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AI Chatbot Adoption in SMEs for Sustainable Manufacturing Supply Chain Performance: A Mediational Research in an Emerging Country

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Abstract: AI chatbots (AICs) have the potential to increase the sustainability of a manufacturing supply chain (SC) through sales engagement and customer engagement to accomplish various activities related to logistics and SC in real time. Industry 4.0 (I4.0) has opened up several opportunities with internet-based technologies, along with challenges for small and medium enterprises (SMEs). SMEs are beginning to adopt such technologies for their competitive advantages and the required sustainability in the manufacturing supply chain. AICs may help in accomplishing supply chain visibility (SCV) to enhance sustainable supply chain performance (SSCP). Innovation capability (IC) is also due to disruptive technologies being adopted by SMEs. The present research investigates the role of AICs in SCV and IC, which lead to SSCP, by employing structural equation modeling (SEM). An empirical study based on dynamic capability (DC) theory was carried out using 246 responses, and later Smart PLS-4.0 was used for SEM. The analysis revealed that AICs positively influence SCV and IC to support SSCP. SCV and IC also partially mediate the relationship between the adoption of AICs and SSCP.

Keywords: artificial intelligence chatbot; emerging country; innovative capability; small and medium enterprises; supply chain visibility; sustainable supply chain performances; manufacturing sustainability

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1. Introduction

Sustainability in a supply chain (SC) is essential as it helps to reduce production costs while keeping environmental impact to a minimum, thus tending to boost economic growth and offer more opportunities in local and global markets [1]. The sustainable supply chain process (SSCP) deals with excelling in the SC activities of materials management, manufacturing activities, and distribution activities related to raw materials, parts, or products, leading to effective distribution management while keeping a check on economic, environmental, and social causes [2]. Emerging countries struggle with their economic development and need more growth and stability in emerging markets. Small and medium enterprises (SMEs) and large enterprises (LEs) contribute to maintaining the country's sustainable development [3]. Sustainable development helps countries maintain their resources without compromising the needs of future generations.

As SMEs and LEs face the challenges of Industry 4.0 (I4.0), internet-enabled technologies like the Internet of Things (IoT), Industrial Internet of Things (IIoT), cloud computing (CC), robotics and automation, cyber-physical systems (CPS), blockchain, and artificial intelligence (AI) are changing manufacturing activities. Apart from such disruptive technologies, artificial intelligence chatbots (AICs) have emerged in the era of I4.0. AICs can help SMEs and LEs provide effective and productive human interaction to manage their online customers. Notable AI applications, like ChatGPT from OpenAI, Amazon's Alexa, Salesforce's Einstein, Oracle's Crosswise, IBM's Interact, and Microsoft's Genie, possess varying degrees of learning capacity, connectivity, and adaptability. AICs' evolution took place rapidly, as shown in Figure 1. The basic chatbot initially offered a limited number of frequently asked questions (FAQs), and it came with application programming interfaces (APIs). The next was an intermediate chatbot with self-service automation and external system integration. The advanced chatbot based on natural language processing (NLP) evolved to understand user intent and have a wider scope, like transaction capabilities, machine learning (ML), and conversational AI capabilities.

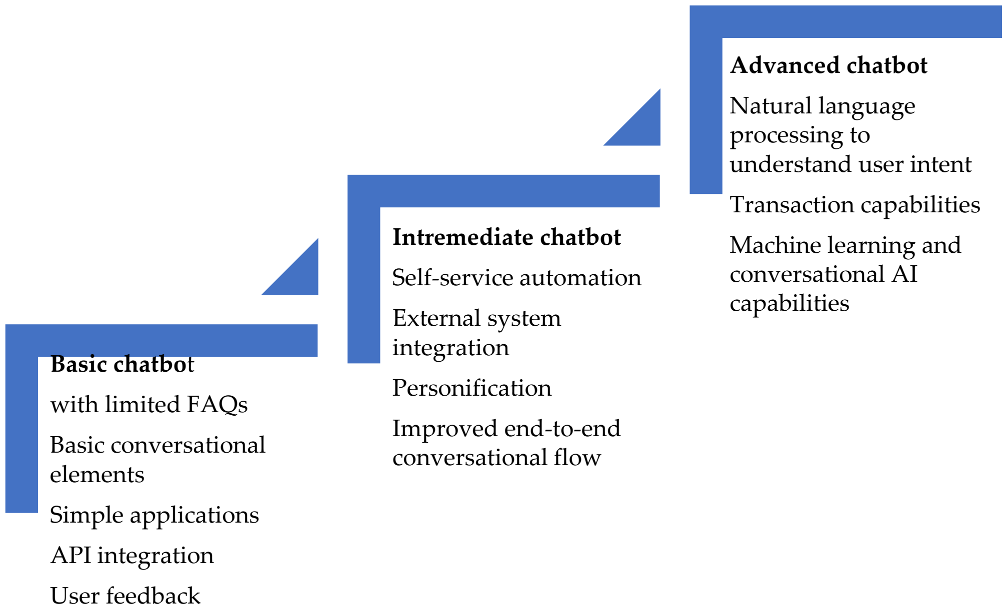

Figure 1. Rapid evolution of chatbot [4].

SC collaboration using AICs in local and global markets has become inevitable for entrepreneurs in order to create resilient SCs. These days, more and more complexity in logistics and SC operations is seen due to the large operational volume. AICs can be a major asset in logistics and SCM since they play a major role in the customer experience. The company can enhance its conversion rate optimization using AICs. A quick response may make logistics easier to acquire. It improves sales engagement and supplier engagement for better SC performance. AICs can help in automatically placing orders for raw materials, in arranging the logistics, and in sales once manufacture is complete. AICs can link various activities in a complex supply chain. AICs can help in the warehousing activities by navigating the product or raw material locations. AICs also help with resource deployment and recovery in a SC. AICs' active and proactive actions help in providing effective solutions to an SC. AICs can help manage inventory by managing stock-keeping units (SKUs).

Dynamic capabilities (DC) theory helps firms integrate, build, and reconfigure their internal and external resources and competencies to address new challenges and reshape them rapidly to meet the changing business environments [5]. Further, looking at the role of AICs in managing real-time customer response and related logistics activities and SC operations, organizations may use AICs to cope with the new challenges of I4.0. The role of AIC usage in such challenges is an interesting avenue for further investigation. Thus, to ensure the long-term deployment of AICs, further empirical studies on the views and attitudes of customers towards AICs in this context must be performed [6].

This investigation addresses the subsequent research questions:

RQ1: What is the impact of adopting AICs on sustainable supply chain performance?
RQ2: How does the DC theory unify AICs, SCV, and IC to achieve SSCP in SMEs?

Empirical validity was ensured in the present investigation using structural equation modeling (SEM). The present study uses PLS-SEM to uncover the underlying relationships and patterns in the formulation of new hypotheses and theoretical frameworks. The present study investigates the role of AICs in SCV and IC. It also investigates the mediating role of SCV and IC on SSCP, thus providing a significant contribution and implications for policymakers and SME entrepreneurs.

The remainder of the article is organized as follows: After the introduction, the literature review is presented in Section 2. The theoretical framework and hypotheses are developed in Section 3. The research methodology is provided in Section 4. The results of the present research are provided in Section 5. The discussion is provided in Section 6, which is followed by managerial implications in Section 7, and the paper concludes with a conclusion, limitations, and future research direction in Section 8.

2. Literature Review

In recent years, the usage of chatbots in several industries—including marketing, supporting systems, education, healthcare, cultural heritage, and entertainment—has advanced quickly. A study has proved that immersive virtual reality technology helps in engineering interactions using a question-and-answer chatbot with realistic graphical views to excel over 91% [7]. AICs help to create a customer experience and opportunities for a firm to interact with customers. It has been shown that AICs' usability has extrinsic values for customer experience and further boosts customer satisfaction [8]. There are several types of AICs; a detailed classification is presented in Table 1.

Table 1. AICs' classification [9].

Main Classification	Types
Knowledge domain	Generic
	Open domain
	Close domain
Service provided	Interpersonal
	Intrapersonal
	Inter-agent
Goals	Informative
	Chat based/Conversational
	Task based
Response generation method	Rule based
	Retrieval based
	Generative
Human aid	Human mediated
	Autonomous
Permissions	open source
	commercial
Communication channels	Text
	Voice
	Image

AICs help in solving the query of SC issues by answering accurately but find difficulty in providing operational breakthroughs in the operations. Thus, AICs exhibit both pros and cons [10]. AICs are a powerful tool supporting various SC activities like data analysis, interfacing with SC stakeholders, inventory management, predictive maintenance on equipment, route optimization, providing sustainability reports, identifying the best suppliers, mapping with SC having less risk, etc. [11]. AICs may become a game changer in the future in the areas of supply network planning, sourcing, making, delivering, and returning activities in forward and reverse SC [12]. AICs helps in enhancing customer satisfaction, process efficiency, and cost reduction in an SC because they can streamline communication with customers (having accurate information in real time) and suppliers (solving supply chain issues using effective communication in real time) [13]. Effective AICs can support faster customer service and route optimization by analyzing order and shipping data and making subsequent cost-reduction suggestions for better delivery performance. They can also support activities like order processing, and invoicing, reducing errors in communication, reducing waste, and reducing delays in logistics activities [14].

AICs can be a useful SC tool, helping in process automation, providing insight into SCM, and supporting communication throughout the SC partners [15]. AICs offer increased visibility, communications streamlining, and operation optimization for their stakeholders. They can integrate with the IoT to generate data and derive key performance indicators (KPIs). There are several KPIs to evaluate and measure the effectiveness of AICs, for instance, chatbot activity volume, bounce, interaction, retention, non-response, self-service rate, etc. They can integrate with the IoT to generate data and derive KPIs. There are several KPIs to evaluate and measure the effectiveness of AICs, for instance, chatbot activity volume, bounce, interaction, retention, non-response, self-service rate, etc. AICs can also help in demand forecasting, inventory management, supplier relationships, supply chain visibility (SCV), and transparency [16]. AICs help in route optimization by analyzing data for speeding deliveries and help in warehouse management through the visibility of real-time inventory and optimization of storage space [17].

Looking at the role played by I4.0-based disruptive technologies, SMEs are also compelled to imbibe them in their day-to-day production activities. SMEs will undergo major changes in their functioning by introducing AICs. According to a comprehensive review of the literature, there have been no attempts to study AICs' implementation in SMEs from the standpoint of DC theory. The current research adds value to the existing literature by using the theoretical framework to determine the factors influencing the adoption of AICs in SMEs.

3. Theoretical Foundations and Hypothesis Development

Sustainable supply chain management (SSCM) is a multi-faceted discipline that draws upon various theories and frameworks to address environmental, social, and economic challenges while ensuring long-term viability.

Several theories, like the triple bottom line (TBL) approach, stakeholder theory, institutional theory, etc., are found in the body of literature that may be employed to investigate the direct or indirect adoption of new technology. However, rational choice models were frequently chastised for being too rigid in their predictions of technology adoption, rather than user and business centric. Therefore, the present study used DC theory because it emphasizes an organization's ability to recognize the potential benefits of new technologies like AICs and integrate them into their supply chain processes to bring real value [11]. By adopting AICs, organizations can enhance SCV [18], streamline operations, and respond more effectively to market demands [19]. DC theory also highlights the importance of building resilience to cope with disruptions and uncertainties. By adopting AI technologies, organizations can better predict and manage supply chain risks, leading to increased resilience and sustainability [19].

3.1. Adoption of AICs and SSCP

Inefficiencies and low-quality data often seriously hinder an organization's business operations. The DC theory posits that organizations must continuously develop and refine their capabilities to effectively respond to dynamic markets and uncertainties. When it comes to AICs, organizations that embrace and integrate AI technologies into their business processes demonstrate the ability to enhance their analytical and decision-making capacities [20]. One prominent example of such AI-powered technology is the chatbot, which facilitates non-face-to-face interactions between users and artificial intelligence through text and voice communication. Utilizing conversational interactions based on customer queries and chatbot responses, chatbot services have evolved to be perceived by customers as communication objects rather than simple machines [21]. For SMEs, AICs serve as valuable sustainability tools, assisting in evaluating a firm's performance concerning sustainability objectives by efficiently processing relevant data. By segmenting details by department, these AICs offer a comprehensive analysis of a company's progress towards its sustainability goals [22]. Thus, firms may maximize revenues while limiting resource usage, improving efficiency, and increasing sustainability through AI-driven decision making. AI-based technology can also provide automated customer service, the fastest production process paths, and manufacturing technique advice. This innovative technology alerts personnel to production line abnormalities. Its application in SME manufacturing will reduce cost and time, improve the client experience, and attract new clients. Based on the above, the following hypothesis is proposed:

H1. *Adoption of AICs has a positive effect on SSCP.*

3.2. Adoption of AICs and SCV

By incorporating an AIC, businesses can improve their customer interactions, streamline communication, and respond quickly to customer queries, enabling them to dynamically adjust their customer service approach [23]. AICs' learning and intelligence capabilities empower organizations to stay agile and proactively address evolving customer needs and preferences. Simultaneously, implementing SCV through advanced technologies allows organizations to monitor and analyze supply chain operations in real time. This fosters better decision making, risk mitigation, and the ability to seize opportunities, leading to enhanced supply chain responsiveness and efficiency [24]. With improved visibility, companies can identify potential bottlenecks, optimize processes, and adapt to changing market demands, thus reinforcing their dynamic capabilities to navigate uncertainties and achieve sustainable competitive advantages effectively [25]. AICs can analyze data and appraise a company's performance and efficiency. It will increase the visibility of the SC. The firm's or SME's SC can be included using contemporary technology. Supply chain processes such as shipment monitoring, inventory management, and customer and stakeholder updates are all automated using AICs. AI-based technologies' transparency allows for the development of insights into a phenomenon's possible long-term effects on the entire SC [26]. Based on these arguments, the following hypothesis was proposed:

H2. *Adoption of AICs has a significant impact on SCV.*

3.3. Adoption of AICs and IC

Based on the arguments proposed by the authors, AICs offer a novel and efficient way to interact with customers, partners, and employees, facilitating seamless communication and information exchange. AI-powered service innovations, leveraging big data, cloud platforms, and robust processing capabilities, are revolutionizing various industries, including banking, insurance, marketing, healthcare, education, travel, entertainment, and more. AI-powered service innovation is expected to redefine the service innovation process, service ecosystems, adoption, and diffusion, as well as organizational resources and capabilities. Its transformative potential is bound to reshape industries and unleash new possibilities for growth and advancement. The adoption of AICs can significantly enhance IC within organizations. The adoption of AI-powered industrial robots (InRos) not only improves manufacturing efficiency and productivity but also fosters a culture of innovation. As manufacturers witness the positive impact of InRos on their processes, they are encouraged to explore further technological advancements and invest in more sophisticated AI solutions, propelling continuous process innovations and strengthening their competitive position in the market [27]. AICs in various workflows can optimize and automate processes, leading to increased efficiency and resource utilization. This freed-up capacity can be redirected towards innovation initiatives and exploring new opportunities. The proposed hypothesis is:

H3. *The adoption of AICs influences the IC of SC.*

3.4. IC and SCV Influence on SSCP

The ability to innovate within the supply chain, driven by advanced technologies, process improvements, and collaboration, enables companies to develop more sustainable practices, reduce waste, and enhance resource efficiency. Additionally, SCV, achieved through real-time data monitoring and analytics, empowers organizations to identify potential risks and opportunities, optimize logistics, and make informed decisions that positively impact sustainability goals. Together, supply chain innovation capabilities and visibility contribute to a more resilient and environmentally responsible supply chain, ultimately enhancing overall SSCP [19]. AI-powered service innovation is projected to change service ecosystems, adoption, diffusion, organizational resources, and capabilities. It will revolutionize industries and open new development and advancement opportunities. AI-powered industrial robots boost manufacturing efficiency and productivity and encourage innovation.

As manufacturers see the positive effects of InRos on their processes, they are inspired to explore new technologies and invest in more advanced AI solutions, driving ongoing process innovation and increasing their market position [27]. External SCV plays a crucial role in enhancing overall business execution, particularly when it comes to identifying supply chain partners and gathering essential data [28]. Companies can ensure effective SCV by sharing information among the participants in the supply chain. This enables the companies to be aware of events and patterns and take precise steps to maintain or attract customers, strengthen channel relationships, and compete with other businesses [29,30]. Lack of visibility can lead to inventory buffering as a risk mitigation strategy among different supply chain members [31]. As SCV becomes increasingly important for productivity and effectiveness, businesses are investing in enhancing this capability in SMEs [32]. Effective supply chain management helps ensure seamless processes and minimizes disruptions while also promoting sustainable growth [33]. It is possible to gain a comprehensive perspective on operations through the exchange of data across departments and organizations. This helps ensure that customers continue to receive high-quality products and services, especially in highly competitive marketplaces. The adoption of AIC technology positively impacts organizational performance by optimizing business processes using smart contracts, reducing operational costs, enhancing security, and improving collaboration efficiency [4]. Moreover, the trust and transparency brought by AI contribute to improved supply chain management practices and sustainable performance. Information sharing is required for managerial operations, supported by the instrumental function of SCV in SCM. It has been seen that SCV has a significant impact on performance. In the current study, the authors intend to assess the mediational effect of SCV among AICs and SSCP. Based on the preceding discussion, the following hypotheses have been proposed:

H4. *SCV has a significant effect on SSCP.*

H5. *IC has a significant effect on SSCP.*

3.5. Mediational Effect of SCV and IC among AICs and SSCP

AI-based technology plays a pivotal role in enhancing SCV [19] by facilitating real-time data sharing, improved communication, and streamlined information flow among supply chain partners. This improved visibility allows organizations to make data-driven decisions, identify potential risks, and respond swiftly to disruptions, thereby enhancing the overall efficiency and resilience of the supply chain [23]. As per the arguments of Deng and Noorliza [34], in today's competitive and sustainable business landscape, organizations recognize the importance of resilience and IC. To address this, this research paper aims to explore the relationship between external integration, resilience, innovation capability, and the operational performance of logistics service providers. The visibility that AICs provide allows companies to strengthen their relationships with essential stakeholders through full transparency [15].

AI algorithms and systems enable the processing and analysis of vast amounts of data, facilitating real-time insights and informed decision making. This ability to process data efficiently represents the equivalent of blocks in a blockchain network. By harnessing AI's capabilities [35], companies can maintain a decentralized database and effectively structure their data, enabling seamless access to information. Moreover, AI systems can be integrated with other technologies, creating a smart contract-like mechanism that ensures stakeholders across the supply chain network are simultaneously updated whenever new information becomes available.

Innovation plays a crucial role in mediating the relationship between supply chain management practices and performance. It has been seen that organizational green culture positively influences green performance and competitive advantage, with green innovation serving as a significant mediator in this relationship. The findings indicate that when companies foster a culture of green innovation, it completely mediates the link between their green culture and green performance. Additionally, green innovation also has a partial mediating effect on the link between green culture and competitive advantage. Another study, in line with earlier findings, explains that sustainable innovation acts as a mediator between dynamic data analytics and sustainable supply chain performance, indicating that the ability to continuously innovate sustainable practices enhances overall SC performance [19]. In today's dynamic business environment, organizations must prioritize IC and include senior management to innovate and stay competitive. Companies seeking long-term success in the face of market difficulties and uncertainty must emphasize innovation and SCV through technology. The present study proposes hypotheses of parallel mediation effects:

H6. *Mediational effect of SCV among AICs and SSCP.*

H7. *Mediational effect of IC among AICs and SSCP.*

Conceptual Framework

According to the DC theory, a company can combine, develop, and reconfigure its internal and external resources and competencies to deal with the rapidly evolving business environment. Thus, the DC theory may be used to assess the role of AICs, SCV, and IC on the SSCP. The influence of AICs' role in manufacturing SSCP enhancement may be empirically measured and verified by measuring its direct influence. Thus, AICs may have a direct influence on SCV, IC, and SSCP. It has been well established that SCV and IC influence SSCP; hence, it can be empirically verified that SCV and IC influence the manufacturing SSCP. Thus, AIC and DC theory-based hypotheses may be formulated, as displayed in Figure 2. Thus, this study presents the conceptual framework to investigate the relationship between AIC adoption and sustainable firm performance, along with the mediating effects of SCV and IC. The framework proposes that AIC adoption directly influences sustainable firm performance, and this relationship is further influenced by the mediating factors of SCV and IC.

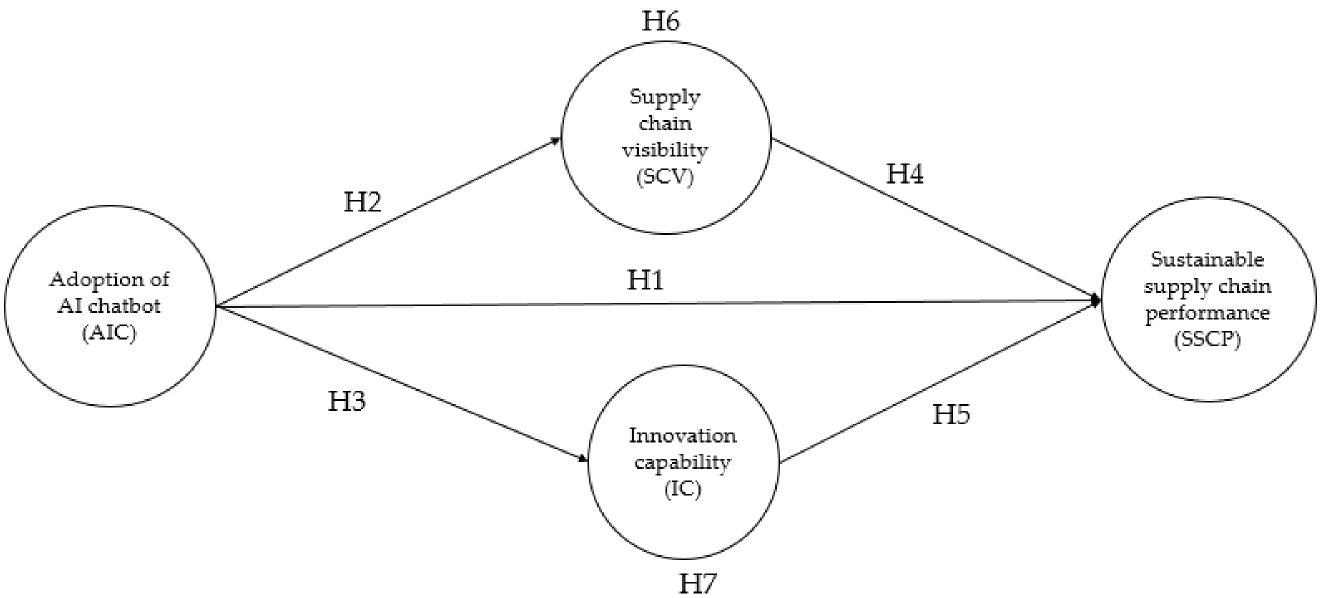

Figure 2. Conceptual model.

4. Research Methodology

4.1. Measurement Scale

This study uses measurement scales from previous studies that looked at AI-based technology and supply chain performance in small- and medium-sized enterprises (SMEs) from the point of view of an emerging country to find what effect AI technology has on supply chain performance in terms of sustainability. These studies have examined the relationship between AI-based technology and SSCP in Indian SMEs. The adoption of AICs as independent variables (using a reflective measurement scale) was referred to in [36–38], whereas SSCP as dependent variables (using a reflective measurement scale) is from the literature of [39–41]. SCV as the first mediation (reflective measurement scale) is referred to in [40,42] and IC as the second mediator (reflective measurement) is referred to in [18,43]. All the measurement items are listed in Table 2.

Table 2. Measurement items.

Latent Variables	Items	Sources
Supply chain visibility (SCV)	SCV1: Our firm provides information that is useful to stakeholders for making informed decisions.	[40,42]
	SCV2: Our firm is willing to share just about any information stakeholders request from it.	
	SCV3: Our firm wants to understand how its decisions affect stakeholders.	
	SCV4: Our firm considers stakeholder feedback when attempting sustainable supply chain improvement.	
	SCV5: Our firm takes time with stakeholders to understand their needs.	
	SCV6: Our firm wants to be accountable to suppliers for its actions.	
	SCV7: Our firm asks for feedback from stakeholders about the quality of its information.	
Adoption of AI chatbot (AAIC)	AAIC1: The firm will find ways to embrace AIC technology in the future.	[36–38]
	AAIC2: The firm expects to receive this latest technology in the future.	
	AAIC3: We do not intend to adopt any AI services soon.	
	AAIC4: We are already using some AI-based applications in our firm.	

Table 2. *Cont.*

Latent Variables	Items	Sources
Sustainable supply chain performance (SSCP)	SSCP1: AIC adoption is affordable.	[39–41]
	SSCP2: Potential savings on energy and materials.	
	SSCP3: Adopting cutting-edge technology, such as an AIC, will help reduce operating costs.	
	SSCP4: The use of an AIC improves security and efficiency.	
	SSCP5: Cost savings with respect to climate change.	
	SSCP6: Adoption of AICs can improve social and economic viability.	
Innovations capabilities (IC)	IC1: Our company's cross-functional teams that deal with supply chain operations are designed to foster a culture of constant innovation.	[18,43]
	IC2: Firms uncover reliable suppliers using innovative supplier selection/evaluation processes.	
	IC3: Adapting to customer demand with remarkable flexibility is a core strength of our firm.	
	IC4: The seamless integration of our IT/IS with supply chain management is geared towards fostering innovation.	
	IC5: The company's efforts in adopting eco-friendly and sustainable practices in its supply chain, considering factors such as waste management, and responsible sourcing.	
	IC6: The company promotes a culture of learning and knowledge-sharing within the supply chain.	

The questionnaire was designed with two distinct sections. The first part focused on gathering respondents' demographic characteristics, including age, gender, education level, work experience, and organizational position. The second part of the questionnaire aimed to assess respondents' perceptions and opinions regarding the research constructs using a five-point Likert scale. The Likert scale provided a range of response options, allowing respondents to indicate their level of agreement or disagreement with statements related to the research constructs.

4.2. Sampling and Data Collections

This study focused on participants holding managerial positions in manufacturing organizations in India's SMEs. The primary data was collected through a structured questionnaire using a convenience sampling approach. Convenience sampling is a type of non-probability sampling technique used to assess population characteristics.

The sample size for this study was determined using G*power version 3.1.9.7, a software tool commonly used to determine the required sample size in social science research and management studies [44]. For calculations of sample size, various parameters are being used as standards of measurement, as referred to and suggested effect [44], i.e., the effect size is 0.05 and α is 0.05, indicating a 5% chance of committing a Type I error and a power level of 0.95 (1–β) was chosen for correctly rejecting a false null hypothesis. Researchers typically aim for a high level of power, often set at 0.80 or 0.95, which corresponds to an 80% or 95% probability of correctly detecting an effect [44], respectively. Based on this power level, the minimum required sample size was calculated to be 213 respondents.

However, the researchers decided to use a larger sample size of 246 respondents for the present study. This larger sample size is deemed appropriate and satisfactory, as it can provide more robust and reliable results. To ensure adequate statistical power in the analysis, it was advised to use a sample size of 213 or more for the study. To achieve the minimum sample size, 348 questionnaires were distributed to various Indian SMEs under manufacturing units. The SMEs were approached and asked to complete an online questionnaire. Out of the 348 questionnaires given, 179 were deemed usable, resulting in a response rate of 51.5%. The respondents were followed up, which increased the response rate from 51.5% to 78.22%, with a total collected response of 271 out of which 246 valid responses were extracted for analysis. It was filtered based on completeness and unbiased response. Data collection occurred between November and February of 2023. By collecting data during this period, the researchers ensured that the information obtained was up to date and relevant to their study.

4.3. Sample Characteristics

The respondents' demographic variables encompassed gender, age, years of experience, education level, position, and the number of employees. The data reveals that male respondents constituted a higher proportion (74%—182 responses) compared to female respondents (26%—64 responses). Most participants fell within the age group of 30 to 40 years old, representing (48.5%—119 responses) of the sample. Respondents with 5 to 10 years of experience accounted for the largest portion at 41.65% (102 responses). Additionally, a significant percentage of 76.0% was from an undergraduate degree, amounting to 187 responses. Among the respondents, 69.5% were first-line managers, giving 171 responses. Finally, organizations with employee counts ranging from 20 to 85 constituted 49.2% of the participants, making 121 responses.

5. Results

In this section, the analysis focused on the data obtained from the survey, which involved 246 respondents. The collected data were analyzed primarily using the multi-collinearity test in SPSS version 24. The Smart PLS v 4.0 was utilized to conduct SEM, which involved evaluating both the measurement model and the structural model to assess the proposed hypotheses and their relationships within the data. The process of verifying the statistics of descriptive analysis and multicollinearity was carried out following the earlier literature [18].

5.1. Measurement Model

The measurement model is a statistical model used to assess the quality of measurement instruments or scales in a research study. It involves measuring different constructs or variables using multiple items or indicators. The primary purpose of the measurement model is to ensure that the items effectively capture the underlying concepts they are intended to measure. This is achieved by evaluating various criteria such as factor loadings, internal consistency (Cronbach's alpha), composite reliability (CR), average variance extracted (AVE), and discriminant validity [45]. A well-constructed measurement model ensures the reliability and validity of the data collected and provides a solid foundation for subsequent statistical analyses in the research study.

The table presents the quality assessment parameters for the measurement model, which consists of four constructs: adoption of AICs, SCV, IC, and SSCP. Each construct is measured using multiple items, and the quality of the measurement model is evaluated based on several criteria. The first criterion is factor loading, which measures the strength of the relationship between each item and its corresponding construct. All items have relatively high factor loadings, ranging from 0.663 to 0.911, indicating that they are well-aligned with their respective constructs. The second criterion is Cronbach's alpha which assesses the internal consistency or reliability of the items within each construct. The values for Cronbach's alpha are above the recommended threshold of 0.7 for all constructs, indicating good internal consistency. AICs have the highest alpha value (0.902), followed by SCV (0.893), IC (0.855), and SSCP (0.791). The third criterion is composite reliability (CR), which is another measure of the internal consistency of the construct, and all constructs exhibit high CR values above 070, suggesting good reliability. The fourth criterion is rho A, which measures the construct's composite reliability, which is like CR. All constructs have high rho A values, ranging from 0.815 to 0.903, which are above the threshold limit of 0.70. The fifth criterion is average variance extracted (AVE), which represents the amount of variance captured by the construct's items. AVE values range from 0.548 to 0.774, with AICs having the highest value and SSCP having the lowest. All constructs meet the recommended threshold of 0.5 for AVE [46], indicating that the constructs explain a substantial portion of the variance in their items are depicted in Table 3.

Table 3. Quality assessment parameters.

Constructs	Items	Factor Loading	Cronbach's Alpha	Composite Reliability (CR)	rho A	Average Variance Extracted (AVE)
Adoption of AI Chatbot (AIC)	AIC1	0.858	0.902	0.932	0.903	0.774
	AIC2	0.911				
	AIC3	0.891				
	AIC4	0.857				
Supply chain visibility (SCV)	SCV1	0.808	0.893	0.921	0.897	0.701
	SCV2	0.858				
	SCV3	0.795				
	SCV4	0.897				
	SCV5	0.823				
Innovation capabilities (IC)	IC1	0.876	0.855	0.896	0.889	0.635
	IC2	0.860				
	IC3	0.663				
	IC4	0.798				
	IC5	0.770				
Sustainable Supply chain Performances (SSCP)	SSCP1	0.840	0.791	0.857	0.815	0.548
	SSCP2	0.780				
	SSCP3	0.776				
	SSCP4	0.691				
	SSCP5	0.589				

In the information presented in Table 3, the focus is on assessing discriminant validity using two criteria: the heterotrait-monotrait ratio (HTMT) and the Fornell–Larcker criterion.

HTMT ratio: HTMT is a measure of the ratio of the correlations between constructs (heterotrait correlations) and the correlations of each construct with itself (monotrait correlations). The HTMT values indicate whether the constructions are sufficiently distinct. Since a construct's correlation with itself should always be below the threshold, the diagonal elements of the HTMT matrix are all 0.85 [47]. The off-diagonal elements show the HTMT ratios between the constructs. The HTMT ratio between AICs and IC is 0.548, between SCV and IC is 0.464, and between SCV and AICs is 0.826, all within the threshold limit of 0.85 [48,49]. In HTMT, scores below 0.85 indicate adequate discriminant validity. All HTMT ratios in Table 3 meet this criterion, indicating discriminant validity.

Fornell–Larcker criterion: The Fornell–Larcker criterion compares the square root of the AVE values to construct correlations to assess discriminant validity. The correlation values show the shared variation between constructs, whereas the square root of AVE shows the highest shared variance. Fornell–Larcker matrix diagonal elements are built AVE values (the square root of the AVE values from Table 4). The Fornell–Larcker criterion suggests that for discriminant validity, the AVE values should be greater than the correlations between constructs [50]. All the AVE values are greater than the corresponding correlation values, supporting the presence of discriminant validity among the constructs.

Table 4. Discriminant validity HTMT and Fornell–Larcker criterion.

		HTMT—Matrix		
	AIC	**IC**	**SCV**	**SSCP**
AIC				
IC	0.548			
SCV	0.826	0.464		
SSCP	0.520	0.414	0.526	
		Fornell–Larcker criterion		
	AIC	IC	SCV	SSCP
AIC	0.880			
IC	0.499	0.797		
SCV	0.745	0.406	0.837	
SSCP	0.445	0.351	0.447	0.740

PLS-SEM uses fit indices to evaluate model fit. The standardized root-mean-square residual (SRMR), d ULS, and d G are examples. These indications are 0.079, 1.187, and 0.826, which are below the SRMR criterion of 0.08; lesser values imply a better fit for both d ULS and d G, indicating the measurement model meets the model fit criteria [51].

5.2. Structural Model

The structural model serves as the basis for assessing the relationships between the independent variables (predictors or antecedents), i.e., AIC, SCV, IC, and the dependent variables (outcomes), i.e., SSCP. It allows researchers to understand how changes in AICs, IC and SCV with SSCP affect the structural relationship. This study estimates path coefficient significance and model fit using PLS-SEM and bootstrapping (5000 samples), as recommended by the literature [18]. Structural models help to examine the direct and indirect effects between the constructs, allowing researchers to test their proposed hypotheses and theoretical frameworks (refer to Figure 3).

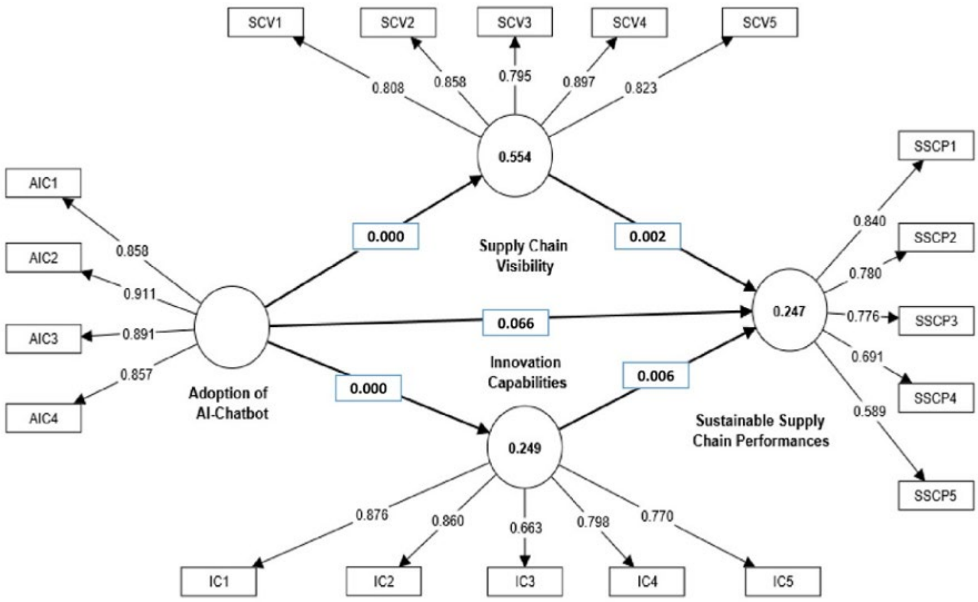

Figure 3. Structural model. Legends: artificial intelligence chatbot (AIC), supply chain visibility (SCV), innovative capability (IC), and sustainable supply chain performance (SSCP).

IC and SCV mediating effects among AICs and SSCP were tested using the bootstrap (5000 samplings) method by using PLS-SEM as suggested by [52,53], and their mediating role was assessed. The bootstrap number was set at 5000, and the level of confidence was set at 95%. In the PLS-SEM modelling strategy, the variance accounted for (VAF) indicators have been used to probe the mediation analysis by calculating the relative weight of direct and indirect effects [51]. The mediator's power is founded on the VAF. If the value of VAF is greater than 0.8 it implies that impact will be full mediation, whereas if the VAF value is between 0.2 and 0.8 it shows partial mediation. IC as a mediator value of t-statistics and p-value will be (AIC → IC → SSCP) with 95% t-statistics → 2.479, $p < 0.05$) with VAF value 0.307 and SCV as a mediator value of t-statistics → 3.035 and $p < 0.05$ will be (AIC → SCV → SSCP), with 95% confidence level with VAF value 0.502. The study identified that both mediator ID and KIM show a partial mediation effect [54], which is shown in Table 5.

Table 5. Mediational Analysis.

Constructs Relationship	Direct Effect (a)	Indirect Effect (b)	Total Effect (a + b)	t-Statistics	VAF [b/(a + b)]	Decision on Mediation Effect
AIC → IC → SSCP	0.182	0.081	0.263	2.479	0.307	Partial mediation effect
AIC → SCV → SSCP	0.182	0.184	0.366	3.035	0.502	Partial mediation effect

The results of the path analysis for the seven hypotheses as presented in Table 6 help to assess the validity of the hypotheses and explore complex relationships between AICs, SCV, and IC with SSCP. H1 predicts a positive direct link between (AIC → SSCP), with a beta coefficient of 0.182 (showing a moderate effect size), t-statistic 1.839, and a p-value of 0.066, suggesting that the relationship is not statistically significant at the 0.05 level. H2 shows a strong positive direct link between (AIC → SCV) and a beta coefficient of 0.745 (indicating a substantial effect size). The t-statistic is 25.512 and the p-value is 0.000, showing a highly powerful connection. The (AIC → IC) relationship of H3, shows a beta coefficient of 0.499 (indicates a moderate effect size), the t-statistic is 8.501, and the p-value is 0.000, indicating a significant association. In H4, the association between (SCV → SSCP) shows a beta coefficient of 0.247 (indicates a moderate effect size), the t-statistic is 3.068, and the p-value is 0.002, indicating a statistically significant association. (IC → SSCP), H5 shows a positive direct relationship between IC and SSCP. The beta coefficient is 0.160 (indicating a moderate effect size), the t-statistic is −2.743, and the p-value is −0.006, indicating that the relationship is statistically significant.

Table 6. Hypothesis and path analysis.

Hypothesis	Direct Relationship	Beta Coefficient [Original Sample (O)]	Standard Deviation (STDEV)	t-Statistics (|O/STDEV|)	p Values
H1	AIC → SSCP	0.182	0.099	1.839	0.066
H2	AIC → SCV	0.745	0.029	25.512	0.000
H3	AIC → IC	0.499	0.059	8.501	0.000
H4	SCV → SSCP	0.247	0.080	3.068	0.002
H5	IC → SSCP	0.160	0.058	2.743	0.006
		Mediational Relationship			
H6	AIC → IC → SSCP	0.080	0.032	2.479	0.013
H7	AIC → SCV → SSCP	0.184	0.060	3.035	0.002

Hypothesis H6 (AIC → IC → SSCP), suggests that the first mediational relationship between variables is positive, with a beta coefficient for the indirect effect of 0.080, a t-statistic of −2.479, and a *p*-value of −0.013, which indicates that the mediational relationship is also statistically significant. The second mediational relationship of (AIC → SCV → SSCP) indicates a positive mediational link between adoption of AICs, SCV, and SSCP with a beta coefficient of 0.184, a t-statistic of 3.035, and a *p*-value of 0.002.

6. Discussion

I4.0-based disruptive technologies have provided a paradigm shift in the manufacturing world. SMEs and LEs have experienced unprecedented changes in their logistics and SC-related activities. The I4.0-based disruptive technologies have helped both SMEs and LEs to have more SCV and IC in their logistics and SC-related activities. The SCV has helped the stakeholders to optimize SC efficiency and enhance SSCP. Like other internet-enabled technologies, AICs are also gaining a comfortable place in the manufacturing of SC, SMEs, and LEs. To enhance customer experiences, many SMEs are spending money on digital services. Supply chain professionals and logistics managers may use the output of AICs for their strategy making. They can evaluate the effectiveness of AICs through quantitative KPIs.

AICs assist customers, automate tasks, reduce costs, and control personnel and part inventories for efficient management. AICs can manage warehouse automation to streamline warehousing activities to help customers pick the parts in real time without wasting time on foiled attempts at locating the part. AIC usage in logistics and SCM is on the rise as it helps in managing logistics activities and various SC operations. AICs help society by delivering optimized solutions and effective information without any delay. The knowledge and information available through AICs help in quick decision making.

The present research has established that the adoption of AICs not only enhances SCV but also helps in attaining IC. SCV and IV help in achieving SSSP. The mediating effect of SCV and IC has also been investigated, and it has been revealed that there is an influence of SCV and IC on SSCP. Manufacturing SMEs will benefit from increased agility and reactivity in SC operations using AICs. AICs assist SMEs in perfecting SC management by keeping track of stock, shipping dates, and client demand. AICs can help businesses check stock, organize shipments, and anticipate consumer preferences [4]. AIC usage in logistics and SC results in a variety of ICs that revolutionize how businesses handle their logistics and SC operations [55].

7. Managerial Implications

This study's findings have important theoretical and managerial implications that can be used to address present logistics and SCM-related problems and discover new opportunities in the I4.0 environment. With the growing interest in AI-based technology, SMEs' and LEs' managers are looking for productive changes in their manufacturing systems. From a theoretical perspective, this study helps to provide findings of AICs to enhance the SSCP that helps managers imbibe new technology to enhance the SCV and IC. This study has significant theoretical implications, especially when it comes to the concept of "dynamic capacities", which refers to an organization's capacity to recognize, seize, and adjust its resources to changing situations to adopt new technologies. While considering the mediating impacts of IC and SCV, the study clarifies the importance of dynamic capabilities in explaining the influence of the adoption of AICs on SSCP. Practicing managers of SMEs may have a deeper understanding of the relationships between AI, SCV, and IC. Policymakers can formulate effective strategies to promote and support the adoption of AI technologies in the SC.

8. Conclusions, Limitations, and Future Research Direction

This study makes a substantial contribution by examining the impact of AICs on SSCP while considering the mediating effects of IC and SCV. It also presents the unique relationship between the adoption of AICs and their significant effect on SSCP (H1) → (β—0.182, *p*—0.066), partially supported Wamba-Taguimdje et al.'s (2020), [56] case study research, which focuses on the impact of artificial intelligence on changes in business processes as well as organizational innovations. AIC → SCV (H2) (β—0.745, *p*—0.000), the output is supported by [23], where researchers found that technology adoption has a mediation effect of SCV among Industrial IoT (IIoT) and sustainable performances.

AIC → IC → (H3) (β—0.499, *p*—0.000), suggests innovativeness benefits from technology adoption, which is in line with the recent literature [57]. These studies stressed sustainable supply chain management and encouraged organizations to adopt innovative practices that improve resource efficiency, reduce waste, and address environmental challenges. These innovations lead to improved product design, process optimization, competitive advantages, and overall supply chain performance.

SCV → SSCP (H4) (β—0.247, *p*—0.002), indicates that visibility in the long term affects the sustainable performance of the supply chain. The finding is supported by a study by [40]. In a world where firms must innovate or fall behind, knowledge is one of the most powerful tools. Organizational and production knowledge management that encourages AI-based adoption and boosts SCV is one of the best ways to boost long-term SSCP. Few studies focus on the innovativeness of the prospects of green SCM and SC outcomes [58], but the IC link positively influences SSCP. Finally, the novelty of this study is to present the mediation effect of IC among AICs and SSCP (H6) → [(β—0.080, *p*—0.013, VAF score—0.307 (partial mediation)] and H7 indicates SCV among AICs and SSCP [(β—0.184, *p*—0.002, VAF score—0.502 also presenting partial mediation [59] effect.

SCV systems give precise, real-time information about inventory levels, order status, transportation, and other essential supply chain variables. Prior research [60] encourages technology uptake and SMEs' performances. Visibility is also crucial to autonomous vehicle adoption [59]. Visibility and other innovation traits are vital for productivity and efficiency. Few studies examine visibility in supply management. The study [61] found that SCV links SC mapping and resilience. Researchers advocate supply chain mapping for visibility and reliability [62]. The data also shows that SCs' visibility depends on maintaining tight relationships with key suppliers. The research provides novel insights into how IC and SCV play a mediating role in defining the relationship between the adoption of AICs and SSCP, offering valuable guidance for future research in this field.

The relatively small sample size and its exclusive focus on SME manufacturing firms in emerging countries may limit the generalizability of the findings. Conducting studies with larger and more diverse samples across different regions and SME sectors would enhance the robustness of the results. There is a need for more causality research based on empirical investigations to reveal intangible phenomena like VSC, sustainability, and IC. There is a significant opportunity for future research endeavors to delve deeper into the exploration of mediating relationships involving both IC and SCV concerning other variables that can have a substantial impact on TBL performances within SCs.

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