



Artificial Intelligence in Green Supply Chain Management: Towards Climate-Smart Decision Support Systems

Muhammad Muzammil Asghar^{1*}, Muhammad Faisal Razzaq²

¹ Research Scholar, School of Economics, Bahauddin Zakariya University, Multan, Pakistan.

Email: muzammilasghar42@gmail.com

² MPhil Scholar, School of Economics, Bahauddin Zakariya University Multan, Pakistan.

Email: afaisalrazzaq@yamil.com

ARTICLE INFO	ABSTRACT
Article History: Received: May 15, 2026 Revised: June 07, 2026 Accepted: June 25, 2026 Available Online: July 02, 2026 Keywords: Green Supply Chain management, Artificial Intelligence (AI), Climate Changes, Technology Solutions Corresponding Author: Muhammad Muzammil Asghar Email: muzammilasghar42@gmail.com	<i>In industrial markets, artificial intelligence (AI) has the potential to revolutionize industries and hasten humanity's fight against climate change. This study explores the innovative capabilities of AI-powered climate services within the resource-hungry and pollution-intensive green supply chain management field. This research creates and verifies an artificial intelligence model that has 13 sub dimensions in addition to four main dimensions. The results demonstrate that AI-powered climate service innovation skills have a major impact on market and environmental performance based on a manufacturing industry dataset. To assess the proposed research model, we extensively polled manufacturing companies in Pakistan. A questionnaire survey was conducted to obtain information. Survey items were obtained from previous empirical research projects. Our 5-point Likert scale makes it easier to access market surveys. Variance-based SEM (VB-SEM) was used to evaluate data. For this purpose, we used the fourth version of the SmartPLS. The measuring model was evaluated by examining discriminant validity, convergent validity, and construct reliability. The discriminant validity of the test was evaluated using a cross-loading matrix. Because the diagonal element in our analysis was greater than the off-diagonal correlation in the rows and columns, it satisfied the Fornell-Larcker criterion. The significance of the putative association was determined using a bootstrapping approach with 500 observations; p-values were considered during this procedure. The study's conclusions emphasize the importance of combining cutting-edge technologies, such as artificial intelligence (AI), with eco-friendly supply chain practices to address the various problems caused by climate change.</i> © 2026 The Authors, Published by VIPRC. This is an Open Access Article under the Creative Commons Attribution License - CC BY- 4.0

1. Introduction

Common issues such as frequent pollution, rapid resource depletion, dangerous climate change, and dwindling biodiversity threaten the natural equilibrium [1, 2]. In many countries, minimizing the damaging impact of anthropogenic activities on the environment is of utmost importance [3]. However, supply chains cannot be excluded from these measures. All legislation and initiatives aimed at reducing pollution and saving energy have producers as their main target [4]. Consequently, these constraints have led to the creation of supply networks that are environmentally benign [5]. Rather than considering the environment, a regular system was designed with cost reduction and enhanced service [6]. However, external influences such as the derivative compression factor, price compression, and enforced compression factor have gradually forced firms to design production network systems that address environmental concerns [5, 6].

Several associations have recognized the green supply chain in the last ten years. Managers have made efforts to implement modernized management across the market [6].

GSCM, a supply chain-wide management approach for environmental management that aids companies in achieving their environmental goals, includes environmental practices and strategic positioning [7, 8]. GSCM has drawn more attention in recent decades owing to the issues of resource depletion and global warming, which put firms under pressure from regulations, the public interest, or business possibilities [7, 9]. One strategy for environmental conservation is green supply chain management. It was originally presented in 1996 by the Michigan State University Industrial Research Association [10]. Raw materials, product design and production, product usage, and product recycling are all covered in GSCM when considering the product life cycle from the standpoint of sales and transportation [11]. By combining supply chain management with green technology, businesses may maximize their energy and resource usage while minimizing their negative environmental consequences [12].

Furthermore, it has become clear that a crucial organizational strategy for boosting business operational performance, achieving long-term gains, and gaining a competitive edge is green supply chain management, or GSCM [13]. Organizations, however, are increasingly demanding answers and solutions from businesses that, as a result of their production activities, have a major negative influence on the environment, such as climate change [14]. Companies must use the best strategies and tools available to them in order to overcome these obstacles and maintain their competitiveness [15]. Artificial intelligence (AI), which encompasses the Internet of Things, cloud computing, and big data analysis (BDA), is one of the most important technologies [16].

The major objective of artificial intelligence (AI), a subfield of computer science [17, 18], is to create computer systems with human-like behaviors and thought processes. Eventually, these intelligent machines can mimic, pick up, and even replace human intelligence [19]. Artificial intelligence (AI) integration across numerous commercial domains has garnered significant attention in recent years (Figure 1) [20]. It is anticipated that artificial intelligence (AI) will play a major role in combating climate change [21]. Over the past ten years, artificial intelligence (AI) has grown significantly in capability, particularly in terms of machines' ability to learn from large amounts of data [14].

Firms adopt artificial intelligence because it changes the economics of production and supply chain operations. By leveraging AI, organizations can make the most of their limited resources, cut manufacturing waste, streamline stock control, lower logistics expenses, and make informed decisions in uncertain situations. These enhancements reduce operational expenses and boost productivity and environmental sustainability [19]. The other economic advantages of Green Supply Chain Management are the savings in the use of resources and in energy consumption, the reduction of waste disposal costs and the ability to meet environmental regulations. Due to the digital infrastructure, software, employee training, and organizational changes necessary to implement AI, companies are willing to make these investments, but they believe they will yield long-term economic benefits, such as improved efficiency and competitiveness [7, 8].

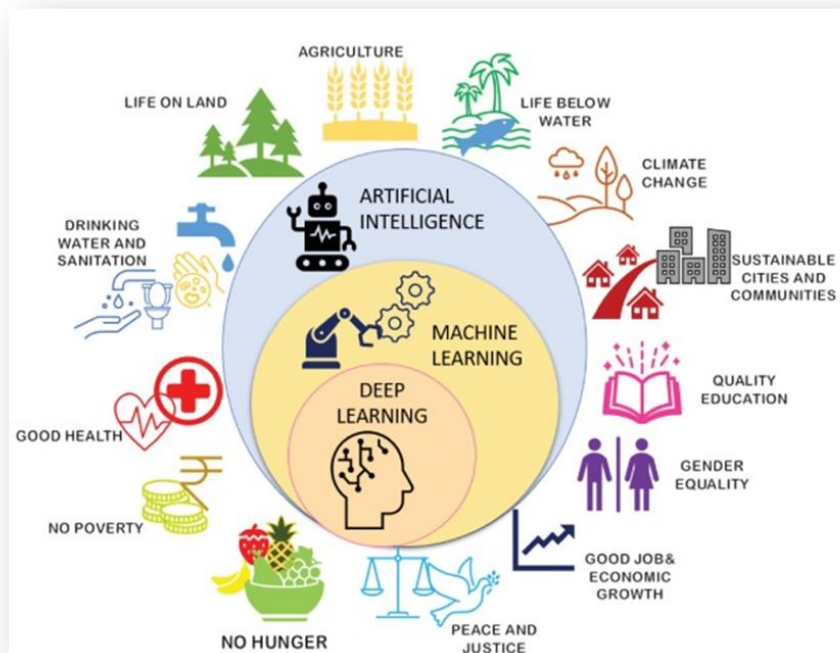


Figure 1: Incorporation of artificial intelligence (AI) into business sectors [22].

This study explored the development of Climate-Smart Decision Support Systems (DSS) by integrating Artificial Intelligence (AI) into Green Supply Chain Management (GSCM). The principal aim is to improve sustainability practices in supply chains while addressing the difficulties posed by climate change.

2 Literature review and hypothesis development:

Upon further investigation, we addressed the literature review of GSCM in the face of climate change.

Green Supply Chain Management (GSCM)

The Michigan State University Industrial Research Association created green supply chain management (GSCM) in 1996. This signifies a significant change in the way environmental protection is implemented. Green supply chain management addresses every stage of a product's lifetime, including raw material procurement, product design and manufacture, product sales and transportation, product use, and product recycling. Using supply chain management and green technologies, a company can reduce its negative environmental consequences and achieve optimal resource and energy utilization. The process of integrating environmental norms or concerns into a supply chain at every stage is known as supply chain greening. Green supply chain management and its approach of considering environmental factors or concerns at each stage of the supply chain link supply chain management with environmental requirements at every turn, including supplier chain selection, product design, and greening [10, 23]. The creation of supply management guidelines that consider the environment when designing, distributing, using, recycling, and disposing business services is known as green supply chain management. As opposed to traditional supply chain management, green supply chain management (GSCM) is primarily concerned with implementing a green development plan while controlling both internal corporate innovation drivers and external environmental pressures. A comparison between GSCM and traditional supply chain management revealed three key differences [24]. Sustainable or green supply chain management (GSCM) has garnered significant interest from academics and industry professionals worldwide. Severe climate

change that has affected humanity has recently been primarily ascribed to human activities. Harmful emissions are the main cause of recent climate change and present major issues and risks to all human species, including global warming, earthquakes, storms, tsunamis, and floods [6]. Furthermore, it has become clear that a crucial organizational strategy for boosting business operational performance, achieving long-term gains, and gaining a competitive edge is green supply chain management, or GSCM [13]. However, organizations are becoming increasingly demanding answers and solutions from businesses whose manufacturing activities have a major negative influence on the environment [11, 14].

The Role of Artificial Intelligence in GSCM

The rapid growth of technology has resulted in its increased incorporation into a wide range of companies across multiple economic sectors. The advantages of advanced technologies, such as BDA, IoT, machine learning, and AI, for the advancement of supply chain management (SCM), particularly for environmental (green) practices, have been investigated [25]. Using data-driven insights to improve sustainability initiatives and expedite processes is essential for integrating artificial intelligence (AI) into supply chain management. For example, by precisely anticipating customer needs, demand forecasting driven by AI can reduce waste and surplus inventories [26].

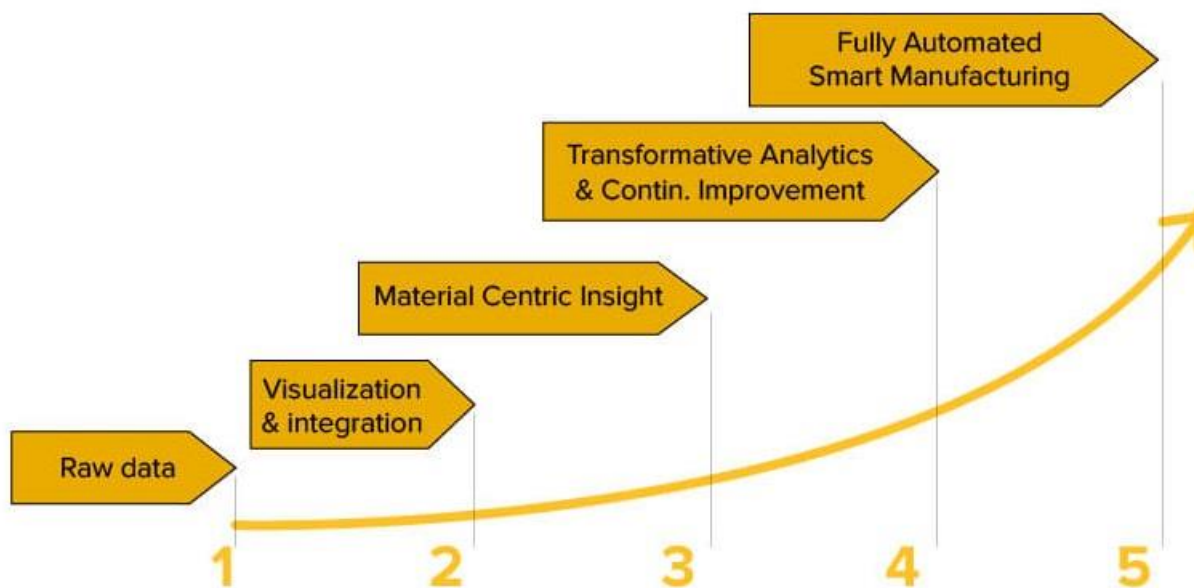


Figure 2. AI driving the green supply chain management [27].

Since it aids in tracking the competitiveness and management of supply chains (SC), artificial intelligence (AI) has been regarded as a key enabler of SC. As a result, AI is becoming increasingly well-known in management (Figure 2). Nevertheless, no scholarly work has provided an in-depth analysis of a particular artificial intelligence method. Although a number of assessments that have already been written in this area offer valuable insights, they are frequently overly broad. Artificial intelligence (AI) integration into green supply chain management has drawn much interest as a potentially effective way to meet sustainability targets and boost operational effectiveness [28]. Artificial intelligence refers to a computer system that can make decisions or carry out tasks that a human being is able to execute. These days, artificial intelligence is a subset of sophisticated analysis built on optimization, machine learning, and deep learning [10].

To address growing concerns and achieve environmental sustainability, industrial and service organizations are looking for efficient technologies and methodologies. This is because there has been significant demand in recent years for environmental sustainability and green supply chains. Artificial

intelligence (AI) is an effective method to improving Green Supply Chain Management (GSCM) and achieve long-term gains is artificial intelligence (AI) [11].

In the field of supply chain management, artificial intelligence technologies such as expert systems, genetic algorithms, and agent-based systems are becoming increasingly common. AI systems can be utilized for methodological system management, control, and planning.

As GSCM is a complicated process, the system as a whole may not produce the intended outcomes without adequate planning and control. Gathering information from each stage of the process is essential to obtain important details. Data collection can be facilitated by intelligent technology, and supply chain management for sustainability can be planned and controlled with the help of AI. There is a gap in the literature that can be attributed to the lack of comprehensive integration of AI systems into the GSCM process. More research is required to determine how much AI is being used for information processing in automotive and related manufacturing companies that use GSCM more research is required [12].

Climate Change and Its Implications for Supply Chains

In recent years, climate change has become one of the most significant challenges in almost all commercial and public decision-making levels. This represents a significant shift from the general consensus a few years ago. Global warming-related climate change is a widely acknowledged issue that affects human culture, commercial operations, and the environment in many ways. Corporate strategic responses to sustainability issues are characterized and understood by considering institutional, resource-based, supply chain, and stakeholder perspectives. Businesses must carry out their climate change-prone operations in an increasingly demanding and hazardous environment [29].

One of the most important environmental issues facing the world today is climate change, which affects numerous industrial sectors. Risks related to core operations, risks to the value chain, and risks resulting from more significant changes in the infrastructure and economy are the three categories of climate change risk that might have an impact on the company. Moreover, the implementation of mitigation and adaptation measures in response to climate change may indirectly affect company activities. Regulations addressing climate change affect energy pricing and availability, among other things, and have a cascade effect across an organization's entire value chain; thus, businesses should see them as market issues [30]. There are two primary research streams in the literature regarding SCM and climate change. The first stream of research is primarily theoretical and addresses supply chain carbon management primarily in terms of reducing overall costs by accounting for carbon emission factors or trading mechanisms. The psychological consequences of climate change (temperature swings, extreme weather patterns, etc.) on crops and food production are the subject of second line of research. It also examines how companies create carbon footprint inventories. Because climate change is highly context-specific, depending on latitude, different sectors within the same industry may have different effects [31].

Businesses and governments are now compelled by climate change to investigate ways of mitigating future disasters. Climate change risk management in international supply chains is an urgent requirement. [32, 33]. The frequency of weather-related and climate-related calamities has increased, making climate change (CC) management more urgent. CC is considered a humanity's "code red" warning.

The Effectiveness of Technological Solutions in Mitigating Climate Risks

Climate change is one of the most important problems that the world is currently confronting due to its profound effects on the environment, economy, and society. The long-term sustainable development of enterprises may be adversely affected by rising sea levels, increased frequency of natural disasters, and global warming. As such, research on sustainability and corporate social responsibility in connection with

environmental protection has received considerable attention in the field of modern marketing. [34, 35]. According to the PricewaterhouseCoopers (PwC) study report from 2023, technological obstacles remain a major deterrent for businesses wanting to implement climate risk-management strategies. In light of recent rapid advancements in artificial intelligence, the BCG poll of world executives reveals that AI has the potential to overcome technological obstacles and will be a valuable tool for many businesses in the future as they tackle climate change [35].

AI presents enormous potential for corporate climate risk management initiatives, and as a disruptive invention, it may encourage businesses to rethink their business models [36]. Three key areas demonstrate how AI helps corporations take climate action: detecting and quantifying climate change, enhancing adaptive and predictive capacities, and advancing fundamental research [37, 38]. Building and utilizing these resources and competencies can greatly reduce a company's vulnerability to supply chain and operational costs related to climate change, as well as the hazards involved. As a result, AI is crucial to corporate digital social responsibility for businesses that are exposed to climate-related hazards [39], as it makes it possible to detect and quantify emissions and climate change at both macro and micro levels (Figure 3).

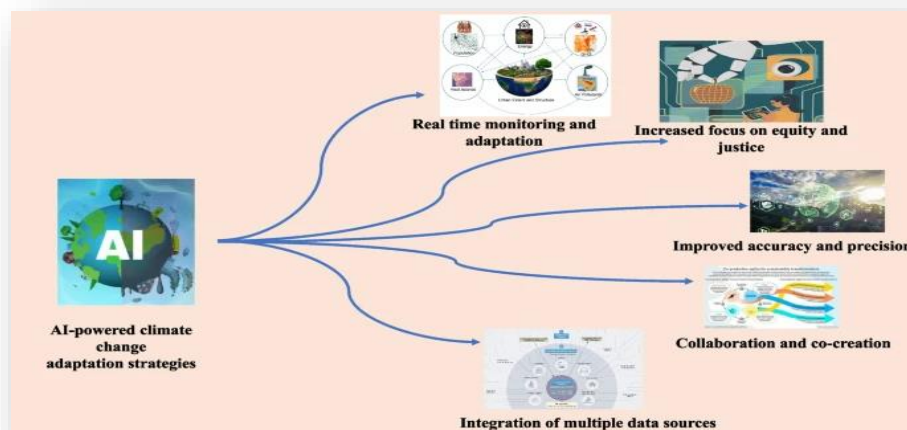


Figure 3. Future developments in AI-powered methods for adapting to climate change (derived from literature [40, 41, 42])

To effectively promote corporate climate initiatives using AI technology, organizations need to establish a distinct technical environment and strategic direction [43]. For example, according to the BCG poll from 2022, approximately 78% of businesses said they were unable to get enough AI help or find suitable AI solutions to implement corporate climate initiatives. As a result, major professional investments and related adjustments to staffing and business plans are necessary for successful AI deployment. This is reflected in AI orientation, a comprehensive plan that directs businesses' use, application, and management of AI technology [35, 44].

Businesses that are now leaning toward a green strategy may find it difficult to embrace an AI strategic direction in real-world business settings. The high cost of computers and applications, the dearth of talent and experience in AI, data issues, and the impossibility of achieving scale applications are some of these problems. Additionally, research indicates that in January 2023, OpenAI may have consumed as much electricity as 175 000 Danish households (Digital Information World, 2023). Companies that have green initiatives and wish to consume less energy may encounter this conflict. Businesses that have a strategic direction towards AI may not face these adoption barriers because they have financial advantages and

robust capacity to deal with these problems [45]. An AI-oriented approach can greatly improve an organization's capacity to identify climate risks, generate and integrate internal and external resources, and adapt to changing environments. Therefore, it is imperative to investigate the relationship between B2B enterprises' climate activities and corporate AI attitudes. Thus, we present our fourth research question:

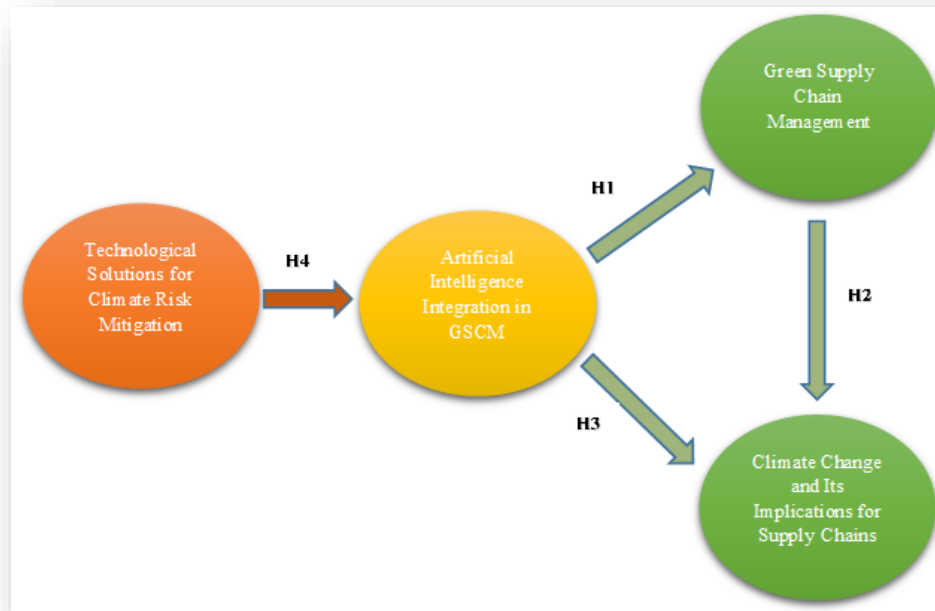


Fig 4. Framework of study

Hypothesis development

This section presents the basis for developing the theoretical framework and testing the research strategy. Based on some of the more significant articles on GSCM and the GSCM framework, which point to vital directions, four components were determined to be crucial for the development of AI-GSCM systems in the manufacturing industry. The constructs and measurements are listed in Table 1. The components of the system include supply chain implications of climate change (CC-ISC), technological solutions for managing climate risk (Tec-CRM), and internal environmental management (GSCM Process) (green purchasing, eco-design, customer cooperation, eco-management, and investment recovery). The outputs of the GSCM system are the final items and data affecting the aircraft. (Figure 4).

The majority of earlier GSCM models were studied in isolation, which presents a restriction. Nonetheless, the model possesses several unique qualities that are impossible to describe in isolation. We use our system-based model to capture unique qualities. Numerous studies have shown that manufacturing and service companies benefit from AI in industrial markets. Numerous studies have shown that manufacturing and service companies can benefit from AI in industrial markets [46, 47].

The firm's AI system in the model (Figure 4) consists of practices, rules, and processes that support AI projects. The company's market, environmental, and AI orientation capabilities are included in its Tec-CRM capacity. The term "AI orientation" describes a company's capacity to use AI-based technology in the design of novel services that address issues while upholding moral and ethical principles. Based on micro-foundations, this study posits that Tec-CRM, as a dynamic capability, offers a catalyst for

developing capabilities oriented toward the environment, market, and AI-GCM, and for leveraging resources to improve market and environmental performance. To represent the relationship between Tec-CRM, AI-GCM, GSCM, and CC-ISC, a conceptual model is suggested [48].

H1. *Technological solutions for climate risk mitigation positively influences artificial intelligence integration in GSCM (Tec-CRM → AI-GSCM).*

Businesses may identify opportunities and challenges associated with climate change through Tec-CRM's dynamic capabilities (DC) and then strategically plan and create structures and processes to address them. Artificial intelligence (AI) has the potential to significantly impact the industrial sector by forecasting customer demands and streamlining manufacturing procedures [49, 50]. The DC view's micro-foundations support a company's strategic application of AI to climate service analytics. This application of AI is thought to help decision-makers create marketing plans that address lowering costs, improve brand perception, break into new markets, increase profit margins, expand market share, and win over consumers [50]. According to this theory, artificial intelligence has become more integrated into green supply chain management techniques as technological solutions for mitigating climate risk are adopted and put into reality.

H2. *Artificial Intelligence integration in GSCM positively influences Green Supply Chain Management (AI-GSCM → GSCM).*

AI can be used for GSCM planning and control. Through information-sharing across supply chain verticals, AI-based technology enablement can be a useful tool for connecting internal environmental management, green purchasing, customer cooperation, eco-design, and investment recovery. In green logistics management (GSCM), genetic algorithms (GAs) can be applied to problems with material handling, container loading, and vehicle routing and scheduling. Thus, AI-enabled technology has an impact on the choice of appropriate strategies and plans of action [51].

Businesses typically combine many GSCMS to improve GSCMP. The ultimate goal is to improve IEM, GP, ECO, CC, and IR. Businesses place great emphasis on implementing the right GSCM through cooperative partnerships, acquiring specialized knowledge, and utilizing cutting-edge technology to improve business performance [52, 53]. Therefore, this hypothesis proposes that the efficacy and efficiency of green supply chain management increase when artificial intelligence technologies are incorporated into practices.

H3. *Artificial intelligence integration in GSCM positively influences climate change and its implications for supply chains (AI-GCM → CCIS).*

The body of research on environmental management suggests that a company's environmental orientation, which is shaped by how it uses digital technology in the modern world, has a significant impact on its success in the market and environment. Adopting such technology (such as AI and BDA) improves a company's ability to manage innovative climate services in a more dynamic manner. However, AI-driven solutions must be able to continuously detect the underlying climate challenges in the relevant market and modify resources to seize opportunities or avoid dangers. The overall favorable impact of the AI-GCM on market and environmental performance may eventually become less pronounced if it is unable to effectively address climate-related issues. According to this theory, managing supply networks and comprehending climate change and its effects can be improved by integrating artificial intelligence into green supply chain management [31].

H4. *Green Supply Chain Management positively influences climate change and its implications for supply chains (GSCM → CCIS).*

By incorporating sustainable practices at every stage of the supply chain, by obtaining raw materials for product delivery, green supply chain management (GSCM) mitigates the effects of climate change. By emphasizing energy efficiency, cutting waste, and lowering carbon emissions, GSCM contributes to a reduction in the overall environmental effects of the manufacturing and logistics sectors. For example, employing renewable energy sources and streamlining transportation routes can significantly reduce greenhouse-gas emissions. A circular economy that reduces resource depletion and environmental degradation is also promoted by GSCM, which encourages the use of ecologically friendly products and procedures. By lowering the carbon footprint of supply chain operations and promoting sustainable business practices, these initiatives can help mitigate climate change [54]. Thus we pose hypothesis that effective green supply chain management practices contribute to well understanding and management of climate change and its implications for supply chains.

3. Methodology

Questionnaire development

Information was gathered using a survey questionnaire (Table 1). The survey items were taken from earlier empirical research projects [55]. The study's questionnaire used a five-point Likert scale, with 1 denoting "strongly disagree," 2 "disagree," 3 "neutral," 4 "agree," and 5 "strongly agree," to gauge how much respondents agreed or disagreed with a particular GSCM technique [12].

1.1. Sample Size

The sample size was calculated using the following formula:

$$n = N / [1 + N(e)^2]$$

Where;

n= sample size

N= Total population

e = Error

The sample size was 300 [12]; with a margin of error of 5%, a confidence level of 95%, and a response distribution of 50%. The entire population comprises approximately 1200 companies.

Data Collection

Purposive sampling was employed to gather data from managers of 280 industrial companies in Pakistan through survey questionnaires. The goal of this study is to thoroughly investigate the function of artificial intelligence (AI) in green supply chain management. To obtain comprehensive and wide-ranging insights regarding AI adoption and its implications for creating Climate-Smart Decision Support Systems, this method will incorporate a purposive sampling technique [28].

An overview poll was used to acquire the information. The review was led by three analysts. The author provides an internet link to the surveys for information collection through careful inspection. A total of 300 votes were cast, and 280 surveys were returned. These may be used after filtering, based on the average response rate for the green supply chain management study. The questionnaire was tailored to the Pakistani market by drawing on the existing literature. Our 5-point Likert scale makes it easier to access the market survey [3].

Analytical approach using SmartPLS:

We used variance-based SEM (VB-SEM) to evaluate the data. For this, we used the SmartPLS 4.0. Similar to SEM, we started by building the measurement model. Thus, we constructed and evaluated various construct reliability, validity, and model fit indices, in addition to carrying out confirmatory factor analysis. To investigate the suggested theories, we created and examined a structural model [56, 57].

4. Results

The methodological framework was proposed in the previous section, and the data were gathered in accordance with this framework. This section examines the validity and reliability of the study, statistical analysis of the data, and a discussion of the findings in relation to testing the hypotheses.

Measurement Development

We created a list of 40 measurement items that are typically considered significant for implementation by manufacturers to create a measurement scale for how well technological solutions for mitigating climate risk integrate with artificial intelligence in GSCM (Table 1). The literature provided the foundation for the development of the measurement items. A survey questionnaire containing all 40 measurement items was sent to the manufacturers. A five-point Likert scale (1 = strongly disagree," 2 = disagree," 3 = neutral," 4 = agree, 5 = strongly agree") was provided to the target respondents (Table 1).

Data Collection

The promotion and application of digital technology in Pakistan's economy is greatly aided by the nation's manufacturing sector[58]. Thus, to evaluate the proposed research methodology, we conducted a comprehensive analysis of Pakistani manufacturing firms. There were several Pakistani cities in the sample. To further ensure the validity of the results, we restricted the responses to middle and senior managers in the organization [59, 60]. On www.lusha.com, sample businesses were listed with the appropriate contact information. To request participation from experienced managers of randomly selected firms, emails including online survey questions were issued.

Initially, we sent the questionnaire by email to a sample of 300 manufacturing companies that produced automobiles, textiles, iron and steel, machinery, rubber goods, food and drinks, and pharmaceuticals. Survey takers, who at first did not reply to the email, received a follow-up email after three weeks. Follow-ups over the phone were conducted to make sure businesses realized the significance of the poll. In response to these requests, 280 completed questionnaires were obtained. The extrapolation method developed by Armstrong & Overton (1977) was used to consider the possibility of a non-response bias. The respondents were split into early and late response groups and late respondents were used as proxies for non-respondents. Independent-samples t-tests were used to compare the demographic characteristics and the mean scores across the principal constructs of the study across both groups. There were no differences that met the criterion of being statistically significant ($p > .05$) suggesting that the non-response bias is not likely to threaten the results' validity.

Table 1: Results of the Non-Response Bias Test (Early vs. Late Respondents)

Variable	Early Mean	Late Mean	p-value
AI	4.12	4.09	.48
GSCM	4.01	3.97	.55
Market Orientation	3.95	3.91	.60

Demographic profile of the respondents is given in table 2. The results showed that the responses were collected from experienced managerial personnel, as most participants were Senior Managers (36.07%), followed by Managers (24.64%) and Deputy Managers (21.43%). Seventy percent of respondents were employed by an organization with 1-5 years of experience, and 39.33% were working with an organization that has 250-500 employees. Iron and Steel (28.00%) and Textiles (20.67%) and Rubber Products (18.33%) showed the highest representation and were representative of manufacturing sector of Pakistan.

Table 2: Demographic of Respondent

Particulars	Respondents	N	%

Ranks	Managing Director (MD)	18	6.43
	Senior Manager	101	36.07
	Manager	69	24.64
	Deputy Manager	60	21.43
	Assistant Manager	32	11.43
Working Experience	> 10 years	75	26.79
	6- 10 years	93	33.21
	1 - 5 years	112	40.00
Number of Employees	> 500	95	31.67
	250 - 500	118	39.33
	101 - 249	56	18.67
	< 100	31	10.33
Industry	Automobile	12	4.00
	Textiles	62	20.67
	Iron and Steel	84	28.00
	Machinery	10	3.33
	Rubber Products	55	18.33
	Food and Beverages	42	14.00
	Pharmaceuticals	35	11.67

Measurement Mode, Validity and Reliability

The data in this study were processed using Smart PLS software version 4.0 and PLS-SEM. The robustness and relevance of the study model in this field has been demonstrated by the growing use of PLS-SEM. We employed this methodology in this study for several reasons. First, it was demonstrated that the current recommendations for utilizing PLS-SEM are effective in measuring moderation and mediation. Mediation and moderation analyses are required for this research paradigm. Second, because of the complexity of the research model used in this study, which includes over 32 items, first-order and second-order variables, and other elements, PLS-SEM is the most suitable and ideal option for analysis. Third, compared to CB-SEM, PLS-SEM has higher statistical power. Therefore, PLS-SEM is the most powerful and successful method for studying population relationships. Lastly, PLS-SEM may function concurrently with a small sample size and several measurement scales.

Table 3: Confirmatory factor analysis (CFA)

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ACICM	0.707	0.716	0.711	0.552
AI-DSS-GSM	0.866	0.867	0.866	0.618
AI-GCM	0.958	0.959	0.959	0.623
CC-ISC	0.837	0.838	0.838	0.563
ECO	0.886	0.886	0.886	0.721
GP	0.900	0.906	0.901	0.648
GSCM	0.975	0.976	0.976	0.689

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
GSCM-HD	0.945	0.946	0.946	0.635
IEM	0.947	0.947	0.947	0.718
IR	0.881	0.882	0.882	0.713
MAOR	0.850	0.850	0.850	0.654
SCC	0.776	0.776	0.776	0.634
Tec-CRM	0.878	0.878	0.878	0.642

Convergent validity, discriminant validity, and construct reliability were assessed to appraise the measuring model [61]. Initially, we examined the construct's composite reliability and Cronbach's alpha to evaluate the dependability of the model. Our observations indicate that the construct's composite reliability falls between 0.716 and 0.976 (Table 3). Second, convergent validity was evaluated using the average variance extracted (AVE) measure[62]. The AVE values for each construct were found to fall within the range of 0.552 to 0.689 and >0.50 threshold, indicating that the convergent validity of our model was found to be good (Figure 2) [63]. Moreover, Cronbach's alpha exceeded the 0.7 threshold, ranging from 0.707 to 0.975, indicating that the architecture of our measurement model was dependable and appropriate for the model (Figure 3) [61].

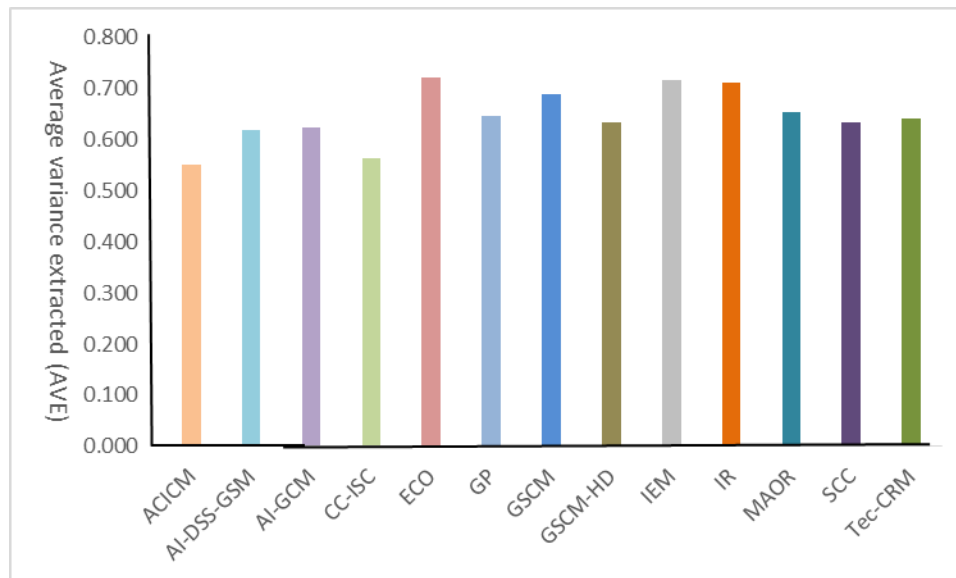


Figure 5: Bar Chart – Average Variance Extracted (AVE)

The discriminant validity of the test was thoroughly assessed using the criteria from [54]. To meet the cross-loading requirement, the outer loadings of the measurement items on a linked build must be larger than all their outer loadings on other structures. Our analysis of the cross-loading matrix data revealed that each assessment item had a higher loading on the target constructs. As per the standards mentioned in [54] the square root of the average variance for each construct should be larger than the maximum correlation with any other construct [52].

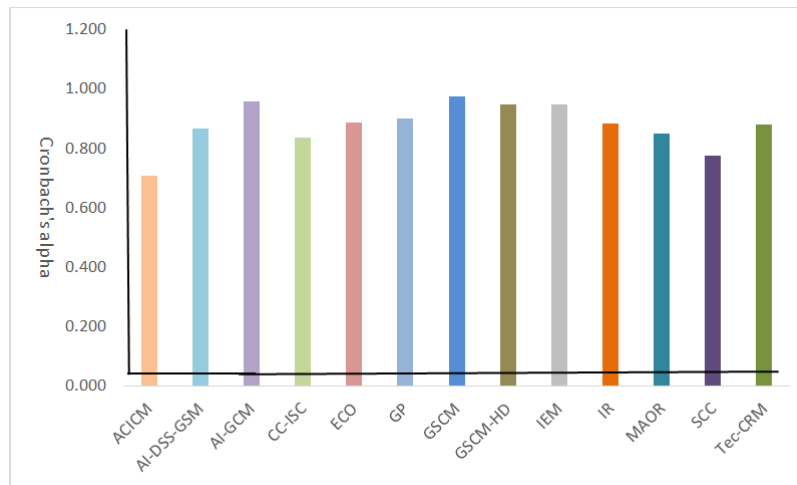


Figure 6: Bar chart – Cronbach's alpha

The Fornell-Larcker criterion evaluates the relationship between the reflective variables and their indicators. It is a potent and popular measure of discriminant validity. The dependability index value should ideally be greater than 0.70 when using this metric to operationalize a group of factors related to or unrelated to a case study (Table 4). The results of cross-loading and Fornell-Larcker criteria showed that the data's discriminant validity was met.

Table 4: Discriminant validity (Fornell-Larcker criterion >0.70)

	ACI CM	AI- DS S- GS M	AI- GC M	CC - IS C	EC O	GP	GS CM	GSC M- HD	IE M	IR	MA OR	MA PE	SC C	Tec - CR M
ACICM	0.743													
AI-DSS- GSM	0.941	0.786												
AI-GCM	0.984	0.032	0.789											
CC-ISC	0.185	0.903	0.923	0.751										
ECO	0.923	0.838	0.817	0.960	0.849									
GP	0.974	0.853	0.841	0.998	0.968	0.805								
GSCM	0.952	0.845	0.828	0.989	0.002	0.031	0.830							
GSCM- HD	0.993	0.975	0.039	0.923	0.801	0.829	0.814	0.797						
IEM	0.935	0.847	0.823	0.968	0.980	0.004	0.020	0.807	0.847					
IR	0.951	0.805	0.799	0.014	0.943	0.009	0.008	0.790	0.966	0.844				
MAOR	0.946	0.010	0.998	0.924	0.857	0.889	0.876	0.985	0.879	0.835	0.809			

MAPE	0.739	0.7	0.7	0.6	0.6	0.6	0.66	0.78	0.6	0.6	0.78	0.00		
		46	75	97	59	82	7	1	66	27	1	0		
SCC	0.932	0.8	0.8	0.1	0.9	0.9	0.97	0.80	0.9	0.0	0.85	0.62	0.7	
		21	17	45	48	72	6	9	53	27	5	0	96	
Tec-CRM	0.946	0.9	0.9	0.9	0.8	0.8	0.87	0.98	0.8	0.8	0.13	0.90	0.8	0.8
		96	96	16	53	85	0	8	72	26	1	8	39	02

Common Method Bias

The inner model's Variance Inflation Factor (VIF) values were used to evaluate the common method bias (CMB). Since every VIF value in the current study was less than 3.33, the model may be said to be free of common method bias (Table 5) [64].

Table 5: Common Method Bias and Variance Inflation Factor

	VIF
AI-GCM -> AI-DSS-GSM	1.000
AI-GCM -> CC-ISC	2.791
AI-GCM -> GSCM	1.000
AI-GCM -> GSCM-HD	1.000
CC-ISC -> ACICM	1.000
CC-ISC -> SCC	1.000
GSCM -> CC-ISC	2.791
GSCM -> ECO	1.000
GSCM -> GP	1.000
GSCM -> IEM	1.000
GSCM -> IR	1.000
Tec-CRM -> AI-GCM	1.000
Tec-CRM -> MAOR	1.000
Tec-CRM -> MAPE	1.000

Structural Model

After assessing the validity and reliability of the instrument, the following stage was used to assess the structural relationships between variables. Compared with other algorithms that compute each constructed relation separately, SEM-PLS has the advantage of being able to inspect them all at once. Therefore, we looked at the effects of our structural equation model, which were both direct and indirect. The structural model used in the current study is shown in Figure 5.

With the following fit indices: " $\chi^2 / df = 1.78$, CFI = 0.99, d-ULS = 12.406, and SRMR = 0.075]", the structural model analysis showed a satisfactory fit between the proposed model and the data. These findings support correlations in relation to the hypotheses. First, it was discovered that Tec-CRM and AI-GCM were positively correlated "(H4: $\beta = 0.996$, $p < 0.001$)," supporting hypothesis H4. Furthermore, there was a significant correlation between AI-GCM overload and GSCM "(H1: $\beta = 0.828$, $p < 0.001$)" and between supply chain performance and climate change "(H3: $\beta = -0.923$, $p < 0.01$)", thus supporting Hypotheses H1 and H3. Additionally, GSCM overload and CC-ISC were strongly correlated "(H2: $\beta = 0.715$, $p < 0.001$)", confirming hypothesis H2. These findings suggest that technological solutions for climate risk mitigation positively contribute artificial intelligence integration in GSCM. And these findings also contributes the positively impact of AI-GCM to Green supply and climate changes integration in supply chain managements.

Apart from scrutinizing the principal hypothesis, this study also explored the impact of multiple other variables. Green supply chain management was found to have a significant impact on the EP, ECO, GP, and IR items among these variables, but the study did not support the items associated with cooperation with customers (CC), which had factor loadings between (0.4 and 0.7) and should only be removed from the model if doing so would improve the validity of the model. AI applications in GSCM facilitate real-time monitoring, predictive analytics, and automation, thereby optimizing resource usage, reducing waste, and enhancing sustainability practices.

As a result, GSCM not only contributes to environmental performance by minimizing carbon footprint and resource depletion but also fosters the adoption of green practices, leading to economic benefits and enhanced institutional reputation. These findings align with existing literature on the positive correlation between GSCM practices and environmental, economic, and social outcomes [11].

A bootstrapping method with 500 data points was used to assess the significance of the claimed link; p-values were considered during this process (Table 6). P values were established at a significance level of 0.05. The results showed that the p-value for each hypothesis was less than 0.05. H1, H2, H3, and H4 are therefore supported.

Table 6: Hypothesis testing results

Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AI-GCM -> CC-ISC	0.331	0.330	0.060	5.491	0.000
AI-GCM -> GSCM	0.828	0.827	0.024	34.649	0.000
GSCM -> CC-ISC	0.715	0.715	0.061	11.721	0.000
Tec-CRM -> AI-GCM	0.996	0.997	0.012	85.448	0.000

Discussion

Climate change poses serious physical threats to businesses, which, in turn, poses economic and market problems. These risks differ across various industries, but there may also be some possibilities. Severe weather and other effects associated with global warming can demolish business structures and industrial plants, disrupt commercial operations, encourage consumers and plants, reduce consumer demand and purchasing power, deplete agricultural resources, etc. Policies for climate change adaptation and mitigation have also been implemented. AI presents enormous potential for corporate climate risk management initiatives and, as a disruptive invention, might encourage businesses to rethink their business models [36]. The three main areas—detecting and measuring climate change, improving adaptive and predictive capacities, and promoting fundamental research—illustrate how AI assists corporations in taking climate action [37, 38].

Examining the logical integration of four resource-based characteristics—GSCM and CCIS as dependent factors and TSCRM as independent variables influencing the AI-GSCM mediating variable—was the main goal of this study. Creating a wide measure of GSCM in terms of the five important dimensions was a secondary goal. To accomplish the main goal, this study proposes four hypotheses and examines them through the examination of data gathered from 280 workers in a range of manager's roles within Pakistan's manufacturing industry. We created a measure by examining the measuring model produced during the data analysis based on PSL-SEM.

Pakistan's industrial sector was deemed to have fared better in terms of corporate sustainability. In addition, the study, which included 280 Pakistani firms as participants, discovered that the adoption of

green practices improved companies' social, environmental, and economic sustainability. Efficient green supply chain management techniques also contribute to improving our knowledge and ability to adapt to climate change and its effects on supply chains. If a company is dedicated to the environmental aspect of sustainability, its reputation for corporate sustainability responsibility among customers is more likely to improve according to [65], who used empirical evidence to highlight the importance of green practices in the environmental performance of Chinese manufacturing companies. Ultimately, our research demonstrates that the effectiveness and efficiency of green supply chain management are enhanced by incorporating of artificial intelligence technology into conventional procedures. In summary, the findings of this study demonstrate that a greater integration of artificial intelligence into green supply chain management strategies is a direct result of the adoption and application of technological solutions aimed at mitigating climate risk.

Implications

Theoretical Implications

The need for sustainable production techniques is driven by the effects of manufacturing industries on the environment [66]. We present a new framework for Tec-CRM capabilities to deliver service innovation and performance related to climate change to address these concerns. We investigated the causes and effects of Tec-CRM capabilities, leading to two main theoretical advances. We begin by listing the elements that constitute Tec-CRM's capabilities. This is an important addition, as the aim of this study is to provide comprehensive theoretical knowledge of Tec-CRM capabilities. To improve our understanding of service innovation in the climate domain, three theoretical vantage points are specifically included: market orientation, environmental orientation, and dynamic capacity. Our empirical research demonstrates that the detrimental consequences of global warming are significantly mitigated by technology. Specifically, it highlights the positive effects of technological advancements on the application of artificial intelligence (AI) in green supply chain management (GSCM). Artificial intelligence (AI) in supply chain management (GSCM) has been shown to increase the efficacy of green practices and supply chain mitigation strategies in fighting climate change [67, 68]. However, to identify more sustainable innovations in this space, researchers must investigate a range of technological and market dynamics [69, 70].

Expanding on previous research, we determined that market, environmental, and artificial intelligence (AI) orientations are critical components of technology-enabled climate change mitigation (Tec-CRM) capacities. Through the characterization of these orientations, our research exposes the micro-foundations supporting each dimension, offering a comprehensive understanding of the ways in which these capacities facilitate efficient mitigation of climate change.

The intricacy and diversity of tackling creative solutions in the field of climate change are demonstrated by our research, which integrates three dimensions—AI, environmental, and market orientations—as well as their specific sub-dimensions. To improve supply chains' resilience and sustainability, a comprehensive strategy that integrates technological, environmental, and market-driven views is essential, as this holistic approach is clear.

Our results are consistent with earlier research, supporting the idea that attaining notable advancements in GSCM and Climate Change Supply Chain Management (CC-SCM) requires a multifaceted approach to Tec-CRM skills [71, 72]. In addition to advancing theoretical knowledge, this integration offers useful insights for companies seeking to use technological innovation to execute initiatives to mitigate climate change.

Practical Implications

According to the study's findings, managers in the manufacturing sector should place a high priority on the development of AI-driven skills, such as Tec-CRM, in order to maintain or even boost market

performance while reducing the negative environmental and climate effects of their operations. However, the results also showed that AI is not a stand-alone therapy. They contend that a significant investment in other complementary skills, most notably in the areas of environmental, AI, and market orientation, is necessary for it to reach its full potential. Firms have historically lean towards to concentrate exclusively on one of these orientations, but our findings indicate that they should develop all of the AIPCSI capability's micro- or sub-dimensions [67, 68].

Based on our findings, we propose that manufacturing companies have a great deal of room to grow in terms of their ability to harness AI, particularly Tec-CRM and AI-GCM, in ways that will significantly enhance their environmental performance. This is especially true when one considers the extent to which AI can help with risk assessment, forecasting, and management, which are directly related to climate change [73]. These hazards include those related to the company's reputation, and legal standing should it fail to take steps to slow global warming and move the economy away from fossil fuels. Numerous industry publications and media analysts have noted that these AI-informed tactics and the operational adjustments they bring about include supply chain and logistics optimization, decreased energy consumption and waste in production, and a transition to renewable energy sources. These, along with other possible advantages, such as design and quality control automation and AI use to assess customer preference data, lead to production and sustainability. It is clear that a number of top industrial businesses have already started using these AI-driven solutions because they view them as a critical tool for reducing the environmental effects of their operations and for fulfilling reporting and emission-related criteria.

Based on our findings, we propose that companies can lower reputational risk when they leverage Tec-CRM capabilities to create and carry out meaningful climate action. Furthermore, we propose that policymakers and the manufacturing sector will be crucial in defining ethical guidelines for AI's application of AI, particularly in areas where it affects data security, privacy, and bias management [74]. This is especially true if AI is widely implemented in the sector as we have described. These factors are especially crucial when key stakeholders' judgments and preferences (such as those of clients, investors, and prospective workers) are increasingly affected by a company's ability to exhibit truly moral and sustainable business practices [67, 68].

In assessing the costs and benefits of AI investments from an economic standpoint, it's important to consider the investment through a life cycle cost-benefit perspective and not take it for granted that the use of AI is automatically good for the environment. While AI-driven Green Supply Chain Management can help decrease material waste, enhance inventory management, optimize logistics, and cut down on operational costs, it can also raise the electricity footprint and Scope 2 emissions, especially in economies where electricity generation is fossil fuel-based. Complements should be made to maximise economic and environmental benefits, and managers should therefore consider complementary investments in renewable energy, energy-efficient computing infrastructure and low carbon electricity procurement.

Our results offer strong evidence that the industrial sector can benefit from investing in Tec-CRM and AI-GCM capabilities, as these investments enhance market and environmental performance, two crucial outcomes for any profit-driven business. AI can be viewed as a strategic investment because it supports and enhances a company's continuous efforts to increase its market performance through environmental performance (i.e., the moderating effect). Therefore, continuous improvements in AI capability through R&D, innovation, and collaboration are needed to satisfy the evolving demands and expectations of stakeholders, as well as new climatic issues. To put it briefly, businesses need to build the micro foundations of Tec-CRM and AI-GCM from the standpoint of dynamic capacities to continuously recognize, seize, and rearrange climate possibilities and threats in a way that allows them to stay competitive.

5. Conclusion, Limitation and Future Research

Green supply chain management (GSCM) has become a popular option for management researchers because of its dynamic characteristics. This study looked at GSCM and related components as a web or full system to understand the distinctive qualities of GSCM and how its technological dimensions, which are based on artificial intelligence (AI), affect GSCM strategy.

This study concluded a close gaps between evolving degrees of product complexity and the concepts of GSCM capability by offering a new method for organizing and managing green supply chain management initiatives. All of the research points to the importance of combining cutting-edge technologies, such as artificial intelligence (AI), with environmentally friendly supply chain methods to tackle the many different issues that climate change presents. In an increasingly complex and dynamic business environment, firms can cultivate sustainability, resilience, and competitive advantage by embracing innovation and implementing a holistic approach to green supply chain management.

Notwithstanding the insightful information offered by this study, there are a few points to keep in mind. First, the data are cross-sectional, meaning they only represent a moment in time and do not include long-term repercussions and trends. Furthermore, the research depends on self-reported information, which could be influenced by biases including social desirability or incomplete reporting. Furthermore, owing to the intricacy of AI technologies and their swift development, our conclusions may not hold up to the latest developments.

To improve the generalizability of the results, future studies should attempt to address these constraints by investigating the application of Tec-CRM and AI in GSCM across various sectors. Longitudinal studies would be helpful to fully capture the dynamic nature of AI integration and its long-term effects on economic and environmental performance.

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