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# Exploring the Barriers to Artificial Intelligence Integration in Green Supply Chain Using Interpretive Structural Modeling Approach: Insights from Bangladesh's Multi-Stakeholder Perspective

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**ABSTRACT**

In recent years, Artificial Intelligence (AI) integration to Green Supply Chains (GSC) has been identified as a vital organizational practice for achieving profitability by reducing both environmental and social risks. So far, no study has explored the barriers to implementing AI integrate GSC. The current research will analyze the barriers to adopting the concept of AI in GSC through multi-stakeholder aspect with regard to opinions provided by industry practitioners, government, and academics. The study utilized a thorough literature analysis, and consultations with experts resulted in a list of 11 barriers to AI implementation in GSC. These are the low top management commitment, the high cost of investing in AI, low digital infrastructure etc. This study used Interpretive Structural Modeling (ISM) to represent the contextual relationships between the barriers, resulting in a hierarchical model. The results of the study show that obstacles are categorized into six hierarchic levels in the model with the top management commitment and Government support are identified as the leading drivers. Addressing the main cause of the problem, which is improving infrastructure, raising awareness, and developing professional ability, is critical to encouraging AI adoption. One limitation is that the study is based on the opinions of experts limited to Bangladesh, which may reduce generalizability. The implications include the recommendation that policymakers and supply chain managers focus on initiatives to address the driving barriers and develop supporting policies to assist AI-enabled practices in the sustainable process of resource-constrained situations.

Keywords: Green Supply Chain (GSC), Interpretive Structural Modeling (ISM), Artificial Intelligence (AI).

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## 1. Introduction

Environmental sustainability and technology innovation are two of the core concerns of businesses, policymakers, and scholars in the recent years. What started as a marginal concept has now become a strategic requirement to address the problem of environmental degradation, loss of resources, and stricter regulations and thus Green Supply Chain Management (GSCM). In the interim, Artificial Intelligence (AI) has a radical effect on the supply chain management that has input real-time analytics, predictive forecasting, waste minimization, dynamic logistic practices and automation of events [1]. AI integration in GSCM offers a great opportunity to promote efficiency and sustainability, especially in the economies that run short of resources.

In Bangladesh where global buyers, regulators, and NGOs are putting pressure to practice a greener approach in a rapidly growing industrial center of textiles, garments, leather, pharmaceuticals, and food processing, there is pressure to be greener. Nevertheless, it should be known that AI has not been extensively used yet in GSCM and in order to achieve this, there was a lack of digital infrastructure, high cost of implementation, lack of skills, poor institutional assistance, and poor coordination of stakeholders [2].

The current research uses Interpretive Structural Modeling (ISM) to help discover and rank obstacles to AI-empowered GSCM in Bangladesh [3]. ISM allows one to understand the hierarchical nature of the relationship between driving and dependent barriers and thus intervene accordingly. This study has provided practical guidance to both the policymakers and industry leaders, as well as the academicians through the multi-stakeholder's approach. The results also help the discussion on sustainable technological transition because the findings serve as a guide that links the ecological responsibility to economic growth via AI-based innovations.

Although, the Artificial Intelligence (AI) could change professional Green Supply Chain Management (GSCM) and make it more efficient, sustainable, and competitive, it is not used actively in the developing countries, such as in Bangladesh. The obstacles that impact on industries have been characterized as the lack of proper infrastructure, high costs, skills gap, facilitation and lack of co-ordination of stakeholders by the government. The miracles can minimize the rate of technological transition and negatively influence achieving sustainable development. These challenges must, therefore, be researched and identified strategically and

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classified into ranking to provide reasonable considerations that AI can beneficially contribute towards effective inclusion in GSCM.

**1.1 Objectives**

(a) To selectively identify reasons behind AIs non-implementation in the Green Supply Chains by mean of literature search and validation by experts.
(b) To examine the relations of these barriers with one another via Interpretive Structural Modeling (ISM) approach.
(c) To classify the barriers under driving and dependent forces using the MICMAC analysis.
(d) To provide policy and recommendations to policymakers, industry participants and onlookers to surmount the pushing elements and develop successful AI-based sustainable supply chains.

**2. Theoretical Background**

This section provides a detailed account of the theoretical concepts on which this analysis is based, i.e. Green Supply Chain Management (GSCM), Artificial Intelligence (AI) within a supply chain, and Interpretive Structural Modeling (ISM) approach. These theories constitute the theoretical framework of comprehending what has been preventing the implementation of AI in the green supply chains, especially in the environment of developing countries, like Bangladesh [4].

2.1 Green Supply Chain Management (GSCM)

Green Supply Chain Management (GSCM) takes conventional supply chain one step further by introducing environmental factors into the entire spectrum of the supply chain including design, manufacture, distribution, use and disposal of the product [5]. Its main set of practices consists of resource convergence, shrinkage, sustainable packaging, retrograde transport, and implementation of renewables to lessen the impairment to the environment.
Over the last few decades, GSCM has emerged as a strategy to address environmental issues and to deal with regulatory pressures among the researchers, industries and policymakers. In addition to being ecology friendly, it is also cost effective and improves the corporate reputation.
Nevertheless, deployment of GSCM in the developing nations such as Bangladesh is still difficult because of poor awareness, technical expertise, regulatory implementation, government benefit, stakeholder integration, and high initial start-up capital [6].

2.2 Interpretive Structural Modeling (ISM)

Interpretive Structural Modeling (ISM) is a methodology that was developed by Warfield in 1974, to analyze decision problems, where the process is complex and interdependent factors [7]. ISM assists the scholars and practitioners to develop a directed graph (also called a structural model) that shows the direction and sequence between variables. It is most useful in exploratory studies and when information is scarce on the matter of study but one is surrounded with experts to give insight.

2.3 Artificial Intelligence(AI) in Supply Chain Management

The interpretation structural modeling (ISM) process entails the extraction of barriers, development of Structural Self Interaction Matrix (SSIM), development of Reachability matrix as well as the development of a hierarchical structure [8]. Such a framework separates driving barriers (the barriers that affect others) and dependent barriers (those that are affected), which provides a clear guide to prioritizing in the challenges of AI integration in green supply chains.
Artificial intelligence (AI) based on human intelligence pattern copying processes of self-learning and correction, and reasoning is gaining popularity in the supply chains to predict demand, improve inventory, predictive maintenance, offer customer support and manage the environment. Machine learning, deep learning, and NLP are technologies, which allow the supply chains to adjust to internal and external dynamic stimuli.
Within Green Supply Chain Management (GSCM) AI may increase sustainability in the following ways:
(a) Surveillance and forecasting of carbon emission
(b) Automation of energy and water resource utilization
(c) Real-time non-compliance observation
Although it has the potential, AI usage in supply chains of Bangladesh has so far been limited because of the hugely expensive nature of investments, atrocious development of data infrastructure, departmental dynamics, as well as the absence of state promotion [9]. These structural roadblocks have to be addressed in order to achieve sustainable and efficient success in digital transformation.

**3. Methodology**

This paper uses the Interpretive Structural Modeling (ISM) to determine and examine the complexities between the key Barriers to Artificial Intelligence Integration in Green Supply Chain [10]. The research method is a combination of the steps that have been utilized in previous researches, which mixes skillful evaluation and structural modeling.

3.1 Research Design Overview

The study was carried out in the below-mentioned steps which have been demonstrated in Fig.1 with flow diagram:
(a) Review of literature into possible barriers applicable in AI Integration in Green Supply Chain.
(b) Veteran input in screening, narrowing and completion of list of barriers.
(c) ISM methodology to represent the connection of the barriers with each other.
(d) MICMAC analysis to categorize the barriers in the terms of driving and dependence power.

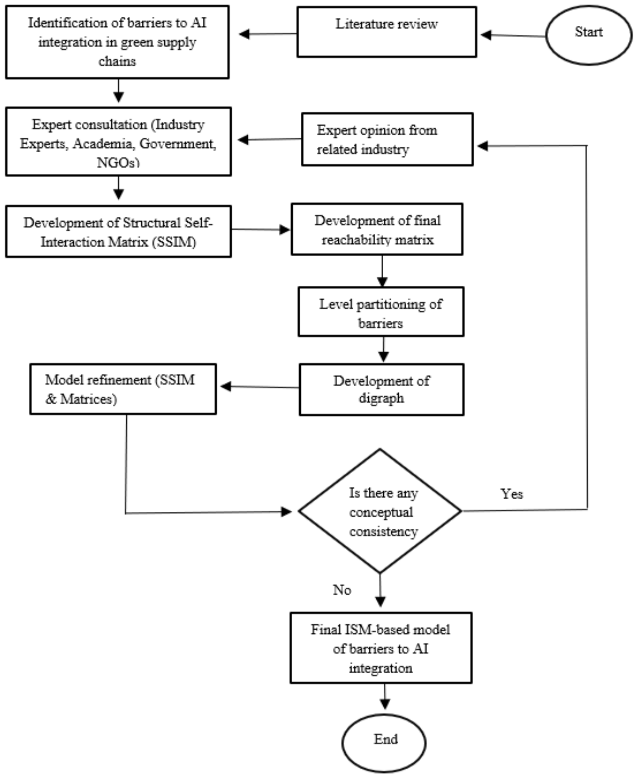


Fig.1: Flow diagram for preparing the ISM model

3.2 Expert Panel Formation & Factors Identification

In an attempt to establish the major obstacles to integration of Artificial Intelligence (AI) in Green Supply Chains in the Bangladeshi setting, two steps methodology was used. To start with, a substantial literature review was conducted in order to generate a preliminary list of possible impediments which were reported in earlier studies addressing AI adoption, sustainability in supply chains, and technological shift in general [11]. The factors are shown in table 1 with description. Secondly, expert consultations that entailed 12 industry, academia, government, and non-governmental organization actor actors were used to refine this list. The experts analyzed, debated and confirmed the barriers so as to achieve relevance and completeness of the barriers [12]. This process led to the end-result of a list of eleven most important factors that constitute a combination of organizational, technological, financial, policy, and awareness-related issues, each of which is elaborated and provides the main input to the later ISM and MICMAC analysis.

Table 1: Barriers to Al Integration in Green Supply Chains

| SL No | Critical Factors | Description |
|---|---|---|
| 1 | Insufficient commitment by the top management | Poor commitment by the top management impedes decision-making and destabilizes in the quest to realize organizational sustainability. |
| 2 | Very expensive cost of introducing AI technologies | The cost of high AI implementation is expensive to organizations that need massive spending in terms of infrastructure, computer software, skilled workforce and maintenance of such. |
| 3 | Shortage of quality AI and green technology human resources | The lack of competent workers in the field of AI and green technologies narrows down innovation and makes the attempt to implement it effective. |
| 4 | Inadequate digital infrastructure | There are poor digital infrastructures, which deter the use of AI, leading to connectivity issues and inability to deploy sustainable technological solutions. |
| 5 | Awareness gaps over the advantage of AI in green supply chains | There is also a lack of awareness and information gaps in the benefits of using AI in green supply chains that obstruct adoption and higher efficiency. |
| 6 | Data availability and data quality problems | The inadequate quality and scarcity of the data decrease the dependability of the AI models, thus debilitating the green supply chain operations through decision-making. |
| 7 | Resistance to change of supply chain participants | The AI adoption is impeded by resistance to change among supply chain actors, which is caused by uncertainty, job security issues and disruptions to commenced processes. |
| 8 | Lack of sufficient government support, incentives or policy | Government assistance, encouraging and policies are inadequate and this stems out AI implementation and slows down its sustainable changes in organizations. |
| 9 | Incompatibility between the stakeholders in the supply chain | Lack of coordination between stakeholder objectives and systems that are not aligned impedes the integration of the AI-driven green initiatives in the supply chains. |
| 10 | Poor enforcement of the environmental laws | The poor enforcement of environmental laws allows unsustainable operations and takes away the pressure to embrace AI as a means to achieve greener supply chains. |
| 11 | Insecurity with regard to return on investment to AI on sustainability | Doubtful AI payoff on investment, as well as the variability of payback periods, discourage the use of sustainable technological solutions by organizations. |

## 4. Result

4.1 Development of Structural Self-Interaction Matrix (SSIM)

Considering the finalized barriers, experts were requested to facilitate pairwise comparisons for the ability to answer the questions that relate to the direction in table 2 and nature of contextual relationship through notations as follows:

(a) When the (i, j) element of SSIM is V denoting that element i affects element j, the (i, j) cell of the reachability matrix will have 1 and the converse (j, i) cell will have 0.

(b) In case of (i, j) entry A in which the element j affects the element i, the (i, j) place is saved as 0, and the (j, i) is saved as 1.

(c) In case (i, j) entry is X, denoting the mutual influence of elements i and j, the (i, j) and (j, i) entries are made 1.

(d) When the (i, j) entry is O, there is no relation between elements i and j, then both the (i, j) and (j, i) position are to be filled in as 0 [13].

Table 2: Structural self-interaction matrix

| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | | V | V | V | V | V | V | V | V | V | V |
| **2** | | | V | V | V | V | V | V | V | V | V |
| **3** | | | | A | V | V | V | V | V | O | V |
| **4** | | | | | X | V | O | V | V | O | V |
| **5** | | | | | | X | O | A | V | O | V |
| **6** | | | | | | | O | A | V | O | V |
| **7** | | | | | | | | A | V | O | V |
| **8** | | | | | | | | | V | V | V |
| **9** | | | | | | | | | | V | V |
| **10** | | | | | | | | | | | O |
| **11** | | | | | | | | | | | |

4.2 Reachability Matrix Construction

The SSIM was next converted into a binary reachability matrix by means of the usual ISM conversion rules [14]. Indirect relationships were detected with the use of transitivity in table 3.

Table 3: Initial reachability matrix

| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | Driving Power |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 11 |
| **2** | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 10 |
| **3** | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 7 |
| **4** | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 7 |
| **5** | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 5 |
| **6** | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 4 |
| **7** | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 3 |
| **8** | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 7 |
| **9** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 3 |
| **10** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 |
| **11** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| **Dependence Power** | 1 | 2 | 4 | 4 | 7 | 7 | 5 | 5 | 9 | 5 | 10 | 59/59 |

4.3 Level Partitioning

The reachability set and antecedent set was then calculated against each barrier in table 4 and this was repeated to get the levels until all barriers were accommodated in a hierarchical structure [15].

Table 4: Level partitioning (LP)

| Elements | Reachability Set | Antecedent Set | Intersection Set | Level |
|---|---|---|---|---|
| **1** | 1 | 1 | 1 | 6 |
| **2** | 2 | 1, 2 | 2 | 5 |
| **3** | 3, 4, 5, 6, 8 | 1, 2, 3, 4, 5, 6, 8 | 3, 4, 5, 6, 8 | 4 |
| **4** | 3, 4, 5, 6, 8 | 1, 2, 3, 4, 5, 6, 8 | 3, 4, 5, 6, 8 | 4 |
| **5** | 3, 4, 5, 6, 8 | 1, 2, 3, 4, 5, 6, 8 | 3, 4, 5, 6, 8 | 4 |
| **6** | 3, 4, 5, 6, 8 | 1, 2, 3, 4, 5, 6, 8 | 3, 4, 5, 6, 8 | 4 |
| **7** | 7 | 1, 2, 3, 4, 5, 6, 7, 8 | 7 | 3 |
| **8** | 3, 4, 5, 6, 8 | 1, 2, 3, 4, 5, 6, 8 | 3, 4, 5, 6, 8 | 4 |
| **9** | 9 | 1, 2, 3, 4, 5, 6, 7, 8, 9 | 9 | 2 |
| **10** | 10 | 1, 2, 3, 4, 5, 6, 7, 8, 9,10 | 10 | 1 |
| **11** | 11 | 1, 2, 3, 4, 5, 6, 7, 8, 9,11 | 11 | 1 |

4.4 ISM Model Development

The hierarchy levels were used to draw a directed diagraph of the relationships and the driving-dependence structure of the barriers to provide an illustration in Fig.2.

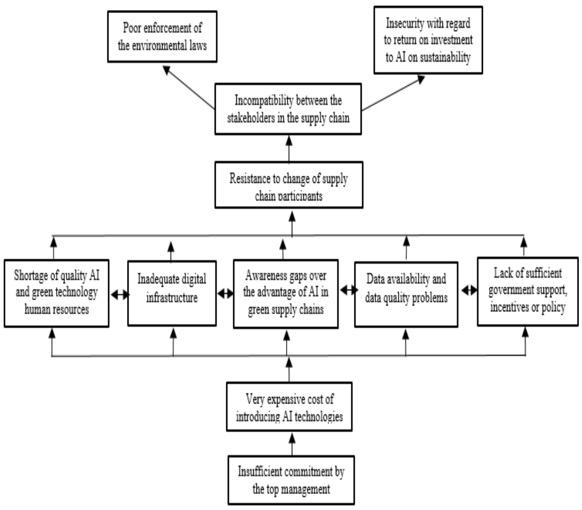


Fig.2: ISM based model of barriers to AI implementation

4.5 MICMAC Analysis

Fig. 3 illustrates the distribution of the barriers in their driver and dependence powers. This is because the Quadrant IV of barriers 1 and 2 is classified under significant independent drivers, more persuasive yet not induced by other drivers. These barriers are known as Quadrant III barriers (3, 4, 5, 6, and 8) as they are linkage variables with significant mutual effects and possible feedbacks. The II (7 and 9) barriers are readily related to an upstream actual phenomenon, while the I (10 and 11) ones are self-sufficient and relative irrelevance to the system. The importance of such a classification is that its priorities are independent drivers, and, when the linkage variables are under control, sustainable improvements can be ensured.

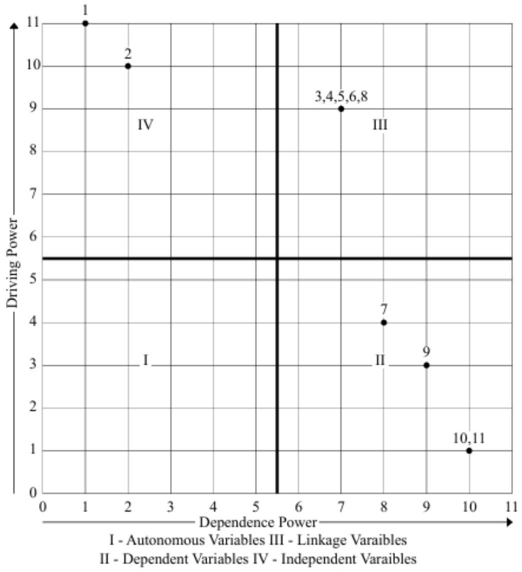


Fig.3: MICMAC diagram

**5. Discussion**

The hierarchical model based on the ISM gave a clear idea on the interaction of the different barriers to the implementation of AI in Green Supply Chains (GSCs), in case of Bangladesh [16]. The top management commitment and the government support were within the lowest levels of the hierarchy in the analysis and hence would act as the most important role players towards solving other challenges. The driving power is very high as indicated by the MICMAC map thereby indicating that improvement in this area can flow down to other dependent barriers such as poor digital infrastructure, high implementation cost, lack of qualified personnel, and lack of stakeholder coordination [17].

The results indicate that leadership commitment does not only define the budgetary allocation and the attainment of strategic synchronization but also promotes the readiness of an organization to embrace AI-enabled sustainability programs. In the same way, government active policies can give necessary incentives, regulatory systems, and the partnerships between the public and the private sector to minimize the risks of adoption. Conversely, the lower-level dependent barriers, e.g. the lack of awareness of the environmental benefits of AI, or a lack of coherent interdepartmental cooperation, are more likely to be consequences of a lack of powerful top-level drivers [18].

These insights were further supported by the MICMAC categorization that it is possible to place most of the challenges connected to infrastructure and skills in the high-driving classification, i.e., they have to be resolved at the very beginning of an AI adoption approach [19]. These findings correlate with the researches of a global level that emphasis the importance of enabling environments in digital transformation but also reflect on the specificity of the situation in Bangladesh with its lesser resources disproportionate technological readiness, and weaknesses in the internal regulations. Improving upon the high-driving blocks will open up the systemic alteration, establishing a favorable ecosystem facilitating the integration of AI that, in addition to enhancing the effectiveness of operations, will also support environmental sustainability under-goings.

**6. Conclusion**

In this research paper, the authors demonstrate and list the primary challenges hindering the application of artificial intelligence (AI) to green supply chains (GSCs) using Interpretive Structural Modeling (ISM) and MICMAC. Eleven barriers that have a close relationship were categorically rated to develop a hierarchical model that shows cause and effect relationship and also the magnitude of each barrier. These findings indicate that insufficient commitment of senior management and lack of government support, incentives or policies are the most influential driving forces that initiate a chain of technological, financial, and capability induced barriers. The impact of these barriers exacerbates threats, such as high implementation cost, lack of digital infrastructure, inefficient human resource, and inefficient data availability. In addition, lack of compatibility between the parties, change resistance, and lack of certainty about returns on investing all contribute to the lack of willingness to adopt AI in GSCs.

The nature of the theoretical and practical contributions of the findings is theoretical. So the framework can give a decent guideline to the policymakers on how the enabling regulations can be developed, how the environmental regulations can be implemented more vigorously and how incentive

**7. Implications**

This research makes a direct contribution to the practice as far as AI integration into green supply chains is of concern to managers, policymakers, and stakeholders [20]. With the aid of the ISM model, it is able to define barriers and prioritize them and hence have the ability to focus on underlying issues which include inadequate technological infrastructure, skills shortages as well as lack of funds. The focus of managers must be capacity building especially in the digital up skilling, and there should be proper interconnectivity of the AI implementation across the IT, operation, and sustainability functions [21]. To ascertain value-based adoption, AI applications have to be aligned to environment-related performance objectives such as minimizing emissions and optimizing use of resources.

It is also postulated in the study that there is need to liaise with external players such as regulators and technology providers to overcome the challenges that are systemic and can be defined as such [22]. Moreover, policy advocacy is central in the determination of enabling environment in a technological shift towards environmentally friendly operations. Offering a strategic pathway amid the three components of organizational preparedness, coalition-building between parties and policy promotion, findings provide an opportunity to speed up the implementation of sustainable AI across supply chains, especially in developing economies.

**References**


[1] N. A. B. Hassan, "Integrating Advanced Artificial Intelligence Models for Predictive Analytics and Real-Time Optimization in Global Supply Chain Networks," *Int. J. Appl. Bus. Intell.*, vol. 2, no. 12, pp. 1–6, 2022.

[2] J. Hangl, V. J. Behrens, and S. Krause, "Barriers, drivers, and social considerations for AI adoption in supply chain management: a tertiary study," *Logistics*, vol. 6, no. 3, p. 63, 2022.

[3] M.-H. Do, Y.-F. Huang, and V.-D.-V. Phan, "Analyzing the barriers to green supply chain management implementation: a case study of the Vietnamese agriculture sector," *J. Enterp. Inf. Manag.*, vol. 37, no. 1, pp. 125–147, 2024.

[4] A. Rashid, N. Baloch, R. Rasheed, and A. H. Ngah, "Big data analytics-artificial intelligence and sustainable performance through green supply chain practices in manufacturing firms of a developing country," *J. Sci. Technol. Policy Manag.*, vol. 16, no. 1, pp. 42–67, 2025.

[5] B. M. Beamon, "Designing the green supply chain," *Logist. Inf. Manag.*, vol. 12, no. 4, pp. 332–342, 1999.

[6] S. Kasana, M. Chavan, D. Sedera, Z. Cheng, and M. Ganzin, "Unlocking circular start-ups: A model of barriers," *Bus. Strategy Environ.*, vol. 33, no. 3, pp. 2546–2577, 2024.

[7] R. Attri, N. Dev, and V. Sharma, "Interpretive structural modelling (ISM) approach: an overview," *Res. J. Manag. Sci.*, vol. 2319, no. 2, p. 1171, 2013.

[8] P. S. Poduval, V. Pramod, and J. R. VP, "Interpretive structural modeling (ISM) and its application in analyzing factors inhibiting implementation of total productive maintenance (TPM)," *Int. J. Qual. Reliab. Manag.*, vol. 32, no. 3, pp. 308–331, 2015.

[9] M. T. Islam, M. M. Hasan, M. Redwanuzzaman, and M. K. Hossain, "Practices of artificial intelligence to improve the business in Bangladesh," *Soc. Sci. Humanit. Open*, vol. 9, p. 100766, 2024.

[10] S. Roy, S. M. Ali, and M. Alghababsheh, "Integrated fuzzy total interpretive structural modeling and partial least squares structural equation modeling to understand resource efficient circular supply chains," *Ann. Oper. Res.*, pp. 1–35, 2025.

[11] Y. Wang, J. H. Han, and P. Beynon-Davies, "Understanding blockchain technology for future supply chains: a systematic literature review and research agenda," *Supply Chain Manag. Int. J.*, vol. 24, no. 1, pp. 62–84, 2019.

[12] D. Lewis, N. Kanji, and N. S. Themudo, *Non-governmental organizations and development*. Routledge, 2020.

[13] A. Mandal and S. Deshmukh, "Vendor selection using interpretive structural modelling (ISM)," *Int. J. Oper. Prod. Manag.*, vol. 14, no. 6, pp. 52–59, 1994.

[14] Sushil, "Modified ISM/TISM process with simultaneous transitivity checks for reducing direct pair comparisons," *Glob. J. Flex. Syst. Manag.*, vol. 18, no. 4, pp. 331–351, 2017.

[15] S. C. Cheung and J. Kramer, "Context constraints for compositional reachability analysis," *ACM Trans. Softw. Eng. Methodol. TOSEM*, vol. 5, no. 4, pp. 334–377, 1996.

[16] S. Luthra, D. Garg, and A. Haleem, "Critical success factors of green supply chain management for achieving sustainability in Indian automobile industry," *Prod. Plan. Control*, vol. 26, no. 5, pp. 339–362, 2015.

[17] S. Gorane and R. Kant, "Modelling the SCM enablers: an integrated ISM-fuzzy MICMAC approach," *Asia Pac. J. Mark. Logist.*, vol. 25, no. 2, pp. 263–286, 2013.

[18] D. Bakhtiari Asi and E. Öhman, "The Integration of Artificial Intelligence in Business Process Automation: Implications for Traditional Workflows and Organizational Structures Across Industries," 2025.

[19] V. Uren and J. S. Edwards, "Technology readiness and the organizational journey towards AI adoption: An empirical study," *Int. J. Inf. Manag.*, vol. 68, p. 102588, 2023.

[20] S. Saad and M. Khamkham, "The applications of AI in GSCM-A systematic literature review," 2022.

[21] M. Almansour, "How do green intellectual and co-creational capitals drive artificial intelligence innovation and green innovation in start-ups?," *Eur. J. Innov. Manag.*, vol. 28, no. 4, pp. 1649–1666, 2025.

[22] N. C. Ohalete, A. O. Aderibigbe, E. C. Ani, P. E. Ohenhen, D. O. Daraojimba, and B. A. Odulaja, "AI-driven solutions in renewable energy: A review of data science applications in solar and wind energy optimization," *World J. Adv. Res. Rev.*, vol. 20, no. 3, pp. 401–417, 2023.