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Artificial Intelligence Capabilities and Sustainable Performance in Pakistan's Telecommunication Industry

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ABSTRACT

Purpose—The purpose of this research is to analyze the association between AI capabilities and sustainable performance in the telecommunication industry of Pakistan. With the increase in use of AI technology by telecommunication companies to improve their efficiency, this research attempts to find out how AI capabilities impact sustainable performance. Four hypotheses (H1–H4) are proposed in this study that explore the impact of different aspects of AI capabilities on sustainable performance.

Methodology/Design/Approach—Quantitative research methodology was used for this study, where data was collected using a questionnaire survey on 480 managers employed in the telecommunications sector in Pakistan. Sampling was done in such a way that managerial level employees were considered so that respondents would have enough organizational knowledge in order to evaluate the capability of AI as well as its impact on sustainability. For the analysis of data, the SPSS program was used along with descriptive statistics, reliability analysis (to establish the internal consistency of the measuring scales), correlation analysis, and regression analysis.

Findings—All the four hypotheses have been supported by the empirical evidence. It has been revealed that there exists a positive and significant impact of artificial intelligence capabilities on sustainable performance. The results thus prove that companies with high AI capabilities perform better in terms of sustainability.

Practical Implications—Implications of the results for telecommunication organizations and their managers include taking proactive steps regarding the use of AI tools as a way to boost sustainability in the organization. Companies need to focus on infrastructure, talent, and processes related to AI in order to improve sustainable performance.

Originality/Value—This research adds to the scanty empirical studies in the area of AI–sustainability interface, which has been conducted in the telecom sector of a developing economy, adding to the body of theory and providing a basis for further research.

Keywords: Artificial Intelligence Capabilities, Sustainable Performance, Artificial Intelligence Customer Value Proposition, Artificial Intelligence Key Process Optimization, Artificial Intelligence Key Resource Optimization, Artificial Intelligence Societal Good

JEL Classification Codes: O32, O33, M15, Q01, Q56

1 | INTRODUCTION

Despite growing adoption of AI across the telecom sector around the world and increasing dependence of organizations on AI-based capabilities for gaining competitive advantage, very few manager-level

empirical studies have been conducted so far to investigate the role of dimensions of AI capabilities in achieving sustainable performance. This problem has become even more pronounced with regard to the telecom sector of a developing country like Pakistan, where the differences in regulatory environment, resource availability, and technological factors distinguish the case from existing AIC and sustainability studies focusing on manufacturing sector in developed market environments. The present research tries to bridge this gap by investigating the impact of AI capabilities on sustainable performance in the telecom industry of Pakistan.

The rapid development of artificial intelligence (AI) technologies has introduced a new age of innovation, which has impacted various industries and challenged the limits of sustainable performance. The adoption of AI in the telecom industry has evolved from the science fiction world to become an integral component that helps boost the efficiency of operations and deliver value to consumers and society at large. While the use of AI competencies is extensive, there is a huge information gap as far as how these competencies—AI customer value proposition, AI process optimization, and societal value of AI—are interrelated and generate sustainable performance. The use of artificial intelligence would be one of the most powerful solutions in addressing these challenges. It enables telecommunications companies to enable processes, provide personalized customer care services, and promote social development. The use of machine learning and artificial intelligence, such as Ericsson's artificial intelligence network management, has become a necessity in the reduction of energy consumption (Ericsson, 2021).

Similarly, AI-enabled customer value propositions such as the use of virtual assistants at AT&T have also revolutionized the interaction process between customers and the organization, offering real-time and personalized assistance (AT&T, 2020). Artificial intelligence is capable of contributing immensely not only to operational and consumer sectors but to social welfare as well. It has great potential in supporting disaster relief through data analysis and increasing digital access in underdeveloped regions (GSMA, 2022). The proposed innovation utilizes the principles of artificial intelligence to transform AI potentials into tangible results by means of sustainability. For example, Vodafone managed to apply AI-based predictive maintenance, which not only resulted in saving operational costs but also in saving resources and in reaching sustainability goals (Vodafone, 2021). Therefore, the aim of the research is to contribute to the existing body of knowledge concerning the efficiency of AI in the context of sustainability by means of a framework that includes relevant variables of AI potential and sustainable performance. The research will be useful for telecommunications organizations that are willing to implement AI potential into sustainability practices. The findings will contribute not only to filling the theoretical gap but also to providing an actionable plan for industry professionals dealing with complex issues related to AI implementation into sustainability practices.

Although there is considerable research on the association between AI capabilities and sustainable performance, three main gaps exist. The first gap is in the methodology of the research, since a lot of literature on this issue is either qualitative in nature or based on SEM of private firms but not quantitative regression testing. The second gap is in the empirical literature, which mostly focuses on Chinese manufacturing firms using AI capabilities as the base for sustainable competitive advantage but does not focus on AI technology

as the base. The third gap is related to context as well, as the developing economies of countries like Pakistan provide an interesting context of mixed AI adoption and weak regulations, but have been empirically neglected till now.

The current research has theoretical, practical, policy, and contextual importance. First, from the theoretical perspective, the research adds value to the emerging yet fragmented literature on artificial intelligence capabilities and sustainable performance through testing the connection between the two variables using quantitative research methodology. Recent works that have explored the impact of artificial intelligence capabilities on sustainability have mainly used qualitative research methods, SME-oriented models, or industry panels from the manufacturing sector, but not the service industry. In addition, the research adds to the knowledge of resource-based view and dynamic capabilities theory by applying it to the service industry (telecommunication industry) and extending AIC and sustainability framework in such industry, which has been unexplored in previous literature on AIC and sustainability.

In practice, this study offers guidance to telecom management and leadership with respect to the critical AI capability dimensions that have the strongest effect on sustainability, thus facilitating prioritization of investment in technological infrastructure, managerial AI capability, and organization adaptability rather than adoption of AI technologies without any considerations. Considering the fact that industry reports indicate the existence of many telecom companies operating in fragmented stages of AI implementation, where returns on investment remain unclear, this research contributes empirically in providing evidence-based guidance in making decisions with respect to AI adoption and sustainable development. From a policy perspective, the results of the research may be important in terms of encouraging regulators and policymakers in Pakistan and other similar developing countries to adopt AI technologies along with their sustainability policies.

Moreover, the research aims to address a contextual gap as there is a considerable number of empirical studies in the domain of AIC and sustainability which investigate mostly Chinese manufacturing companies and more general private companies. As a result, the research contributes to expanding the scope of AIC and sustainability theories and models by investigating the case of telecom managers in the South Asian developing country, namely Pakistan.

2 | LITERATURE REVIEW

2.1 | AI Capabilities and Sustainable Performance

In recent times, academic literature has increasingly shifted from considering AI as a technological means to a business capability with sustainability implications. The basis of such a theoretical development can be traced back to the pioneering contributions made by Mikalef and Gupta (2021). They adopted resource-based theory and the recently emerging research about AI at the organizational level to conceptualize AI resources, devise an instrument of measurement for assessing AI capability, and establish empirically the fact that AI capability leads to organizational creativity and firm performance. Since then, AI capability has been considered theoretically as a concept linked directly to sustainability. On the basis of this background, Fosso Wamba et al. (2024) introduced the concept of AI capability in the framework of sustainable development.

The research was based on resource-based theory, which proposed a high-level conceptual model for AI capability encompassing tangible, intangible, and human resources, linking AI capability with firm performance as well as SDG 9 (industry, innovation, and infrastructure) and SDG 12 (responsible consumption and production). It proved that data-driven culture is an important mediator that ensures sustainable performance, as AI capability alone cannot ensure sustainable performance without the presence of data-driven culture in organizations.

In the context of Pakistan specifically, evidence of this kind has been accumulating in different areas. For instance, Elsa et al. (2025) have studied the impact of artificial intelligence capability on sustainable performance in the case of Pakistani private firms and discovered that the influence takes place through the mechanisms of green absorptive capacity, green knowledge management, and green creativity, showing thus that the effects of artificial intelligence capability on sustainable performance occur indirectly, due to its environmental knowledge-processing capacity, not directly. In the small business hotel sector, Hussain et al. (2024) have used resource-based view theory combined with dynamic capability theory and have formulated the mediated moderation model in the context of studying the effects of green entrepreneurial orientation on sustainable performance of Pakistani small business hotels, discovering that artificial intelligence capability moderates the relation between eco-innovation and sustainable performance. Furthermore, in manufacturing, Jamil et al. (2025) have studied the role of AI implementation and technological readiness in sustainable performance in the case of Pakistani manufacturing SMEs from the export sector.

The AIC and sustainability nexus have been explored using green innovation as the key mechanism. Al Halbusi et al. (2025), on the other hand, investigated the joint effect of AI capability and green innovation on sustainable performance in the presence of big data capability and knowledge management capability, and found that companies that are more endowed with data and knowledge infrastructure have a greater potential to exploit their AI-based green innovation and achieve sustainability. Related but different to the above study conducted in a developed economy setting, Rahman and Latan (2026), in a Pakistani context, used the natural resource-based view framework on a sample of 230 SMEs and revealed that green innovation had a positive effect on sustainable performance, and green knowledge sharing and green dynamic capabilities mediated this effect, with AI moderating the relationship, thus reiterating once again that AI is a capability booster rather than an independent source of sustainability.

On the other hand, when it comes to environmental sustainability in particular, empirical evidence derived from Chinese companies and cross-country panels adds further credibility to the positive relation between AIC and sustainability. In one study based on patent data of AI technology innovation of Chinese listed companies during 2009–2023, it was revealed that AI innovation has a positive impact on corporate environmental sustainability performance, where knowledge management capability acts as the mediating variable. Besides firm-level results, Bergougui (2026) extended the research to the macro level, using panel data of 29 advanced and developing countries during 2005–2024 and measuring national AI capability through the frequency of filing AI patents, and found a strong statistical association in the sense that more AI activities

are consistently linked with an increase in the load capacity factor, which is the composite measure of environmental sustainability.

Finally, on a more general level, systematic reviews warn of the overstatement of AI's empirical contribution to sustainability. It has been observed that there is an increase in the use of AI in relation to sustainability within scientific research, relatively little has been done in order to apply AI towards the normative or transformative aspect of sustainability science even in some SDG domains (such as poverty eradication), where there were only a few reviews and not a single empirical study in the most cited literature. It shows the persistent divide between the potential of AI in terms of sustainability and the empirical evidence of that potential, one which the current research paper aims to fill with a hypothesis-driven quantitative approach in the Pakistani telecoms industry.

The combination of these studies reveals some notable findings on the topic under discussion, including the fact that there is no direct influence of AI capability on sustainable performance but, instead, there exists an intermediary impact via organizational constructs, such as green knowledge management, green innovation, dynamic capabilities, and data culture (Fosso Wamba et al., 2024; Elsa et al., 2025; Al Halbusi et al., 2025; Rahman & Latan, 2026). The relationship between the two variables has been empirically analyzed mainly in China for manufacturing, as well as in Pakistan using data from private sector companies, small and medium enterprises' hotels, and export manufacturing, not telecom (Hussain et al., 2024; Jamil et al., 2025); however, in general, there has been no sufficient research on the dimensions of AI capability in service industries of developing countries—exactly the gap covered by the present study.

2.2 | The Artificial Intelligence Customer Value Proposition and Sustainable Performance

Nowadays, integration of business artificial intelligence (AI) is not a thing of the future anymore but an ongoing reality, which leads to changes in the way of generation, distribution, and value appropriation of companies. This literature review concentrates on the fact that the unique value from artificial intelligence that the customers have could contribute to sustainable business performance through economic, ecological, and social perspectives. Thus, the role of the Artificial Intelligence Customer Value Proposition (AICVP) in sustainable performance will be discussed. Despite the difficulty in isolating the influence of the AICVP separately, this study analyzes data from relevant domains in order to give a complete picture of its impact. Contrary to the customer value proposition that usually consists of product features and price, AICVP includes more than that. It discusses the unique value from artificial intelligence that is offered to the consumer: personalized experience, forecasting, efficiency, and new value creation. Huang and Rust (2018) highlighted the influence of artificial intelligence on consumer and service expectations, while Davenport et al. (2020) emphasized the strategy of consumer value generation via artificial intelligence. First of all, such value generation can serve as a motivation for long-term performance. The approach suggested by Elkington (1997), called the Triple Bottom Line (economic, environmental, and social), serves as a perfect example. AICVP can facilitate all of the above: socially due to the proper application of artificial intelligence and social value creation; environmentally through AI-facilitated sustainability; and economically through higher customer loyalty and revenue. Moreover, the AICVP can facilitate environmental sustainability.

For instance, AI-driven energy management systems have been seen as means of reducing building energy consumption and thus supporting environmental sustainability (Vinuesa et al., 2020). Through AI, it will be easier to make resource utilization easy and also contribute to circular economy practices (Lucivero, 2024). It can be done through AI-driven logistics management that cuts down on transportation costs and carbon emissions, for instance Naz et al. (2022) findings regarding AI in logistics management. The AI technology will make it easy to make recommendations of eco-friendly goods and services to the consumers, hence making it possible for them to be more environmentally friendly (Jude, 2024). A company can make a win–win situation where there is creation of value not only for the consumers but also for the environment through AICVP. Good performance, which is the foundation of any sustainable business, comes through AICVP. Through profitability and cost reduction, AI-driven consumer value propositions will aid economic sustainability. For instance, applying demand forecasting techniques based on AI assists organizations in minimizing their inventories, thereby cutting costs and increasing profits (Fountain et al., 2019).

In addition to that, AI will be able to employ customization and forecasting of consumer demands for maximizing CLV, just like Gupta and Lehmann (2005) said was also critical for treating customers as assets. The use of AI can assist in finding other sources of income, customer retention, and optimization of pricing strategies, which all help to sustain financially (Shiyyab et al., 2023). Higher value provided by artificial intelligence leads to enhanced relationships with customers and, as a result, to sustainable profitability. Satisfying customers' needs and making them more engaged by means of artificial intelligence increases social sustainability as well. For instance, personalized treatment options for patients based on AI-driven healthcare systems increase social sustainability (Rust & Huang, 2021). Social sustainability is increasingly becoming important, so there should be ethical implementation and production of the AICVP (Safdar et al., 2020).

Lack of trust and reduced social sustainability may arise as a result of biased algorithms of artificial intelligence. Hence, there is need at present to develop and use sensible artificial intelligence (Herrmann, 2023). Moreover, artificial intelligence can be used to solve some of the social problems such as inequality, poverty, and lack of access to education and health care. Companies can make the world a better place and achieve greater social sustainability by ensuring that the AICVP is aligned with social welfare. When it comes to AI customer value propositions and sustainability performance, a theoretical framework for understanding the relationship between artificial intelligence systems and the organizational and consumer environments in the context of sustainability is offered by Situated AI Theory, which is as follows: Contextual Alignment: The artificial intelligence system must be relevant to the specific objectives of the organization and its consumers to create value. Dynamic Interactions: The artificial intelligence systems are always interacting with their environment to adapt to changes in customer behavior and market conditions. Co-Creation of Value: AI innovation is a co-creation process among AI systems, organizational stakeholders, and customers (Suchman, 1987; Clancey, 1997). On the basis of the above given argument, the current study proposes the following hypothesis:

H1: *Artificial intelligence customer value proposition is positively related to sustainable performance.*

2.3 | The Artificial Intelligence Key Processes Optimization and Sustainable Performance

Integration of artificial intelligence (AI) into business operation systems has brought about an innovation that allows businesses to streamline processes, reduce cost, and be efficient. Process optimization through AI takes advantage of algorithms, machine learning, and analysis of data to improve workflow, decision-making, and reduce resource consumption. Sustainable performance has been a key target among all organizations in terms of economy, environment, and society. This literature review is focused on the effect of process improvement through AI on sustainable performance in organizations. Some of the topics that will be addressed include the application of AI for process optimization, their contribution to sustainable performance, and empirical evidence from various industries. The fact that artificial intelligence has the ability to automate processes, process large volumes of data, identify patterns, and make decisions intelligently makes it possible to change the way organizations operate. Davenport and Kirby (2016) discussed the revolutionary power of AI in jobs and procedures, therefore setting the stage for understanding its part in optimization. Khabbaz (2024) reveals a rising volume of research on how artificial intelligence is changing BPM. In several areas of a company, artificial intelligence technology can enable automation of operations, cut mistakes, raise efficiency, and facilitate improved decision-making. Incremental optimization is not the point; rather, it is radical reconsideration and renovation of fundamental processes meant to improve efficiency and adaptability.

According to Ghobakhloo and Fathi (2020), AI process optimization lowers operation cost and raises operational efficiency, thus improving economic sustainability. For example, predictive maintenance: AI programs predict equipment failures and save downtime together with maintenance (Ghobakhloo & Fathi, 2020). Ivanov and Dolgui (2020) argue that artificial intelligence-based analytics improve forecast accuracy, therefore lowering inventory costs and overproduction. AI process optimization directly leads to better financial results. AI frees up time for individuals to engage in more creative and strategic work by means of redundant task removal. Greater effectiveness enables significant cost-saving potential. In addition to that, the use of analytics due to artificial intelligence will show possibilities for enhancing forecasts, maximizing prices, and optimizing marketing efforts, thereby increasing the bottom line and profits. While Shiyyab et al. (2023) establish the link between AI acceptance and measures of financial performance, Cao (2022) explains how AI can help achieve optimal financial procedures. By lowering waste and reducing resource use, artificial intelligence supports environmental sustainability. Most important uses are: For lower carbon footprints, artificial intelligence software controls energy usage inside commercial structures (Zhang & Wang, 2020). Quality control systems driven by AI help production operations to cut waste (Kamble et al., 2019). AI optimizes logistics and transportation, therefore conserving fuel and reducing emissions (Dubey et al., 2019). By improving working conditions and enabling ethical behavior, artificial intelligence-driven process optimization fosters social sustainability.

One example is workplace safety: AI-based surveillance systems detect workplace risks and reduce accident frequency (Nishant et al., 2020). Ethical decision-making: AI-based systems analyze information to confirm respect of labor regulations and environmental policies (Cowls et al., 2021). AI's process optimization capability is by definition contextual. If environmental concern is not an explicitly examined component of

the "situation," an AI simplifying a supply chain to save costs, for example, could unintentionally raise carbon emissions. Still, when sustainability measurements are formally introduced into the learning environment of an AI, the system can be made to weigh cost against the environment, a more holistic and sustainable practice. This is consistent with the concept of "ecologically rational" decision-making (Simon, 1990), where an intelligent system utilizing information about the situation is able to make effective and congruent decisions towards more general sustainable objectives. The SAI provides a solid theoretical foundation for understanding the complex relationship between optimization of key processes by means of AI and sustainable performance. SAI highlights the importance of context, interaction, and situationally based knowledge in the design, implementation, and evaluation of AI systems for sustainable performance. With the help of SAI principles, companies are not limited to the use of AI merely for efficiency but for building a better future as well. On the basis of the above given argument, the current study proposes the following hypothesis:

H2: *Artificial intelligence key processes optimization is positively related to sustainable performance.*

2.4 | The Artificial Intelligence Key Resources Optimization and Sustainable Performance

The increasing complexity and dependency of modern business activities demand innovative approaches to the management of resources. The use of artificial intelligence (AI) offers powerful solutions to the management of core resources and affects not only efficiency and profitability but also contributes significantly to achieving sustainable performance. This literature review explores the influence of key resource optimization using AI on sustainable performance by considering the importance of intelligent management of key resources (financial, human, natural, technological, and informational) in achieving sustainable performance from the perspectives of finance, environment, and society. AI capabilities to analyze massive amounts of data, identify patterns, predict future trends, and perform complex tasks create opportunities for new solutions for resource management. AI systems are able to optimize the use of resources, increase efficiency, reduce waste, and improve decision-making in various business areas. This is not just resource management but dynamic and adaptive resource management. The impact of resource optimization through AI extends beyond immediate savings and efficiency, as it is critical in achieving sustainable performance. The "Triple Bottom Line" framework proposed by Elkington (1997), which considers economic, environmental, and social aspects, provides a good example for understanding the connection between them. Resource optimization using AI can have positive impacts on all these three aspects: economic through increased profits and lower costs; environmental by reducing waste and improving resource efficiency; and social through improved working conditions and ethical business practices (Yavuz et al., 2024).

AI has the potential to make the management of financial resources much better. AI-driven forecasts can be used to better manage budgets and financial risks. Working capital management will also be made more efficient through improved cash flow forecasts and inventory management (Gill et al., 2010; Mukami, 2021). AI can help discover new avenues for earning money and provide customized financial services, which helps in achieving financial sustainability. AI can make human resource management much more efficient by automating routine activities. AI-based talent acquisition software can optimize recruitment processes and identify the most suitable candidates (Kim et al., 2010). AI can also personalize training programs and provide

data-driven feedback for performance management, leading to improved employee productivity and engagement (James, 2012). By optimizing human capital, organizations can become more socially sustainable and create a more productive and fulfilling work environment. AI plays a pivotal role in making environmental sustainability possible by maximizing natural resources. AI systems can track resource consumption, determine where it can be optimized, and maximize energy consumption (McLaughlin, 2015). AI can make circular economy strategies possible by maximizing waste utilization and enabling recycling and reuse of resources (Lin, 2023). Through minimizing environmental pressure and maximizing resource efficiency, AI is contributing to making the world sustainable in the future.

AI can be used to maximize the processing of information and technological resources in order to create knowledge and innovation. AI platforms can enable collaboration and sharing of knowledge, resulting in improved innovation processes (Kogan et al., 2017). AI is capable of handling significant amounts of data to reveal trends, generate insights, and guide strategic decisions (Popovi et al., 2018; Sazu, 2022). Through optimal utilization of engaged resources, companies will be in a better position to adapt and flourish during an era of unprecedented change. The relationship between resource optimization and sustainable performance is intricate (Hitka, 2019). AI facilitates a more integrated and comprehensive way of handling resources, considering the interdependence of financial, human, natural, technological, and informational resources. Organizing these resources for optimization allows firms to benefit from synergistic outcomes on all aspects of sustainability (Khan et al., 2024; van et al., 2024). On the basis of the above given argument, the current study proposes the following hypothesis:

H3: *Artificial intelligence key resources optimization is positively related to sustainable performance.*

2.5 | The Artificial Intelligence Societal Good and Sustainable Performance

The rapid development of artificial intelligence (AI) generates opportunities as well as challenges for society. As much as there are genuine worries about job displacement and bias in algorithms, AI also promises significant potential to address fundamental social issues and enable sustainable performance. This paper summarizes the impact of AI projects for social good on various areas of sustainable performance, explaining how a social good focus can also lead to lasting business success. It stands on the shoulders of research across numerous disciplines to build an integrated understanding of this complex relationship. The social potential of AI is extensive in the sense that it encompasses making education and healthcare improved, in addition to ending poverty and inequality. Bostrom (2014) placed into perspective the broad social ramifications of AI, and we must not dismiss the probable implications. Makridakis (2017) shows increasing numbers of research considering these implications, both positive and negative. Tomašev et al. (2020) and Floridi (2021) directly concern AI for social good applications. Vinuesa et al. (2020) look into how AI may help achieve the UN's aggressive sustainable development program. These various uses of AI for social good constitute the basis for achieving their potential for contribution to sustainable performance. AI is an extremely useful tool for solving environmental issues. AI systems can optimize resource allocation, minimize wastage, and assist in preventing climate change (Raihan et al., 2024). From improving power grids to tracking deforestation, AI has the

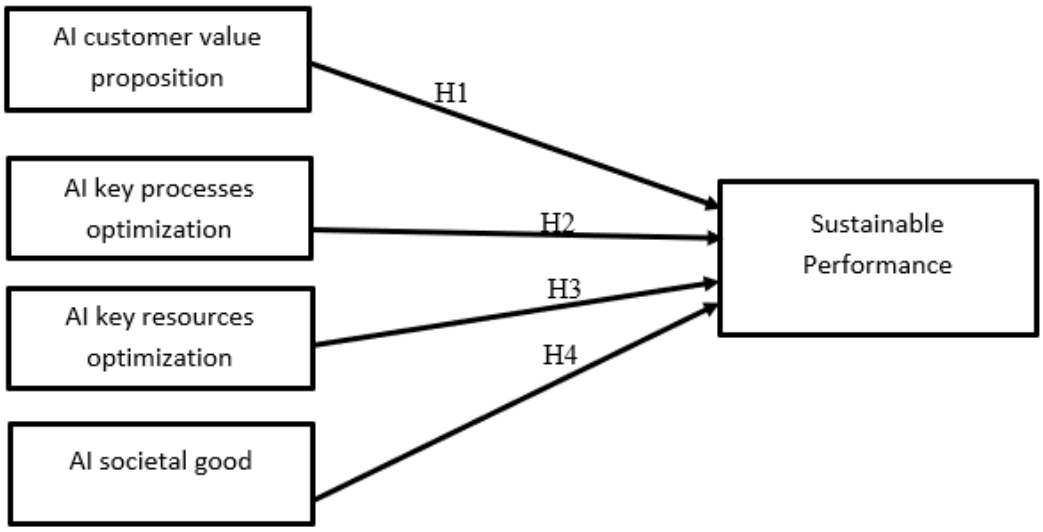
potential to actively safeguard the world and lead to a sustainable future. Cowls et al. (2023) discuss the precise mechanisms by which AI can contribute to climate action.

AI can be employed to end poverty and inequality by increasing access to financial services, offering customized employment training, and connecting people with opportunities. Further, Mhlanga (2020) and Raghavendra et al. (2023) show AI can be employed to enhance social justice by detecting and correcting bias in decision-making (Savaşan, 2024). Through making society more equitable and just, AI can produce social sustainability and position a more prosperous and inclusive future. The intersection of AI social good and sustainable performance is not altruistic alone; it is strategic. Menghwar and Daood (2021) emphasize the way that companies are capable of generating value for themselves and society by filling social needs. By the alignment of AI projects with social good, companies can enhance their stakeholder relations, improve their reputation, and retain and hire top talent. This, in its turn, drives long-term business success (Schaltegger et al., 2019). It is necessary to develop and deploy AI for the common good in a responsible manner so that its effect is positive and fair. Khan et al. (2022) explain the ethical issues of AI, and Gichoya et al. (2023) explain the salient topic of algorithmic bias. Cheng et al. (2021) provide prescriptions for designing and deploying AI in such a way that it is ethical, transparent, and accountable. Through an adherence to ethical principles and social good, companies can make sure that AI helps a more sustainable and equitable world. On the basis of the above given argument, the current study proposes the following hypothesis:

H4: *Artificial intelligence societal good is positively related to sustainable performance.*

Figure 1

Research Model



Note. The research model depicts the four AI capability dimensions—AI customer value proposition, AI key process optimization, AI key resource optimization, and AI societal good—as predictors of sustainable performance. Figure image as supplied in the source file.

3 | RESEARCH METHODOLOGY

3.1 | Research Design

The research design of this study is based on a quantitative, cross-sectional research design to determine the link between the capabilities of artificial intelligence and sustainable performance in the telecommunication sector of Pakistan. Quantitative research design is chosen for this study because it involves testing hypotheses between variables using statistical analysis, generalizing results over a wide range of samples, and filling the research methodology gap that exists in the literature where most artificial intelligence capabilities and sustainability research is qualitative or conceptual.

3.2 | Participants and Procedure

The research used an online, self-administered questionnaire (Google Forms) to gather data as opposed to conducting a face-to-face paper distribution survey. There are various methodological justifications for using an online data collection tool. First, online surveys save on the cost, time and logistics of printing, distributing and manually entering the results, while allowing for simultaneous geographically scattered collection of data that would have been challenging with face-to-face distribution (Evans & Mathur, 2005). Second, online questionnaires have low percentages of unanswered questions, faster turnaround and completion rates because built-in validation and mandatory questions features eliminate the possibility of receiving incomplete surveys (which is a major problem in mailed or hand-delivered questionnaires). Third, the anonymity provided by online questionnaires eliminates the problem of social desirability and evaluation apprehension, making it possible for respondents to provide honest answers without feeling observed or coerced into answering favorably. Lastly, online distribution makes it possible for respondents to fill in the survey at their convenient time, which is very helpful especially in cases where the respondents are busy professionals and an in-person visit and interview would not work. In total, the online survey (Time 1) was sent out to 500 participants via Google Forms. Out of those, 480 replies were received, giving a reply rate of 96%, which is much higher than the rates usually reported for traditional surveys distributed either in print or via mail (Evans & Mathur, 2005). The high reply rate again indicates the validity of the choice of the online survey in this research, as it demonstrates the convenience that this method offered to the participants.

To improve the methodology used in collecting information to ensure the robustness of results and minimize the potential common method bias, two distinct time-lagged data collection waves were employed instead of a one-time data collection approach. In wave one, data for the independent variable were collected using an online Google form from the 480 participants. Two weeks later, the same participants were contacted again through another online Google form to obtain data for the dependent variable. Temporal spacing between measures of independent and dependent variables is a widely accepted solution to common method variance because the use of this technique reduces the chances of the participants' answers to the dependent variable being affected by their recent memory of the way they answered questions on independent variables (Podsakoff et al., 2003). Additionally, this process avoids the effect of cognitive consistency and priming effects that may result in exaggerated relations among single-sitting measured variables. The use of the same online instrument (Google Forms) to collect the two waves of data helped to achieve uniformity in question

format and data collection procedures at each time point, and unique respondent identifiers were used to match individual respondent pairs.

3.3 | Measures

3.3.1 AI Customer Value Proposition. AI customer value proposition was measured using a 4-item scale proposed by Aqueeb et al. (2023). Some sample items for the current study from this scale are "Our company collects post-purchase insights and employs AI to customize the customer experience and ensure the success of our customers" and "Our expert data science team employs tools that help us determine the optimal cost and duration of the warranty for our customer." The scale was measured on a 5-point Likert scale ranging from 1 = *strongly disagree* to 5 = *strongly agree*.

3.3.2 AI Key Processes Optimization. AI key processes optimization was measured by employing a 6-item scale developed by Aqueeb et al. (2023). Some sample items of this scale in the current study are "Our company is using advanced data science in demand forecasting and stocking" and "Our company is making a strategic data acquisition to fulfill customers' orders on time." This scale was measured on a 5-point Likert scale ranging from 1 = *strongly disagree* to 5 = *strongly agree*.

3.3.3 AI Key Resources Optimization. AI key resources optimization was measured through the use of a 4-item scale that was developed by Aqueeb et al. (2023). Some sample items used in measuring this scale for this research are "Our company uses analytics on an integrated data warehouse to optimize the network of our suppliers" and "Our company uses AI to optimize our labor force." This scale was measured using a 5-point Likert scale that ranges from 1 = *strongly disagree* to 5 = *strongly agree*.

3.3.4 AI Societal Good. AI societal good was measured by using a scale consisting of three items developed by Aqueeb et al. (2023). Sample items used in the present study for this scale include "Our company trains AI assistants to improve safety in the workplace" and "Our company applies AI like deep reinforcement learning to reduce our organization's energy use, emissions, waste, and inequality." This scale was measured using a 5-point Likert scale ranging from 1 = *strongly disagree* to 5 = *strongly agree*. The scale was tapped at Time 1.

3.3.5 Sustainable Performance. Measurements of sustainable performance were made using a scale of six items formulated by Kordab, Raudeliuniene, and Meidute-Kavaliauskiene (2020). Some of the sample items of this scale used in the present study include "Our organization provides high-quality services" and "Our organization can adopt new service opportunities." This scale was measured on a 5-point Likert scale, from 1 = *strongly disagree* to 5 = *strongly agree*.

3.3.6 Control Variables. The effect of demographic factors (gender, age, organization name, qualification, total experience, and present organization experience) on sustainable performance was examined using a one-way ANOVA test. The findings showed that there is no need for control because there is no significant relationship between any of the demographic variables and the dependent variable.

3.3.7 Data Analysis Techniques. The process of data analysis involved the use of Statistical Package for the Social Sciences (SPSS). Before testing the hypotheses, descriptive statistics such as means, standard deviations, and frequencies were generated for respondent characteristics and variables. To check whether

scales measured reliable constructs, a reliability test was carried out through Cronbach's alpha, and scores of 0.70 or above were deemed satisfactory for scale reliability. Correlation analysis was also conducted on the bivariate relationships between the dimensions of AI capabilities and sustainable performance through Pearson's correlation coefficient.

3.3.8 Common Method Bias. Common Method Bias (CMB) or Common Method Variance (CMV) is another major issue associated with survey-based studies, especially those that use data gathered from a single source at a single point in time (Podsakoff et al., 2003). It is a phenomenon of systematic variance which is due to measurement methods rather than the construct itself, and it may lead to overestimating or distorting the relationships between variables. To prevent this problem, some procedural steps were taken while gathering data: Respondents were reassured that the procedure would remain confidential and anonymous, no right or wrong answers were provided, and questions were formulated clearly and concisely (Podsakoff et al., 2003). Statistically, Harman's single-factor test (Harman, 1976) was performed, which included entering all the items of measurement into an exploratory factor analysis where the number of factors was set to be equal to one. It was found that all the items loaded to eight different constructs and the first factor explained only 31.123% of variance. This amount is far less than the 50% usually suggested to avoid common method bias (Podsakoff et al., 2003; Podsakoff & Organ, 1986). Thus, the issue is not critical in this study.

4 | RESULTS AND ANALYSIS

4.1 | Measurement Model (Confirmatory Factor Analysis)

Table 1 summarizes the findings of confirmatory factor analysis (CFA). Using AMOS, the rate of CFA is computed to verify the accuracy of data obtained from full measurement models. When CFA first estimated the values of CFI, GFI, AGFI, IFI, TLI, and RMSEA, they were inside the conventional range. Next, according to the modification indices (MI) table, one incorrect term of the item of the same variable was connected. Consequently, the measurement model's results (CMIN = 1473.977, DF = 553, $p < .000$, CMIN/DF = 2.683, CFI = .925, GFI = .902, AGFI = .898, NFI = .889, IFI = .935, TLI = .918, RMSEA = .063) were improved after merging two error terms of the same variable, SP. All of the items were positively loaded on their corresponding latent variables in factor loading; therefore, there was no need to delete them. Browne, MacCallum, and Sugawra (1996) reported that RMSEA values range from 0.06 to 0.08 for good and average fit, respectively, and from 0.01 to 0.05 for outstanding fit. According to the research, an RMSEA value of 0.06 is considered to be a satisfactory fit and is hence acceptable.

Table 1

Results of Confirmatory Factor Analyses

Measure	Initial model	Final model	Threshold
Chi-square (χ^2)	1637.532	1473.977	Lower is better
df	554	553	—
χ^2/df	2.919	2.683	< 3
CFI	.916	.925	≥ .90
GFI	.879	.902	≥ .90
AGFI	.869	.898	≥ .80
NFI	.889	.901	≥ .90
IFI	.912	.935	≥ .90
TLI	.907	.918	≥ .90
RMSEA	.069	.063	≤ .08 acceptable (good ≤ .06)

Note. IMM = initial model measurement; FMM = final model measurement; CFI = comparative fit index; GFI = goodness-of-fit index; AGFI = adjusted goodness-of-fit index; NFI = normed fit index; IFI = incremental fit index; TLI = Tucker–Lewis index; RMSEA = root mean square error of approximation.

This study demonstrates a time-lagged design by collecting data at two lags in order to avoid reverse causation issues and track how independent variables affect dependent variables. Confirmatory factor analysis revealed the discriminant validity of the research factors despite data being received at two-time delays. Gerbing and Anderson (1992, 1988) reported that for every possible combination of components computed at the three-step from comparable sources, four-factor and two-factor models were distinguished with their corresponding one-factor models. To evaluate the study's discriminant validity, confirmatory factor analysis was performed.

Gerbing and Anderson (1988) show that their specific one-factor model should be used to measure one-on-one matching of constructs. Therefore, we first assessed a full measurement model (CFA of all the research factors, such as a 4-factor model) and distinguished it from a one-factor model in which each factor's items were loaded into a single latent variable. Additionally, the one-factor models of those tested at various time lags using similar respondents were validated. The two-factor model outperformed one-factor models in each scenario, demonstrating the study's satisfactory discriminant validity. Table 2 displays the outcomes of CFA.

The full measurement model (full CFA) composed of all five factors used in this study (e.g., AI Customer Value Proposition, AI Key Process Optimization, AI Key Resource Optimization, AI Societal Good, Sustainability Performance) was first verified and approved using confirmatory factor analysis. Table 2 shows that the full factor model's model fit measurements were CMIN = 1473.977, DF = 553, p < .000, CMIN/DF = 2.683, CFI = .925, GFI = .902, AGFI = .898, NFI = .901, IFI = .935, TLI = .918, RMSEA = .063.

Table 2

Confirmatory Factor Analysis Investigating Alternate Measurement Models Against the Measurement Model

Model	Factors	χ^2	*df*	χ^2/df	CFI	GFI	AGFI	IFI	TLI	RMSEA
Hypothesized 5-factor model (AICVP, AKPO, AKRO, ASG, SP)	5	1473.977	553	2.6772	.925	.902	.898	.935	.918	.063

Note. *N* = 480. AICVP = AI Customer Value Proposition; AKPO = AI Key Process Optimization; AKRO = AI Key Resource Optimization; ASG = AI Societal Good; SP = sustainability performance.

SPSS 21 was used for the descriptive analysis. According to the source table, 78.3% of participants were men and 21.7% were women. 47.8% of respondents were graduates, whereas 52.2% had a master's degree. 33.1% of responders were between the ages of 20 and 30, 30.4% of respondents were between the ages of 31 and 40, with 36.5% falling between the ages of 41 and 50.

Table 3

Descriptive Statistics of the Respondents' Profile

Demographic	Category	Percentage
Age group	20–30	33.1
	31–40	30.4
	41–50	36.5
Gender	Male	78.3
	Female	21.7
Marital status	Married	47.1
	Unmarried	52.9
Education	Bachelor's	47.8
	Master's	52.2

Note. The mean and standard deviation columns in the supplied table are not interpretable because of OCR corruption and are therefore omitted.

4.2 | Correlation and Reliability

The Cronbach's alpha reliabilities, correlation values, and descriptive statistics (mean and standard deviation) of the key variables are summarized in Table 4. The correlation values of artificial intelligence customer value proposition with SP ("r" = .77, "p" < .01), artificial intelligence key resources optimization ("r" = .63, "p" < .01), artificial intelligence key process optimization ("r" = .53, "p" < .01), and artificial intelligence societal good ("r" = .71, "p" < .01) are positively associated and significant.

Table 4

Means, Standard Deviations, Correlations, and Reliabilities of Core Variables

Variable	*M*	*SD*	α	1	2	3	4	5
1. AICVP	4.19	.335	.861	1				
2. AIKRO	4.17	.331	.90	.55**	1			
3. AIKPO	4.06	.182	.86	.40**	.60**	1		
4. AISG	4.11	.311	.96	.71**	.63**	.55**	1	
5. SP	4.10	.261	.93	.77**	.55**	.53**	.89**	1

Note. $N = 480$. AICVP = Artificial Intelligence Customer Value Proposition; AIKRO = Artificial Intelligence Key Resources Optimization; AIKPO = Artificial Intelligence Key Process Optimization; AISG = Artificial Intelligence Societal Good; SP = Sustainable Performance; CA = Cronbach's alpha. $p < .05$. *$p < .01$. **$p < .001$.

The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy is a statistic that demonstrates if the data are appropriate for factor analysis. It evaluates the ratio between the magnitude of the correlation coefficients and the magnitude of the partial correlation coefficients, and it varies from 0 to 1 (Kaiser, 1970, 1974). KMO is a crucial statistic because factor analysis is meaningful only if the variables possess some common variance; the lower the KMO, the less connected the items are, and therefore the extracted factors will not be reliable. The acceptable level of KMO is .60 or higher, and the meritorious level is above .80

(Kaiser, 1974; Hair et al., 2019). The current study showed the KMO and Bartlett's test value for AI capabilities for sustainable performance. The results of the Bartlett's test and KMO are displayed in Table 5. This test evaluates whether or not the responses are sufficient for the sample. The obtained KMO value is .821. Table 5 contains the Bartlett's test of sphericity. The closest chi-square value that was calculated is 1738.451. The significance value (*p*) for the Bartlett's test of sphericity is .000, which is less than .001.

Table 5

KMO and Bartlett's Test

Test	Value
Kaiser–Meyer–Olkin measure of sampling adequacy	.821
Bartlett's test of sphericity, approximate χ^2	1738.451
df	—
p	.000

Note. The degrees of freedom for Bartlett's test were not reported in the supplied source.

4.3 | Analysis of Measurement Model

In order to examine discriminant validity, two measures of discriminant validity—the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the heterotrait–monotrait (HTMT) ratio of correlations (Henseler et al., 2015)—were conducted. As seen in Table 6, the square root of AVE of each construct (diagonal values, from .783 for AICVP to .870 for sustainable performance) was higher than correlation with any other construct. The highest correlation was .673 for AIKPO and AIKRO and was lower than square roots of AVE of these constructs (.816 and .834, respectively). It can be concluded that the variance of each construct was shared more with its indicators than with any other construct. In order to deal with the criticism regarding the low sensitivity of the Fornell–Larcker criterion in measuring problems with discriminant validity (Henseler et al., 2015), HTMT was also calculated. As seen in Table 7, all HTMT values were below the conservative boundary of .85 (Kline, 2011). The maximum HTMT value was .749 for AIKPO and AIKRO, while the second maximum HTMT value was .628 for AISG and sustainable performance.

Table 6

Discriminant Validity (Fornell–Larcker Criterion)

Construct	AICVP	AIKPO	AIKRO	AISG	SP
AICVP	.783				
AIKPO	.131	.816			
AIKRO	.180	.673	.834		
AISG	.198	.437	.439	.826	
SP	.064	.444	.405	.351	.833

Note. AICVP = AI Customer Value Proposition; AKPO = AI Key Process Optimization; AKRO = AI Key Resource Optimization; AISG = AI Societal Good; SP = sustainability performance.

Table 7

Discriminant Validity (HTMT Ratio)

Construct	AICVP	AIKPO	AIKRO	AISG	SP
AICVP	—				
AIKPO	.352	—			
AIKRO	.498	.449	—		
AISG	.421	.484	.472	—	
SP	.474	.491	.436	.477	—

Note. AICVP = AI Customer Value Proposition; AKPO = AI Key Process Optimization; AKRO = AI Key Resource Optimization; AISG = AI Societal Good; SP = sustainability performance.

4.4 | Hypothesis Testing

A linear regression technique was used to test the model. Results in Table 8 illustrate that artificial intelligence customer value proposition, artificial intelligence key resources optimization, artificial intelligence key process optimization, and artificial intelligence societal good are significantly related to sustainable performance. In support of H1, the artificial intelligence customer value proposition was significantly and positively related to sustainable performance. In support of H2, artificial intelligence key resources optimization was significantly and positively related to sustainable performance. In support of H3, artificial intelligence key process optimization was significantly and positively related to sustainable performance. In support of H4, artificial intelligence societal good was significantly and positively related to sustainable performance. Hence, Hypotheses 1, 2, 3, and 4 are approved.

Table 8

Regression Results

No.	Variable	*B*	*t*	*p*
1	AICVP on SP	.607	16.460	.000
2	AIKPO on SP	.771	4.317	.000
3	AIKRO on SP	.502	17.119	.000
4	AISG on SP	.751	14.136	.000

Note. AICVP = AI Customer Value Proposition; AIKPO = AI Key Process Optimization; AIKRO = AI Key Resource Optimization; AISG = AI Societal Good; SP = Sustainable Performance.

5 | DISCUSSION

Through Situated AI theory, the model has been designed to determine the AI capabilities impact on sustainable performance. The study claimed that AI capabilities positively impact sustainable performance. The findings are consistent with the findings of the study done previously (Gazi et al., 2024). The study offers empirical evidence that organizations could take.

These findings are in broad consistency with the current body of empirical literature connecting AI capabilities to sustainability outcomes, although the study contributes to literature in a previously underexplored sector and context. The discovered positive relationship between AIC and sustainable performance is consistent with Fosso Wamba et al. (2024), who have found that AI capability contributes to enhanced firm performance from the sustainable development perspective through a mediating effect of data-

driven culture. Similar results have been obtained by Elsa, Jahangir, and Malik (2025), who have shown that AI capability significantly enhances sustainable performance among Pakistani private organizations through green absorptive capacity, green knowledge management, and green creativity, although their research was not focused on telecom as the sector of interest but considered private firms in general. The current findings are also consistent with manufacturing sector findings regarding the fact that AI capabilities, rather than AI technology itself, create sustainable competitive advantages (Shen & Badulescu, 2025), as well as with Rahman et al. (2026), whose NRBV-based study of Pakistani SMEs showed that AI and green dynamic capabilities jointly enhance sustainable performance.

However, certain inconsistencies are also observed. Many of the previous empirical literature, particularly the manufacturing and China-based studies of Shen and Badulescu (2025), used firm-level panel data, patent counts, or SEM-based mediation model analysis rather than direct regression analysis based on managers' perceptions. The regression analysis performed in the current study using SPSS, although focusing on telecom managers' perceptions, provides a much more straightforward test of the AIC and sustainability relationship without the use of mediating constructs that are quite common for the Chinese manufacturing literature. Moreover, while national-level evidence shows that AI capability (proxied by patent activity) enhances environmental sustainability across countries (Bergougui, 2026), the current study operationalizes the concept at the organizational and managerial level, providing much more actionable, firm-level evidence. Finally, while previous telecom-specific research (Ahmad et al., 2025) confirms AI's strategic role in performance improvement and its alignment with SDGs, the current study goes beyond and empirically breaks down AI capability into four different dimensions rather than treating it as a composite construct.

6 | THEORETICAL CONTRIBUTION

Firstly, this research paper offers four insights into the research domain of AI and sustainable business performance. The theoretical basis of this study is Situated AI theory, according to which intelligent systems are not autonomous and context-independent means of support. The value of these systems is created during the interaction with their situational environment, practices and people. This idea implies that in organizations, AI can create performance advantages if it is congruent with the firm's value proposition, resources and processes, as well as its social context.

The first aspect of our study is the expansion of Situated AI theory at the level of business model. Previous studies have been largely focused on either AI as a technical resource or its general effect on firm performance (Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020). Instead, we propose to consider AI as being situated within four different components of the business model: customer value proposition, key resources, key processes, and societal good (Osterwalder & Pigneur, 2010; Teece, 2010). Linking AI customer value proposition (AICVP), AI key resources optimization (AIKRO), AI key process optimization (AIKPO), and AI societal good (AISG) with sustainable performance (SP) reveals that the performance effect of AI depends on its embedding. This is in line with the call for more theoretical development that would explain the contextual dependencies of value creation through AI (Dwivedi et al., 2021; Kaplan & Haenlein, 2019).

Secondly, the study contributes to theories such as resource-based theory and the dynamic capabilities approach. The resource-based approach assumes that sustaining competitive advantage lies in using valuable, scarce, and difficult-to-imitate resources (Barney, 1991), whereas the dynamic capabilities approach stresses the importance of reconfiguring resources and processes (Teece et al., 1997). In the present research, it is demonstrated that AIKRO and AIKPO represent mechanisms that transform resources and routines into sustainable performance using AI. In terms of Situated AI theory, resource-based theory and the dynamic capabilities approach can be complemented in order to explain why the same technologies produce different results for different organizations.

Finally, the study expands the understanding of customer value. The theoretical conceptualization of AICVP highlights that AI brings sustainable performance not only in terms of internal effectiveness but also from a different perspective, through personalized services and responsiveness and creation of new value through AI applications (Davenport & Ronanki, 2018; Osterwalder & Pigneur, 2010). It connects the situated perspective of AI to the outside of the organization in terms of its customer-facing aspects, which was previously not discussed in terms of internal capabilities studies.

Lastly, the study integrates the aspect of societal good into AI–performance research. Currently, most of the AI–performance literature focuses on financial and operational results of the application. In our case, we include the concept of AISG, which ties AI to the three levels of sustainable performance: economic, social, and environmental (Elkington, 1997) and the logic of shared value creation, which means that business organizations generate economic value by taking care of society (Porter & Kramer, 2011). Moreover, we base our study on the research stating that sustainable business models integrate social and environmental value creation in the core of the business (Bocken et al., 2014). On the whole, the research presents a holistic, theory-based framework, where four situational AI factors (AICVP, AIKRO, AIKPO, and AISG) collectively determine sustainable performance. The research moves the discipline away from whether AI contributes to better performance to the issue of how and where AI must be integrated for value sustainability.

7 | PRACTICAL IMPLICATIONS

To telecom managers and organizational leaders, the results provide very clear and actionable guidance. As all four of the AI capability measures were found to predict sustainable performance, telecom companies should ensure that their investments are balanced between technological infrastructure, AI management ability, workforce expertise, and organizational agility and are not limited to acquiring specific pieces of hardware or software alone. It is especially important to note this finding considering the data from industry sources, according to which many telecom companies still struggle with fragmented and premature AI implementation without clear ROI (HTEC, 2026). The results indicate that organizations seeking to realize AI investments in sustainable performance should invest in building necessary capabilities in terms of training, managerial skills development, and organizational agility besides technological acquisitions. To policymakers and regulators in Pakistan, the findings are instrumental in the development of a framework of AI governance and digital transformation policies that directly tie technology adoption incentives to sustainable development

achievements instead of pursuing two distinct policy agendas. Finally, to telecom industry stakeholders, the results provide the empirical basis for replication indicating that regardless of implementation difficulties, developed capabilities can enable the achievement of sustainable performance goals in the context of a developing country.

8 | LIMITATIONS AND FUTURE RECOMMENDATIONS

This study is theoretically and practically significant; however, despite this fact, there are some limitations that give space to future research. First, for the current study, the empirical data were collected from the telecommunications sector in Pakistan; future studies may be carried out on other sectors (manufacturing, health, and textiles) and in other countries, which will resolve the issue of generalizability of findings. In addition, comparative study of different countries/sectors may also be carried out. Second, in the current study the direct relationship between AI capabilities and sustainable performance was investigated; future studies need to investigate underlying mechanisms like sustainable innovation practices or organizational learning, which might explain the direct relationship. Lastly, no moderating effects have been investigated in the current study and need to be investigated in the future. Future research can investigate data-driven culture as a moderator between AI capabilities and sustainable performance.

9 | CONCLUSION

Organizations are striving to attain sustainable success as they become more complex every day. The firm must identify the root causes of eco-friendly challenges in its operations (such as manufacture, shipping, acquisition, and the product) in order to better understand the fundamental environmental concerns and develop effective remedies. The study's empirical model provides compelling evidence that AI capabilities improve Pakistani companies' sustainable performance. The results also show that artificial intelligence customer value proposition, artificial intelligence key processes optimization, artificial intelligence key resources optimization, and artificial intelligence societal good have the strongest positive relationship with sustainable performance.

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