the increased impact at higher knowledge management levels, highlighting the key role of knowledge management in enhancing the effectiveness of AI in driving environmental sustainability through innovation. These interaction plots offer a visual representation of how relationships change

**Table 5**
Structural path analysis.

| | Direct Effect | | | | | Bias and Corrected Bootstrap 95 % CI | | |
|---|---|---|---|---|---|---|---|---|
| Hypothesis | Relationship | Std Beta | Std Error | t- value | p-value | BCI 95 % LL | BCI 95 % UL | Decision |
| H-1 | AI capability -> Green Innovation | 0.411 | 0.088 | 3.484 | 0.000 | 0.114 | 0.352 | Significant |
| H-2 | Green Innovation -> Sustainable Performance | 0.322 | 0.067 | 3.115 | 0.000 | 0.213 | 0.523 | Significant |
| H-3 | Green Innovation -> Circular Economy | 0.386 | 0.060 | 6.467 | 0.000 | 0.275 | 0.475 | Significant |
| **Structural Path Analysis: The Interaction Effect** | | | | | | | | |
| H-4 | AI capability × Big Data Analytics -> Green Innovation | 0.268 | 0.087 | 2.85 | 0.000 | 0.023 | 0.123 | Significant |
| H-5 | AI capability × Knowledge management systems->Green Innovation | 0.187 | 0.076 | 2.23 | 0.000 | 0.010 | 0.274 | Significant |

Note (s): $n = 350$. Bootstrap sample size = 5000. SE = standard error; LL = lower limit; CI = confidence interval; UL = upper limit 95 % bias-correlated CI, Ns = None significant.

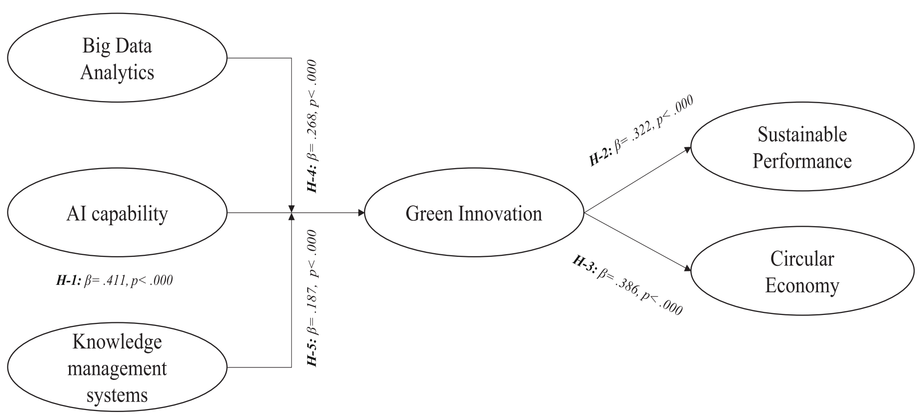


**Fig. 2.** Research model: hypotheses testing.

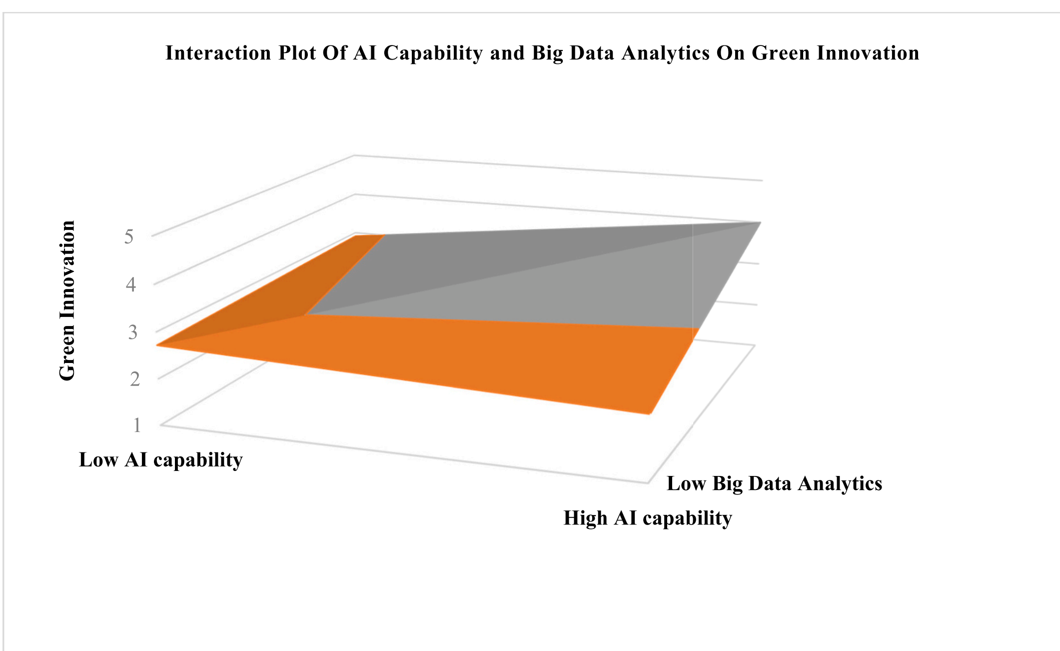


**Fig. 3.** Interaction plot of AI capability and big data analytics on green innovation.

under various conditions, providing important insights into how variables influence moderation within the context of this study.

Finally, the predictive relevance between the independent and dependent variables was evaluated using $R^2$ *and* $Q^2$, *with* $R^2 = 0.611$ for sustainable performance and 0.563 for CE. Furthermore, we employed the Stone-Geisser blindfolding method to evaluate the predictive validity, uncovering $Q^2$ values exceeding 0. This approach effectively demonstrates the research model's ability to predict both sustainable

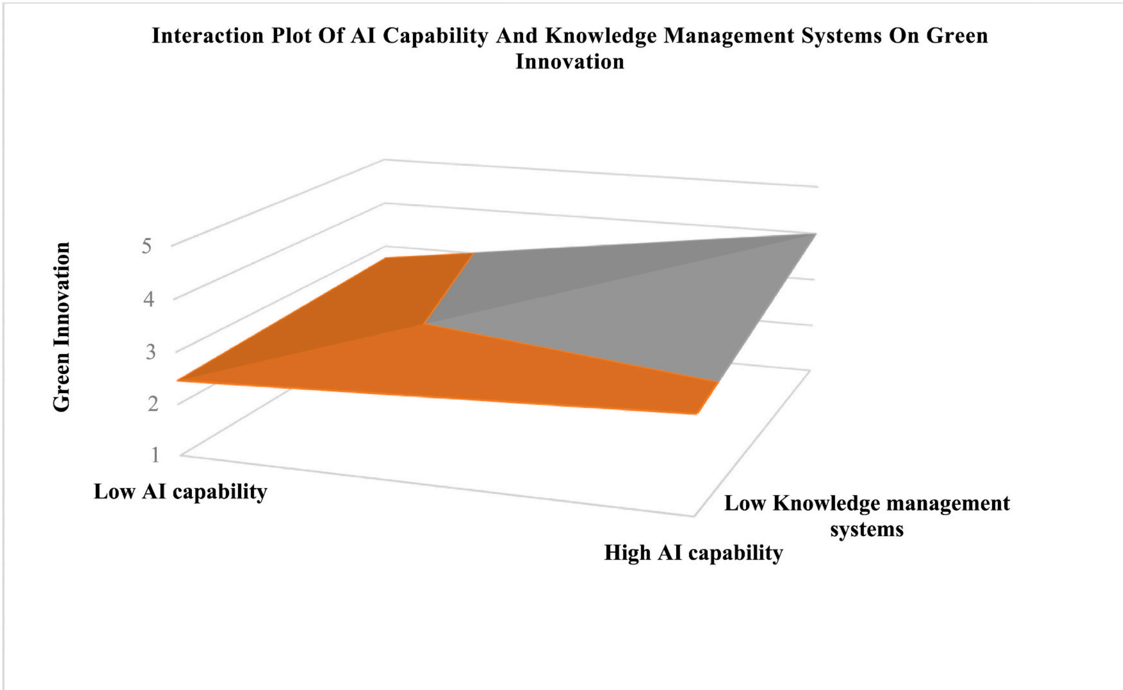


**Fig. 4.** Interaction plot of AI capability and Knowledge management systems on Green Innovation.

performance ($Q^2 = 0.278$) and CE ($Q^2 = 0.231$) (Hair et al., 2017).

### 5.4. Artificial neural network (ANNs)

Artificial Neural Networks (ANNs) are algorithms designed to mimic the manner in which the human brain processes information. They comprise interconnected nodes known as artificial neurons, which are organized into layers responsible for processing information. Therefore, artificial neural networks (ANN) were employed, as integrating it with path analysis offers a strong and complementary method for exploring complex relationships among variables. ANN are particularly useful for non-linear data structures where traditional parametric assumptions, such as normality and linearity, fail. In contrast, while path analysis effectively identifies and tests predefined causal relationships in a structured model, it relies on linearity and often misses non-linear patterns (Leong et al., 2020).

On the other hand, ANN can capture intricate non-linear interactions between variables without the need for pre-specified models, offering a more flexible and adaptive approach. Using an ANN alongside path analysis, this study could detect hidden patterns, complex relationships, and interactions that path analysis might miss. ANN can also handle high-dimensional data and identify subtle relationships between predictors and outcomes, thereby enhancing the predictive accuracy of a model.

Incorporating an ANN allows exploring the model fit from confirmatory (path analysis) and exploratory (ANN) perspectives. Path analysis provides a theoretical and hypothesis-driven understanding of relationships, whereas ANN complement this by uncovering non-linear dependencies and enhancing the robustness of the findings. This dual approach offers a comprehensive analysis, ensuring that the model accounts for the direct and indirect effects and complex non-linear associations that contribute to a more complete understanding of the phenomena being studied.

Thus, neural network analysis supplements path analysis by capturing intricate relationships that path analysis may miss. While path analysis revealed linear links among the variables, neural network analysis revealed hidden patterns and interactions. Together, they offer a more comprehensive perspective; path analysis confirms expected relationships, whereas neural network analysis uncovers nonlinear associations, thereby boosting predictive accuracy. This combined approach ensures a thorough and nuanced understanding of the data, harnessing both linear and nonlinear modeling strengths.

The ANN model was configured with a multilayer perceptron (MLP) structure, including one covered layer, to balance complexity and avoid overfitting. A sigmoid activation function was applied to the hidden layer to model the nonlinear relationships, whereas a linear activation function was employed in the output layer to forecast the continuous results. The backpropagation algorithm was selected owing to its effectiveness in minimizing errors through iterative weight adjustments. A moderate learning rate and appropriate number of epochs, determined through cross-validation, ensured stable convergence without overfitting. These configurations were selected to effectively capture nuanced data patterns and complement the path analysis. However, the activation functions and outcome layers utilize sigmoid functions. The learning process involves multiple phases, leading to fewer faults and improved prediction accuracy. Ninety percent of the samples were designated for training, whereas the remaining samples were set aside for testing. RMSE served as a metric for assessing the predictive precision of the ANN model, as outlined by Leong et al. (2020). Table 6 shows RMSE values of 182.2 and 21.76 for training and testing, respectively, reflecting a slight difference between the values of the study variables.

Simultaneously, sensitivity analysis evaluated each predictor's contribution to sustainable performance and the circular economy. Relative importance, calculated as a percentage, was determined by dividing the relative importance of each added neuron by the highest relative importance. The outcomes revealed that big data analytics had the highest importance (1.00 %) among the predictors, followed by green innovation (91.7 %), AI Capability (0.91 %), and KMS (83.8 %) (refer to Table 7). Finally, H (1:4) emerged as the primary contributing cell to concealed neurons. Concurrently, those of H (1:3) were identified as the most inhibitive neurons, followed by H (1:5), H (1:2), and H (1:1) (see Table 8 and Fig. 5).

**Table 6**
The RMSE for training and testing processes in a ten-fold ANN.

| | Input Neurons: AIC, GI, BDA, KMS | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Output Nodes: Sustainable Performance | | | | | | Output Nodes: Circular Economy | | | | | |
| NNA | Training | | | Testing | | | Training | | | Testing | | |
| | N | RMSE | SSE | N | RMSE | SSE | N | RMSE | SSE | N | RMSE | SSE |
| 1 | 557 | 210.7 | 64.27 | 63 | 24.78 | 0.65 | 558 | 1700.6 | 431.9 | 620.0 | 251.1 | 677.4 |
| 2 | 547 | 220.9 | 70.02 | 73 | 30.89 | 78.08 | 554 | 125.4 | 33.57 | 66 | 20.18 | 48.5 |
| 3 | 560 | 208.2 | 58.57 | 60 | 23.38 | 0.60 | 554 | 130.2 | 0.370 | 66 | 20.95 | 5151.5 |
| 4 | 551 | 165.9 | 43.56 | 69 | 23.72 | 0.55 | 560 | 122.6 | 0.348 | 60 | 17.85 | 4833.3 |
| 5 | 569 | 159.6 | 0.41 | 51 | 14.57 | 0.37 | 559 | 128.2 | 0.361 | 61 | 16.92 | 4098.4 |
| 6 | 563 | 157.0 | 0.41 | 57 | 17.03 | 43.86 | 567 | 235.5 | 0.683 | 53 | 22.19 | 73.6 |
| 7 | 551 | 172.7 | 47.91 | 69 | 21.87 | 46.38 | 564 | 198.0 | 0.534 | 56 | 20.03 | 57.1 |
| 8 | 569 | 200.2 | 0.52 | 51 | 18.11 | 0.55 | 550 | 126.7 | 0.349 | 70 | 18.75 | 47.1 |
| 9 | 549 | 134.4 | 0.37 | 71 | 19.37 | 0.42 | 565 | 155.6 | 0.414 | 55 | 18.77 | 50.9 |
| 10 | 556 | 192.9 | 0.51 | 64 | 23.86 | 0.58 | 559 | 121.3 | 0.335 | 61 | 15.38 | 37.7 |
| Mean | – | 182.2 | 28.66 | – | 21.76 | 17.20 | – | 149.3 | 4.108 | – | 19.00 | 1599.8 |
| SD | – | 28.31 | 30.63 | – | 4.672 | 28.31 | – | 40.68 | 11.05 | – | 2.100 | 2336.6 |

Note (s): N = Number of Data; SSE = Sum Square of Error; RMSE = Root Mean Square of Error.
Keys: AIC = AI Capability; GI = Green Innovation; BDA = Big Data Analytics; KMS = Knowledge Management Systems.

**Table 7**
Sensitivity analysis.

| | Relative Importance | | | |
|---|---|---|---|---|
| NNA | AIC | GI | BDA | KMS |
| 1 | 0.361 | 0.1203 | 0.154 | 0.168 |
| 2 | 0.267 | 0.2413 | 0.220 | 0.270 |
| 3 | 0.222 | 0.3070 | 0.204 | 0.266 |
| 4 | 0.274 | 0.2311 | 0.238 | 0.256 |
| 5 | 0.270 | 0.2414 | 0.240 | 0.247 |
| 6 | 0.244 | 0.2374 | 0.265 | 0.253 |
| 7 | 0.248 | 0.2424 | 0.269 | 0.239 |
| 8 | 0.281 | 0.2313 | 0.268 | 0.219 |
| 9 | 0.245 | 0.2312 | 0.239 | 0.283 |
| 10 | 0.256 | 0.2535 | 0.258 | 0.232 |
| Mean relative importance | 0.248 | 0.2501 | 0.272 | 0.228 |
| Normalized Importance (%) | 0.91 % | 91.7 % | 1.00 % | 83.8 % |

Keys: AIC = AI Capability; GI = Green Innovation; BDA = Big Data Analytics; KMS = Knowledge Management Systems.

## 6. Discussion and implications

This study expands the existing understanding of the leading strategies and mechanisms that business organizations adopt to promote sustainable performance and CE. Therefore, the main objective was to test the direct impact of AI capability on green innovation, and subsequently analyze the influence of these innovations on sustainable performance and CE. Additionally, this study explored the moderating roles of big data analytics and KMS in the relationship between AI capability and green innovation. The current study successfully employed the SEM and ANN approaches to achieve these objectives. Therefore, researchers used multi-sectoral population data from various Qatari industries, including financial services, manufacturing, high-tech, telecommunications, healthcare, and tourism. This comprehensive methodology allows for a robust analysis of the complex relationships among AI capability, green innovations, sustainable performance, and CE.

The statistical findings confirmed the predictions outlined in the conceptual model and research hypotheses. In detail, SEM results strongly supported AI capability in contributing to green innovation ($\beta = 0.411$, $t$-value $= 3.484$, $p < .000$) and sustainable performance ($\beta = 0.322$, $t$-value, $3.115$ $p < .000$). These results are attributed to the high level of AI capability that helps business organizations effectively and efficiently utilize technical resources, predictive maintenance, and optimize production processes, all of which contribute to reducing waste and promoting sustainability. This finding aligns with those of previous studies (i.e., Mikalef and Gupta, 2021; Yu et al., 2023; Lee and Lim, 2021) supporting the transformative possibility of AI in driving environmental sustainability.

The positive effect of AI on green innovation is noteworthy. Nevertheless, this study highlights the amplifying effects of interactions with big data analytics and KMS. This nuanced understanding emphasizes that the beneficial effect of AI capability on promoting green innovation is not isolated, but is instead intricately connected with the dynamic interplay between these technological components. This study's identification of big data analytics and KMS as vital moderators introduces

**Table 8**
Average weights of the input and hidden neurons in the ten-fold ANN.

| Parameter Estimates | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Predictor | | Predicted | | | | | | |
| | | Hidden Layer 1 | | | | | Output Layer | |
| | | H(1:1) | H(1:2) | H(1:3) | H(1:4) | H(1:5) | Sustainable Performance | Circular Economy |
| Input Layer | (Bias) | 1.737 | −0.129 | −1.221 | 0.116 | 0.067 | | |
| | AI Capability | 0.281 | −1.843 | −0.245 | −0.208 | 0.220 | | |
| | Green Innovation | −0.521 | 0.896 | −0.815 | −0.296 | −0.423 | | |
| | Big Data Analytics | −0.935 | −0.013 | −2.849 | 0.050 | 0.259 | | |
| | Knowledge Management Systems | 0.247 | −0.713 | −1.493 | 0.331 | 0.083 | | |
| Hidden Layer 1 | (Bias) | | | | | | −0.003 | 0.696 |
| | H(1:1) | | | | | | −0.226 | −1.182 |
| | H(1:2) | | | | | | −0.247 | −0.439 |
| | H(1:3) | | | | | | −0.737 | −0.378 |
| | H(1:4) | | | | | | 0.181 | 0.098 |
| | H(1:5) | | | | | | −0.340 | 0.220 |

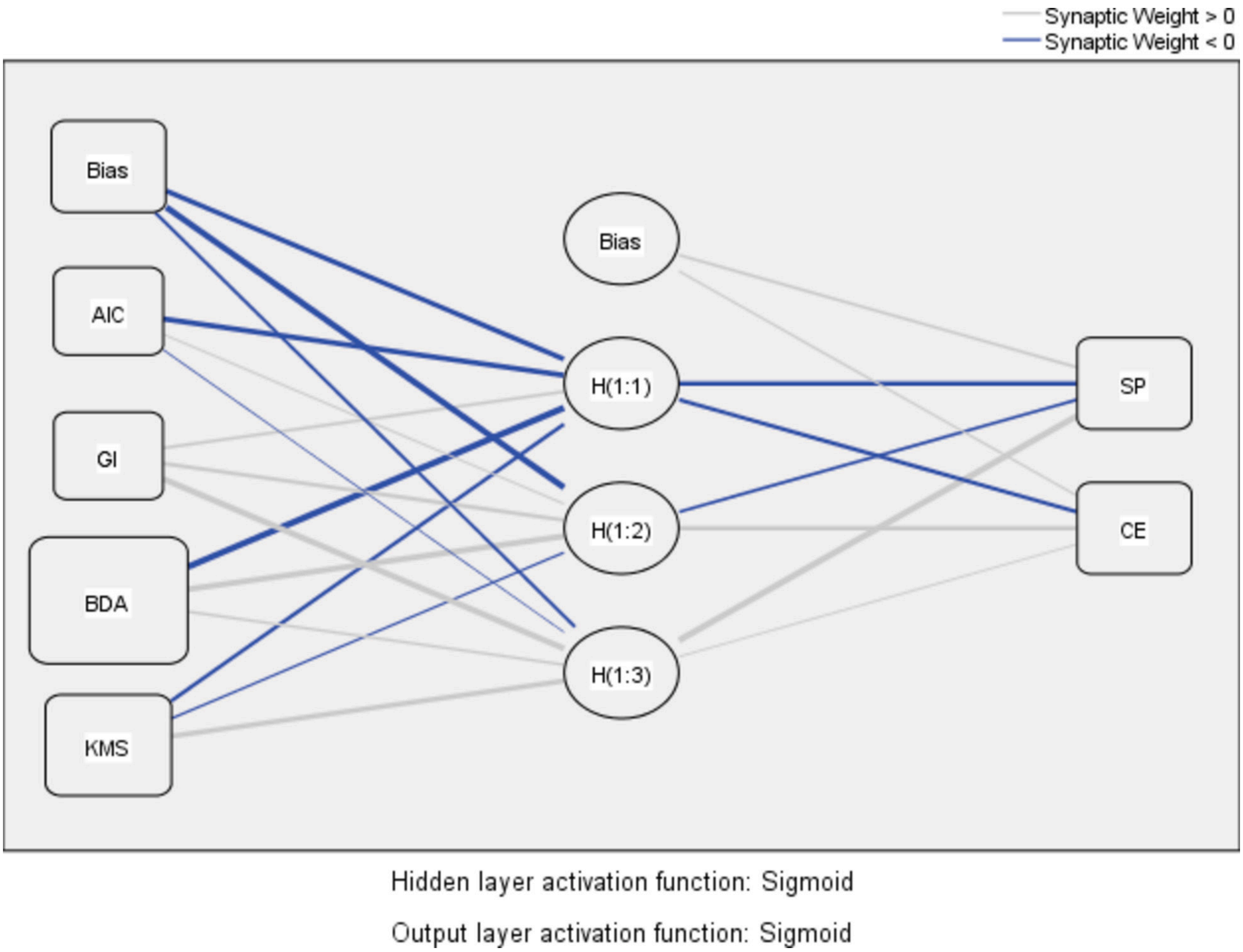


**Fig. 5.** The artificial neural network (ANN) models.
Note (s): AIC = AI capability, GI = Green Innovation, BDA = Big Data Analytics, KMS=Knowledge management systems, SP=Sustainable Performance, CE = Circular Economy.

complexity into the relationship, underlining the need for a comprehensive and integrated approach.

The statistical results endorse the beneficial impact of green innovation in fostering sustainable performance ($\beta = 0.322$, $t$-value $= 3.115$, $p < .000$). These findings demonstrate that green innovation contributes to both environmental practices and overall sustainability. This positive impact can be attributed to the value added by increasing green innovation through enhanced productivity and cost savings, which in turn bolsters sustainable performance while aligning with regulatory and societal expectations for environmental responsibility. These findings support those of Chen et al. (2006), Seman et al. (2019), Liu et al. (2020), and Dong et al. (2022). Likewise, green innovation was statistically approved to be a positive driver of the CE ($\beta = 0.386$, $t$-value $=$ 6.467, $p < .000$), which, in turn, demonstrates how innovative approaches are important for closing the loop of product lifecycles. By encouraging the recycling, reuse, and repurposing of materials, green innovations facilitate changes from linear innovation to CE, which is essential for long-term sustainability. This finding supports the growing recognition of CE as a viable model for reducing resource consumption and waste generation.

### *6.1. Theoretical implications*

This study significantly advances the theoretical landscape by addressing the contemporary challenges of environmental impacts, resource consumption, and waste generation of industries, aligning with recent trends in sustainability research and the CE discourse (Coenen et al., 2020). This research promotes sustainable performance and a CE as strategic responses to mitigate environmental degradation and contributes to ongoing discussions on holistic and ecologically responsible business practices. The examination of the direct influence of AI capability on green innovation is situated within the evolving theoretical framework of technology-driven environmental innovation. Recent studies by Pan et al. (2022) highlighted the transformative potential of AI in driving sustainable practices, aligning with the central principles of technological determinism that underlie this study.

This study was based on the theoretical framework of technological determinism, which suggests that emerging systems (AI applications) can act as major forces driving societal change and innovation. Thus, this study provides a clearer picture of the role of AI capabilities in accelerating green innovation. Therefore, the results of this study clearly explain how digital modernization (AI systems) can effectively influence and enhance sustainable performance and environmental responsibility. In other words, this study provides new evidence of the value that AI systems can add to the implementation of sustainable and CE practices.

Moreover, the novelty of this study lies in its proposition of two critical moderators, big data analytics and KMS, in the connection between AI capability and green innovation. This theoretical advancement builds upon recent research exploring the role of big data in sustainability (Dubey et al., 2019) and KMS in novel areas (e.g., Sahoo et al., 2023). By integrating these variables into a comprehensive framework, this study connects a theoretical gap by recognizing the interconnectedness of AI, big data analytics, and KMS in shaping green innovation and sustainability outcomes. Recent work by Li et al. (2023) highlights the need for a more integrative approach to understanding the role of technology in sustainability, and supports the theoretical orientation of this study.

Comparatively, this research diverges from previous studies that have often focused on isolated aspects of technology, innovation, and sustainability. Simultaneously, it explores the impact of AI on innovation and investigates the role of big data plays a part in sustainability. Adopting a holistic perspective, this study concurrently examines AI, big data analytics, and KMS. Recent studies, such as Shahzad et al. (2022), have emphasized the need for comprehensive analyses that consider the interactions between different technological components in influencing sustainable outcomes, validating the unique theoretical contribution of this research. A novel understanding of the multifaceted relationships among these technological elements and their combined influence on environmental and performance outcomes sets the current study apart as a pioneering contribution to the evolving field of technology-driven sustainability research. In essence, this study addresses contemporary ecological challenges and advances theoretical frameworks, emphasizing the interconnectedness of technological components in shaping sustainable practices within diverse industrial contexts.

### 6.2. Practical implications

The real-world consequences of this study present a distinctive and targeted approach that holds significant relevance for policymakers, specifically in the Qatari context, spanning industries such as financial services, manufacturing, high tech, telecommunications, healthcare, and tourism. This study's nuanced exploration of the direct impact of AI capability on green innovations, along with the moderating roles of big data analytics and KMS, exposes unique opportunities for policymakers to develop transformative initiatives. A fundamental guideline for policymakers is fostering cross-sector collaboration to establish an integrated technological ecosystem. Rather than viewing AI, big data analytics, and KMS in isolation, policymakers should encourage an interconnected framework in which these elements combine to drive sustainable innovation. This involves designing incentive structures that promote collaborative projects among industries, thereby enabling the pooling of AI expertise, data analytic capabilities, and KMS across sectors. Policymakers can unlock the highest capability of these technologies to spur innovative solutions that address the environmental challenges specific to the Qatari industry.

In the financial services sector, for instance, policymakers could incentivize the implementation of AI-driven algorithms for sustainable investment portfolios, leverage big data analytics to assess environmental impacts, and use KMS to disseminate relevant information. In manufacturing, integrating AI-enabled predictive maintenance with robust data analytics and knowledge management may optimize resource utilization and minimize waste. High-tech industries could explore AI applications in energy-efficient technologies, guided by comprehensive data analytics to assess performance, and informed by KMS to disseminate best practices. Policymakers can encourage telecommunications companies to deploy AI to optimize network efficiency, guided by insights gleaned from big data analytics. Simultaneously, KMS facilitates the dissemination of sustainable practices across industries. In the healthcare sector, AI capabilities can be harnessed for predictive diagnostics and personalized treatment plans, aided by extensive data analytics and KMS for informed decision-making and continuous learning. For the tourism sector, AI-driven recommendations for sustainable travel, supported by comprehensive data analytics on carbon footprints and facilitated by KMS that disseminate eco-friendly practices, can contribute to the CE.

The findings underline the necessity for policies prioritizing continuous upskilling and education to equip the workforce with the expertise to harness these technologies effectively. Policymakers can collaborate with educational institutions to design programs on AI literacy, data analytics proficiency, and knowledge-management skills. By developing a skilled workforce, Qatar's industries can exploit the potential of these technologies for sustainable and circular practices, thereby ensuring the long-term success of these initiatives. Thus, this study offers a distinctive pathway for Qatari policymakers by advocating an integrative and collaborative approach to harness AI capabilities, green innovations, big data analytics, and KMS across diverse industries. This interconnected framework provides a holistic solution tailored to Qatar's unique challenges and opportunities and ultimately fosters sustainability, circularity, and innovation from an economic perspective.

### 6.3. Limitations and future research

Although this research enhances our understanding of the interaction between AI capability, green innovation, big data analytics, KMS, sustainable performance, and CE, it is important to recognize certain limitations and propose directions for future research to enrich the comprehensiveness of the framework. One limitation is the potential contextual variations across different industries in Qatar. Hence, future research could explore industry-specific shades and challenges to adapt the framework more precisely while accounting for sector-specific needs and dynamics. Additionally, although this study gathered data over time, it was not an accurate longitudinal study. Therefore, future studies should adopt a longitudinal approach to capture the evolving relationships between these variables over time. Qualitative methodologies could also be instrumental in establishing a thorough understanding of the challenges within the framework of AI capability, green innovation, big data analytics, KMS, sustainable performance, and CE, incorporating stakeholder perspectives and organizational learning.

Another avenue for exploration involves incorporating sociocultural factors, such as environmental stewardship and responsible resource use, which may influence the adoption and effectiveness of AI, green innovation, and circular practices. Examining the effect of cultural attitudes toward sustainability and technology adoption provides valuable insights. Moreover, the study primarily focuses on the direct influence of AI capability on green innovation, leaving room for the exploration of indirect effects and mediating factors such as organizational culture, government regulations and policies, corporate social responsibility (CSR), communication channels, and the degree of innovation encouragement. Thus, future research could investigate the intermediate variables that facilitate or hinder relationships within the proposed framework. For instance, the roles of corporate governance structures, CSR, and regulatory frameworks in influencing the effectiveness of AI-driven sustainability initiatives can be explored. By broadening the framework to encompass these unique variables and considerations, future research can provide a more precise and detailed understanding of the dynamics that foster sustainable and circular practices in diverse industries.

## 7. Conclusion

This study investigates the direct effects of AI capabilities on green innovation and their subsequent impact on sustainable performance and CE. Drawing on the AI Capability perspective (Mikalef and Gupta, 2021), this study develops a conceptual model and formulates hypotheses. Specifically, AI capability was operationalized as a multidimensional construct with seven components: tangible AI capability (data), tangible AI capability (technology), tangible AI capability (Basic Resources), human skills AI capability (Technical Skills), human skills AI capability (Business Skills), intangible AI capability (Inter-Departmental Coordination), intangible AI capability (Organizational Change Capacity), and intangible AI capability (Risk Proclivity).

This study investigated the moderating roles of big data analytics and KMS in the relationship between AI Capability and green innovation. Green innovation is hypothesized to directly influence sustainable performance and CE. Empirical data were collected through questionnaires distributed across various sectors in Qatar, including financial, manufacturing, high tech, telecommunications, healthcare, and tourism industries. The data were analyzed using the PLS-SEM and ANN approaches.

This study confirms that the AI capability significantly influences green innovation and has a notable impact on sustainable performance and CE. Additionally, AI capability and green innovation were positively and significantly moderated by big data analytics and KMS. This study significantly enhances researchers' and practitioners' understanding of the critical aspects shaping the successful use of AI, big data analytics, and KMS to foster environmentally responsible practices across sectors. However, this study has several limitations that present valuable directions for future research.

## CRediT authorship contribution statement

**Hussam Al Halbusi:** Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Khalid Ibrahim Al-Sulaiti:** Supervision, Project administration, Methodology. **Ali Abdallah Alalwan:** Writing – review & editing, Validation, Methodology. **Adil S. Al-Busaidi:** Writing – review & editing, Methodology, Investigation.

## Data availability

Data will be made available on request.

## References


Aftab, J., Abid, N., Sarwar, H., Veneziani, M., 2022. Environmental ethics, green innovation, and sustainable performance: Exploring the role of environmental leadership and environmental strategy. J. Clean. Prod. 378, 134639.

Agrawal, R., Wankhede, V.A., Kumar, A., Luthra, S., Huisingh, D., 2022. Big data analytics and sustainable tourism: a comprehensive review and network-based analysis for potential future research. Int. J. Inf. Manag. Data Insights 2 (2), 100122.

Al Halbusi, H., Soto-Acosta, P., Popa, S., Hassani, A., 2023a. The role of green digital learning orientation and big data analytics in the green innovation–sustainable performance relationship. IEEE Trans. Eng. Manag. 1–11. https://doi.org/10.1109/tem.2023.3277078.

Al Halbusi, H., Klobas, J.E., Ramayah, T., 2023b. Green core competence and firm performance in a post-conflict country, Iraq. Bus. Strategy Environ. 32 (6), 2702–2714.

Al Halbusi, H., Popa, S., Alshibani, S.M., Soto-Acosta, P., 2024. Greening the future: analyzing green entrepreneurial orientation, green knowledge management and digital transformation for sustainable innovation and circular economy. Eur. J. Innov. Manag. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/EJIM-02-2024-0169.

Aldieri, L., Carlucci, F., Cira, A., Ioppolo, G., Vinci, C.P., 2019. Is green innovation an opportunity or a threat to employment? An empirical analysis of three main industrialized areas: the USA, Japan and Europe. J. Clean. Prod. 214, 758–766.

Allal-Chérif, O., Climent, J.C., Berenguer, K.J.U., 2023. Born to be sustainable: How to combine strategic disruption, open innovation, and process digitization to create a sustainable business. J. Bus. Res. 154, 113379.

Armstrong, J.S., Overton, T.S., 1977. Estimating nonresponse bias in mail surveys. J. Mark. Res. 14 (3), 396–402.

Asadi, S., Pourhashemi, S.O., 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. J. Clean. Prod. 258, 120860.

Ashaari, M.A., Singh, K.S.D., Abbasi, G.A., Amran, A., Liebana-Cabanillas, F.J., 2021. Big data analytics capability for improved performance of higher education institutions in the Era of IR 4.0: a multi-analytical SEM & ANN perspective. Technol. Forecast. Soc. Chang. 173, 121119.

Audretsch, D.B., Belitski, M., 2023. Evaluating internal and external knowledge sources in firm innovation and productivity: an industry perspective. R&D Manag. 53 (1), 168–192.

Bag, S., Pretorius, J.H.C., Gupta, S., Dwivedi, Y.K., 2021. Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. Technol. Forecast. Soc. Chang. 163, 120420.

Bag, S., Rahman, M.S., Srivastava, G., Shore, A., Ram, P., 2023. Examining the role of virtue ethics and big data in enhancing viable, sustainable, and digital supply chain performance. Technol. Forecast. Soc. Chang. 186, 122154.

Borah, P.S., Iqbal, S., Akhtar, S., 2022. Linking social media usage and SME's sustainable performance: the role of digital leadership and innovation capabilities. Technol. Soc. 68, 101900.

Chen, W.C., Rau, H., 2023. A product evaluation and innovation process based on the circular design degree and patents evolution. J. Clean. Prod. 405, 136888.

Chen, Y.S., Lai, S.B., Wen, C.T., 2006. The influence of Green Innovation performance on corporate advantage in Taiwan. J. Bus. Ethics 67 (4), 331–339.

Chen, J., Hu, L., Wang, J., Song, S.S., 2024. Eccentric compression behavior of circular concrete-filled steel tubes reinforced with internal latticed steel angles. Struct. Concr. 25 (1), 169–184.

Choi, H.Y., Park, J., 2022. Do data-driven CSR initiatives improve CSR performance? The importance of big data analytics capability. Technol. Forecast. Soc. Chang. 182, 121802.

Chowdhury, S., Dey, P.K., Rodríguez-Espíndola, O., Parkes, G., Tuyet, N.T.A., Long, D.D., Ha, T.P., 2022. Impact of organisational factors on the circular economy practices and sustainable performance of small and medium-sized enterprises in Vietnam. J. Bus. Res. 147, 362–378.

Coenen, T.B.J., Haanstra, W., Jan Braaksma, A.J.J., Santos, J., 2020. CEIMA: a framework for identifying critical interfaces between the Circular Economy and stakeholders in the lifecycle of infrastructure assets. Resour. Conserv. Recycl. 155 (November 2018), 104552.

Dai, D., Fan, Y., Wang, G., Xie, J., 2022. Digital economy, R&D investment, and regional green innovation—analysis based on provincial panel data in China. Sustainability 14 (11), 6508.

Dawson, J.F., 2014. Moderation in management research: what, why, when, and how. J. Bus. Psychol. 29 (1), 1–19.

de Bem Machado, A., Secinaro, S., Calandra, D., Lanzalonga, F., 2022. Knowledge management and digital transformation for Industry 4.0: a structured literature review. Knowl. Manag. Res. Pract. 20 (2), 320–338.

de Medeiros, J.F., Garlet, T.B., Ribeiro, J.L.D., Cortimiglia, M.N., 2022. Success factors for environmentally sustainable product innovation: an updated review. J. Clean. Prod. 131039.

de Oliveira, R.T., Ghobakhloo, M., Figueira, S., 2023. Industry 4.0 towards social and environmental sustainability in multinationals: Enabling circular economy, organizational social practices, and corporate purpose. J. Clean. Prod., 139712

Di Vaio, A., Palladino, R., Pezzi, A., Kalisz, D.E., 2021. The role of digital innovation in knowledge management systems: a systematic literature review. J. Bus. Res. 123, 220–231.

Dong, Q., Wu, Y., Lin, H., Sun, Z., Liang, R., 2022. Fostering green innovation for corporate competitive advantages in big data era: the role of institutional benefits. Tech. Anal. Strat. Manag. 1–14.

Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Luo, Z., Wamba, S.F., Roubaud, D., 2019. Can big data and predictive analytics improve social and environmental sustainability? Technol. Forecast. Soc. Chang. 144, 534–545.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., et al., 2021. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. Int. J. Inf. Manag. 57, 101994.

Dwivedi, Y.K., Hughes, L., Kar, A.K., Baabdullah, A.M., Grover, P., Abbas, R., et al., 2022. Climate change and COP26: Are digital technologies and information management part of the problem or the solution? An editorial reflection and call to action. Int. J. Inf. Manag. 63, 102456.

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. Technol. Forecast. Soc. Chang. 144, 483–498.

Fang, Z., Razzaq, A., Mohsin, M., Irfan, M., 2022. Spatial spillovers and threshold effects of internet development and entrepreneurship on green innovation efficiency in China. Technol. Soc. 68, 101844.

Garcia, C.L., Cayzer, S., 2019. Assessment of the circular economy transition readiness at a national level: The Colombian case. In: The Circular Economy and the Global South. Routledge, pp. 113–133.

Gerassimidou, S., Martin, O.V., Chapman, S.P., Hahladakis, J.N., Iacovidou, E., 2021. Development of an integrated sustainability matrix to depict challenges and trade-offs of introducing bio-based plastics in the food packaging value chain. J. Clean. Prod. 286, 125378.

Gnekpe, C., Plantec, Q., 2023. Regulatory push-pull and technological knowledge dynamics of circular economy innovation. Technol. Forecast. Soc. Change 196, 122767.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S.F., Childe, S.J., Hazen, B., Akter, S., 2017. Big data and predictive analytics for supply chain and organizational performance. J. Bus. Res. 70, 308–317.

Hair, J.F., Hult, G.T.M., Ringle, C., Sarstedt, M., 2017. A Primeron Partial Least Squares Structural Equation Modeling (PLS-SEM), Seconded. SAGE, London, Thousand Oaks.

Hair, J., Risher, J., Sarstedt, M., Ringle, C., 2019. When to use and how to report the results of PLS-SEM. Eur. Bus. Rev. 31 (1), 2–24.

Hamilton, R.H., Sodeman, W.A., 2020. The questions we ask: opportunities and challenges for using big data analytics to strategically manage human capital resources. Bus. Horizons 63 (1), 85–95.

Henseler, J., Ringle, C.M., Sarstedt, M., 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J. Acad. Mark. Sci. 43, 115–135.

Hizarci-Payne, A.K., İpek, İ., Kurt Gümüş, G., 2021. How environmental innovation influences firm performance: a meta-analytic review. Bus. Strateg. Environ. 30 (2), 1174–1190.

Hulland, J., Baumgartner, H., Smith, K.M., 2018. Marketing survey research best practices: evidence and recommendations from a review of JAMS articles. J. Acad. Mark. Sci. 46, 92–108.

Imran, R., Alraja, M.N., Khashab, B., 2021. Sustainable performance and green innovation: green human resources management and big data as antecedents. IEEE Trans. Eng. Manag. 70 (12), 4191–4206.

Islam, M.S., Hasan, N., Islam, M.S., Akter, T., Rafsun, M.F., Fouji, M.M.H., 2024. Investigating waste recycling intentions of top management in Bangladesh's leather industry: A hybrid analytical framework. Clean. Waste Syst. 8, 100140.
Israilidis, J., Odusanya, K., Mazhar, M.U., 2021. Exploring knowledge management perspectives in smart city research: a review and future research agenda. Int. J. Inf. Manag. 56, 101989.
Jarrahi, M.H., Askay, D., Eshraghi, A., Smith, P., 2023. Artificial intelligence and knowledge management: a partnership between human and AI. Bus. Horiz. 66 (1), 87–99.
Karaşan, A., Gündoğdu, F.K., Işık, G., Kaya, İ., İlbahar, E., 2024. Assessment of governmental strategies for sustainable environment regarding greenhouse gas emission reduction under uncertainty. J. Environ. Manag. 349, 119577.
Khan, S.A.R., Jian, C., Zhang, Y., Golpîra, H., Kumar, A., Sharif, A., 2019. Environmental, social and economic growth indicators spur logistics performance: from the perspective of South Asian Association for Regional Cooperation countries. J. Clean. Prod. 214, 1011–1023.
Khan, S.A.R., Zia-ul-haq, H.M., Umar, M., Yu, Z., 2021. Digital technology and circular economy practices: An strategy to improve organizational performance. Bus. Strat. Develop. 4 (4), 482–490.
Kim, H., Moon, H., 2021. Heterogeneous attitudes toward autonomous vehicles: evaluation of consumer acceptance of vehicle automation technology using a latent class approach. Tech. Anal. Strat. Manag. 1–16.
Kolade, O., Owoseni, A., 2022. Employment 5.0: The work of the future and the future of work. Technol. Soc. 71, 102086.
Koseoglu, A., Yucel, A.G., Ulucak, R., 2022. Green innovation and ecological footprint relationship for a sustainable development: Evidence from top 20 green innovator countries. Sustain. Develop. 30 (5), 976–988.
Kumar, P., Polonsky, M., Dwivedi, Y.K., Kar, A., 2021. Green information quality and green brand evaluation: the moderating effects of eco-label credibility and consumer knowledge. Eur. J. Mark. 55 (7), 2037–2071.
Lee, C., Lim, C., 2021. From technological development to social advance: a review of Industry 4.0 through machine learning. Technol. Forecast. Soc. Chang. 167, 120653.
Lengyel, A., 2023. Spatial perspectives on sustainability priorities: key stakeholders' insights. J. Clean. Prod. 420, 138341.
Leong, L.Y., Hew, T.S., Ooi, K.B., Wei, J., 2020. Predicting mobile wallet resistance: a two-staged structural equation modeling-artificial neural network approach. Int. J. Inf. Manag. 51, 102047.
Li, T., Singh, R.K., Cui, L., Xu, Z., Liu, H., Fava, F., et al., 2023. Navigating the landscape of global sustainable livelihood research: past insights and future trajectory. Environ. Sci. Pollut. Res. 30 (46), 103291–103312.
Lichtenthaler, U., Lichtenthaler, E., 2009. A capability-based framework for open innovation: complementing absorptive capacity. J. Manag. Stud. 46 (8), 1315–1338.
Lin, R.J., Tan, K.H., Geng, Y., 2013. Market demand, green product innovation, and firm performance: evidence from Vietnam motorcycle industry. J. Clean. Prod. 40, 101–107.
Liu, Z., Li, X., Peng, X., Lee, S., 2020. Green or nongreen innovation? Different strategic preferences among subsidized enterprises with different ownership types. J. Clean. Prod. 245, 118786.
Lutfi, A., Alrawad, M., Alsyouf, A., Almaiah, M.A., Al-Khasawneh, A., Al-Khasawneh, A. L., et al., 2023. Drivers and impact of big data analytic adoption in the retail industry: a quantitative investigation applying structural equation modeling. J. Retail. Consum. Serv. 70, 103129.
Malinauskaite, J., Jouhara, H., 2019. The trilemma of waste-to-energy: a multi-purpose solution. Energy Policy 129 February, 636–645.
Mikalef, P., Gupta, M., 2021. Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Inf. Manag. 58 (3), 103434.
Mikalef, P., Islam, N., Parida, V., Singh, H., Altwaijry, N., 2023. Artificial intelligence (AI) competencies for organizational performance: a B2B marketing capabilities perspective. J. Bus. Res. 164, 113998.
Momete, D.C., 2020. A unified framework for assessing the readiness of European Union economies to migrate to a circular modelling. Sci. Total Environ. 718, 137375.
Pan, S.L., Carter, L., Tim, Y., Sandeep, M.S., 2022. Digital sustainability, climate change, and information systems solutions: opportunities for future research. Int. J. Inf. Manag. 63, 102444.
Passmore, J., Woodward, W., 2023. Coaching education: wake up to the new digital and AI coaching revolution! Int. Coach. Psychol. Rev. 18 (1), 58–72.
Paul, T., Mondal, S., Islam, N., Rakshit, S., 2021. The impact of blockchain technology on the tea supply chain and its sustainable performance. Technol. Forecast. Soc. Chang. 173, 121163.
Pigosso, D.C., McAloone, T.C., 2021. Making the transition to a circular economy within manufacturing companies: The development and implementation of a self-assessment readiness tool. Sustain. Prod. Consum. 28, 346–358.
Podsakoff, P.M., MacKenzie, S.B., Podsakoff, N.P., 2012. Sources of method bias in social science research and recommendations on how to control it. Annu. Rev. Psychol. 63, 539–569.
Podsakoff, P.M., Podsakoff, N.P., Williams, L.J., Huang, C., Yang, J., 2023. Common method bias: it's bad, it's complex, it's widespread, and it's not easy to fix. Ann. Rev. Organ. Psychol. Organ. Behav. 11 (1). https://doi.org/10.1146/annurev-orgpsych-110721-040030.
Razzaq, A., Ajaz, T., Li, J.C., Irfan, M., Suksatan, W., 2021. Investigating the asymmetric linkages between infrastructure development, green innovation, and consumption-based material footprint: Novel empirical estimations from highly resource-consuming economies. Resour. Policy 74, 102302.
Rehman, S.U., Kraus, S., Shah, S.A., Khanin, D., Mahto, R.V., 2021. Analyzing the relationship between green innovation and environmental performance in large manufacturing firms. Technol. Forecast. Soc. Chang. 163, 120481.
Rowell-Jones, Howard, C., 2019. CIO survey: CIOs have awoken to the importance of AI, retrieved from, 2019. https://www.gartner.com/en/documents/3897266/2019-cio-survey-CIOs-have-awoken-to-the-importance-of-ai.
Sahoo, S., Kumar, A., Upadhyay, A., 2023. How do green knowledge management and green technology innovation impact corporate environmental performance? Understanding the role of green knowledge acquisition. Bus. Strateg. Environ. 32 (1), 551–569.
Santa-Maria, T., Vermeulen, W.J., Baumgartner, R.J., 2022. How do incumbent firms innovate their business models for the circular economy? Identifying micro-foundations of dynamic capabilities. Bus. Strateg. Environ. 31 (4), 1308–1333.
Santoro, G., Vrontis, D., Thrassou, A., Dezi, L., 2018. The internet of things: building a knowledge management system for open innovation and knowledge management capacity. Technol. Forecast. Soc. Chang. 136, 347–354.
Seman, N.A.A., Govindan, K., Mardani, A., Zakuan, N., Saman, M.Z.M., Hooker, R.E., Ozkul, S., 2019. The mediating effect of green innovation on the relationship between green supply chain management and environmental performance. J. Clean. Prod. 229, 115–127.
Shah, T.R., 2022. Can big data analytics help organizations achieve sustainable competitive advantage? A developmental enquiry. Technol. Soc. 68, 101801.
Shahzad, M., Qu, Y., Javed, S.A., Zafar, A.U., Rehman, S.U., 2020. Relation of environment sustainability to CSR and green innovation: a case of Pakistani manufacturing industry. J. Clean. Prod. 253, 119938.
Shahzad, M., Qu, Y., Rehman, S.U., Zafar, A.U., 2022. Adoption of green innovation technology to accelerate sustainable development among manufacturing industry. J. Innov. Knowl. 7 (4), 100231.
Shao, S., Xu, L., Yang, L., Yu, D., 2023. Effectiveness of production-oriented carbon reduction projects: evidence from the top 1000 energy-consuming enterprises program. Ann. Oper. Res. 1–38.
Singh, M., Thind, P.S., John, S., 2018. Health risk assessment of the workers exposed to the heavy metals in e-waste recycling sites of Chandigarh and Ludhiana, Punjab, India. Chemosphere 203, 426–433.
Struckell, E., Ojha, D., Patel, P.C., Dhir, A., 2022. Strategic choice in times of stagnant growth and uncertainty: an institutional theory and organizational change perspective. Technol. Forecast. Soc. Chang. 182, 121839.
Suchek, N., Fernandes, C.I., Kraus, S., Filser, M., Sjögrén, H., 2021. Innovation and the circular economy: a systematic literature review. Bus. Strateg. Environ. 30 (8), 3686–3702.
Teece, D.J., 2007. Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. Strateg. Manag. J. 28 (13), 1319–1350.
Teng, S., Khong, K.W., 2021. Examining actual consumer usage of E-wallet: a case study of big data analytics. Comput. Hum. Behav. 121, 106778.
Wang, J., Xue, Y., Sun, X., Yang, J., 2020. Green learning orientation, green knowledge acquisition and ambidextrous green innovation. J. Clean. Prod. 250, 119475.
Yang, Q., Du, Q., Razzaq, A., Shang, Y., 2022. How volatility in green financing, clean energy, and green economic practices derive sustainable performance through ESG indicators? A sectoral study of G7 countries. Resour. Policy 75, 102526.
Yu, X., Xu, S., Ashton, M., 2023. Antecedents and outcomes of artificial intelligence adoption and application in the workplace: the socio-technical system theory perspective. Inf. Technol. People 36 (1), 454–474.
Zeng, H., Chen, X., Xiao, X., Zhou, Z., 2017. Institutional pressures, sustainable supply chain management, and circular economy capability: empirical evidence from Chinese eco-industrial park firms. J. Clean. Prod. 155, 54–65.
Zhang, D., Pee, L.G., Cui, L., 2021. Artificial intelligence in E-commerce fulfillment: a case study of resource orchestration at Alibaba's Smart Warehouse. Int. J. Inf. Manag. 57, 102304.
Zhang, A., Xie, S., Gong, Y., Li, C., Liu, Y., 2023. Barriers to compulsory waste sorting for a circular economy in China. J. Environ. Manage. 342, 118180.

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