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AI-Driven Supply Chain Integration and Environmental Sustainability in the RMG Sector: Exploring the Mediating Roles of Technological Readiness and Supply Chain Agility

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Abstract: The study aims to explore the complex relationship among AI-SCI, ES, and the RMG sector in Bangladesh. The study uses quantitative research methods and a cross-sectional survey. The sample size was sufficiently large, comprising 389 managerial professionals employed in the RMG sector in Bangladesh. The study used PLS-SEM to test a complex model in management research and to examine the interrelationships among AI-SCI, TR, SCA, and ES. The findings demonstrate a positive statistical association between AI-SCI and ES ($\beta = 0.229$, $p < 0.000$), indicating the role AI technologies could play in promoting sustainable operations. The results show that technological readiness ($\beta = 0.793$, $p < 0.000$) and supply chain agility ($\beta = 0.813$, $p < 0.000$) are crucial mediators that significantly strengthen the effect of AI-SCI on sustainability performance. These results show that the effect of AI-SCI on promoting environmental sustainability is not direct to policymakers but instead mediated by superior technological capabilities and enhanced supply chain integration agility. The study provides helpful implications for RMG companies and policymakers. This study adds to the literature by addressing a knowledge gap on how AI implementation may galvanize sustainable RMG practices, especially in emerging countries.
Keywords: AI-driven Supply Chain Integration, Environmental Sustainability, Technological Readiness, Supply Chain Agility, Ready-Made Garments Sector, PLS-SEM, Emerging Economies, Sustainable Practices.

1. Introduction

The Ready-Made Garment (RMG) sector contributes as the backbone of the Bangladesh economy; it accounts for more than 80% of the country's export earnings and employs around 4 million workers (Rahman & Chowdhury, 2020). However, rapid industrialization in these sectors has led to substantial environmental problems, including excessive water consumption, chemical pollution, and carbon emissions, posing a significant threat to ecological sustainability (Hasan, 2022). With growing pressures worldwide for eco-friendly practices, the introduction of modern technologies, such as artificial intelligence in supply chain management, seems a strategic fillip to align productivity with ecological constraints (Paul et al., 2023).

AI-SCI's implementation complements predictive analysis, real-time information sharing, and automation to achieve efficient resource use, reduced waste, and increased operational visibility (Dubey, 2023). To date, the literature has emphasized AI's potential to enhance sustainability in the manufacturing sector. However, there is scarce empirical evidence on the role of AI-SCI in improving environmental sustainability in emerging markets such as Bangladesh, where technology adoption is constrained by infrastructural and institutional factors (Wamba & Queiroz, 2022). Also, the mediating mechanisms by which AI-SCI leads to sustainable practices are relatively neglected. Technology readiness – an organisation's readiness to adapt and assimilate new technology and supply chain agility, the ability to respond rapidly to market and operational disruptions, are suggested as two important enablers in this relationship (Bag et al., 2021; Kamble et al., 2020).

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The research explores direct and mediating mechanisms by which AI-SCI promotes environmental sustainability in the RMG of Bangladesh. Based on the resource-based view (RBV) and dynamic capability theories, we argue that AI-SCInot contributes not only directly to sustainability but also indirectly by improving technological readiness and supply chain agility. Namely, we propose that technological readiness mediates the AI-SCI-sustainability relationship by endowing firms with the capabilities to adopt eco-efficient practices, and supply chain agility enables rapid adjustment to sustainable practices in turbulent market environments.

By analysing such relationships, this study contributes to the literature by addressing an important lacuna in how AI innovations can be translated into practice to meet the dual needs of industrial growth and ecological conservation in resource-scarce settings. Despite the increasing importance of AI-based supply chain integration (AI-SCI) and its potential benefits for environmental sustainability (ES), empirical evidence remains limited, particularly in developing countries such as Bangladesh. Current research mainly addresses developed markets, ignoring the infrastructural and institutional limitations of developing countries (Aslam, 2018).

In addition, it is hypothesized that TR and SCA are mediators; however, there is still a lack of research demonstrating the specific mediating mechanisms for AI-SCI and ES in the RMG sector (Aziati, 2018). The present study overcomes these limitations by (1) focusing on the direct effects of AI-SCI on ES in the RMG industry of Bangladesh and (2) empirically testing the mediating effects of TR and SCA, and hence provides context-specific.

2. Literature Review

2.1 Overview of the RMG Sector in Bangladesh

Bangladesh's economy largely depends on the garment sector, which has the second-highest earnings from exports and employment. The RMG industry accounted for about 83.49% of Bangladesh's overall exports, worth $36.66 billion in FY 2021-2022, and provided livelihoods for around 4.4 million workers, most of them women (Farhana, 2022; Hasan, 2020; Islam, 2023). This industry has been instrumental in reviving the least developed Bangladesh and catapulting it to a middle-income one, highlighting its economic importance (Akter & M, 2019; Farhana, 2022). However, the enormous expansion of the RMG industry has also not been without problems, especially regarding environmental issues.

The environmental challenges in the RMG industry are huge. The textile industry is well known as a water-intensive industry, consuming approximately 1,500 billion liters/year for dyeing and washing; 42% of this is used by the weaving and fabric preparation sections (Ara, 2019). Furthermore, many factories lack effective environmental management, leading to pollution and resource depletion (Chowdhury et al., 2023). These problems are exacerbated by a lack of knowledge and resources to implement appropriate environmental management plans, as many industries still do not take their role in environmental protection seriously (Chowdhury et al., 2023). Additionally, the industry's operations primarily in non-industrial areas of the country have led to a lack of adherence to safety and environmental regulations, resulting in a larger environmental footprint (Ara, 2019).

In the context of the RMG industry, environmental sustainability at work includes environmentally sound practices that reduce ecological pollution without compromising economic performance. Some performance measures that need to be tracked in this sector include water-use efficiency, waste utilization from the production process, and the implementation of green manufacturing technology (Sarker et al., 2023). Sustainable practices need to be incorporated not only to comply with international rules and regulations, but also to improve the sector's global competitive position (Sarker et al., 2023)—through the adoption of IMS. The implementation of IMS has been advocated as a means of reducing businesses' environmental impact by increasing transparency and resource efficiency (Talapatra et al., 2023).

In summary, the RMG industry is a vital component of Bangladesh's economy, but it faces significant environmental challenges that necessitate a shift towards more sustainable practices. The implementation of AI in supply chain management offers a promising approach to addressing these challenges, enabling the industry to enhance its sustainability performance while maintaining its economic significance.

2.2 AI-Driven Supply Chain Integration

AI-enabled supply chain integration is the integration of artificial intelligence (AI) technologies to enable efficient, resilient, and sustainable supply chain operations. Some of these key components have now been systematically reviewed, including predictive analysis, real-time data segmentation, and intelligent decision-making (Eyo-Udo, 2024; Joel, 2024). These features will facilitate better demand forecasting, inventory management, and logistics, supporting a more agile and innovative supply chain (Krishnan, 2024). In addition, AI methods, including machine learning and natural language processing, are being increasingly used to refine various supply chain tasks, thereby replacing traditional working models with more data-driven ones (Ellaturu, 2024; Singh & S, 2023).

AIM and SCM have immense operational and environmental advantages. Research has shown that AI can enhance operational efficiency by automating mundane tasks, improving demand prediction accuracy, and optimizing resource allocation (Mohsen, 2023; Muthaluri, 2024).

For example, predictive maintenance driven by AI can minimize downtime (via the optimization of the use of assets), reducing costs and increasing service levels. From an environmental perspective, AI helps promote more sustainable practices -for instance, greener transportation, by finding more ecologically friendly logistics routes to reduce emissions, and more transparent supply chains, to ensure better compliance with environmental laws (Kazançoğlu, 2022; Rashid, 2024). The application of AI in supply chains not only enables operational efficiencies but also promotes environmental sustainability.

The evidence for a positive nexus between AI adoption and environmental sustainability is strong. AI-based solutions enable organizations to go green by utilizing their resources more efficiently and reducing waste. For example, AI can analyze data to identify inefficiencies in energy consumption across the supply chain, enabling targeted interventions to reduce carbon footprints (Khan et al., 2021). Furthermore, AI enables more effective tracking and handling of materials, resulting in better recycling and waste management (ibid).

H1: AI-Driven Supply Chain Integration has a positive direct impact on Environmental Sustainability in RMG.

The integration of AI has been found to have a significant impact on a firm's technological readiness, as evidenced by empirical studies in academic literature. The implementation of AI applications requires new and up-to-date digital infrastructure and expertise, creating a climate in which innovation can thrive (Bakri, 2024; Hendriksen, 2023). Firms that successfully adopt AI in their supply chains are typically ready to adopt other new technologies, resulting in a positive, self-reinforcing cycle of technological adoption (Dora, 2021). This preparation is crucial for companies seeking to maintain their edge in rapidly changing markets.

H2: Supply Chain Integration with AI has a direct positive influence on Technological Readiness.

It reached this conclusion, even though it has demonstrated that integrating AI increases supply chain agility by enabling faster, more effective decision-making. The ability to manage large volumes of information in real time enables organizations to respond promptly to market shifts and disruptions (Krishnan, 2024).

It has been reported that the application of AI in supply chain management enables companies to predict demand variations and plan accordingly, thereby enhancing flexibility and speed (Younis et al., 2022). In the 22nd century, as most supply chain operations contend with various business threats, ranging from geopolitical tensions to global pandemics (Chukwu, 2024) This nimbleness is crucial.

H3: AI-driven supply chain integration has a significant, positive direct effect on Supply Chain Agility.

To sum up, ACV-driven supply chain integration comprises several elements to enhance operational efficiency and environmental sustainability. The empirical results provide support for the proposed hypotheses, which suggest that AI integration has a positive impact on environmental sustainability and technological readiness, as well as a significantly positive effect on supply chain agility.

2.3 Technological Readiness

Technological readiness is an important concept within the context of digital transformation and SCM. An organization can adopt and use new technology effectively and efficiently, leading to digital sonority in handling change.

Emphasize that technological readiness is not limited to technology availability but also includes the organizational culture, skills, and mindset required for practical use. Such preparedness is critical in SCM, as the application of digital technologies can increase efficiency, flexibility, and competitiveness (Jewapatarakul, 2024).

Empirical evidence indicates that technological preparedness is significantly correlated with successful technology use in SCM. According to Khan and Rahman (2023), firms with high technological readiness are significantly more likely to adopt advanced technologies such as AI and big data analytics, which may help them improve the efficiency of supply chain operations.

According to their findings, organizations that persist in cultivating their technological capabilities enjoy significant gains in operational performance and customer satisfaction (Azieva, 2021). Moreover, technological readiness is strongly related to proactive change management, which can make transitions during the technology adoption process for new system implementation in organizations easier (Chang & Y, 2023).

On the direct effect of technological readiness towards environmental sustainability, the literature corroborates that businesses with greater technological readiness have greater potential to adopt sustainable actions. Technological preparedness enables companies to adopt green technologies and applications, thereby reducing pollution.

For example, Azieva (2021) claims that firms prepared to adopt digital transformation may use these tools to improve sustainability, such as maximising resource use and minimising waste (Azieva, 2021). This partnership emphasizes the organizational need for a readiness culture to achieve operational excellence and sustainability goals.

H4: Technological Readiness has a positive direct effect on Environmental Sustainability in the RMG sector.

Regarding the mediating role of technological readiness in the relationship between AI-driven integration and environmental performance, the research finds that technological readiness is pivotal. When AI is used in organizations, those with higher technological readiness are more likely to have a positive environmental impact than those with lower technological readiness. That is because they can leverage AI solutions to streamline workflows, increase resource utilization, and promote long-term sustainability. For instance, research suggests that technologically mature companies can use AI for predictive analytics to make better decisions in resource management and waste reduction (Halpern, 2021). Hence, technology readiness is also a facilitator of the acceptance of AI and encourages its environmental sustainability benefits.

H5: Technological Readiness mediates a positive relationship between AI-Driven Supply Chain Integration and Environmental Sustainability.

Thus, technology readiness is a complex construct that is critical in digital transformation and SCM. It has powerful implications on the successful adoption of technologies, is linked to environmental sustainability, and plays an intermediating role in the association between AI implementation and environmental performance. Enhancing technological readiness for digital mastery and sustainable operating practices should be a priority among these institutions.

2.4 Supply Chain Agility

Agility in the supply chain function is the ability of an organization to respond rapidly to changes in market and customer demand, and to factory-level flexibility, enabling it to respond to unexpected events (Aziati, 2018; Rahman, 2021). Such agility is vital in turbulent markets, where consumer desires and environmental realities can change overnight, requiring the organization to react immediately to stay competitive (Makudza, 2023).

Supply chain agility plays a critical role in performance indicators such as on-time delivery, quality, flexibility, and innovation (Aslam, 2018; Yusuf et al., 2014). Under conditions of uncertainty, agile supply chains are better positioned to navigate risks and seize opportunities, thereby more capable of generating sustained operating performance (Wieland & Wallenburg, 2012). The literature shows that SC agility improves organizational operational performance and promotes green practices. Agility allows companies to respond more quickly to regulations and the consumer preference for environmentally friendly products. For example, agile supply chains can rapidly transform sourcing and production structures to incorporate sustainable fabrics and practices, thereby achieving environmental sustainability goals (Al-Zabidi, 2021). Anticipating the market and responding proactively are the main drivers of green supply chain initiatives (Vinodh & Aravindraj, 2013). This flexibility is essential as companies seek to balance profitability and sustainability demands.

The direct influence of supply chain agility on environmental sustainability is also supported by research, which shows an association between agile practices and waste reduction and resource efficiency (Carvalho, 2011; Rehman, 2020). For instance, agile supply chains can incorporate lean practices to reduce surplus inventory in the production system and simplify operations, thereby improving carbon footprints and sustainability performance (Carvalho, 2011; Ciccullo, 2018). It indicates that agility enables a firm to innovate and continuously improve both processes and products, promoting a culture of continuous improvement, which is necessary for long-term survival (Rehman, 2020; Schianchi, 2023).

H6: Supply Chain Agility has a positive direct effect on Environmental Sustainability in the RMG sector.

Furthermore, the literature acknowledges the mediating role of supply chain agility in the relationship between AI integration and environmental sustainability. Supply chain agility is improved through AI technologies that provide up-to-the-second data analytics and predictive analytics, helping firms make decisions in a snap (Far, 2017; Holloway, 2024).

Such AI-agility duality will not only enhance agility and responsiveness but also pave the way for the grassroots cornerstones of sustainable practices to become more aligned and reduce waste (Ciccullo, 2018; Schianchi, 2023). Moreover, the incorporation of AI in agile supply chains supports proactive sustainability; operational-centred sustainability, firms prepare and face environmental challenges and react to them effectively(Rehman, 2020; Schianchi, 2023).

H7: Supply Chain Agility positively mediates the relationship between AI-Driven Supply Chain Integration and Environmental Sustainability.

In conclusion, supply chain agility is an integral aspect for firms doing business in dynamic markets, as it enables organizations to respond more quickly to changes in the competitive landscape and to facilitate sustainable practices. The nexus of agility, AI, and environmental sustainability illustrates the strategic significance of agility in gaining a competitive advantage and ensuring the long-term success of organizations.

2.5 Environmental Sustainability in the RMG Sector

Traditional practices in the supply chain have created environmental challenges in the ready-made garment (RMG) industry, more significantly in developing economies such as Bangladesh. Rapidly advancing these practices results in overproduction of waste, excessive water use, and chemical pollution, which could harm local ecosystems and communities (Chowdhury et al., 2023). The RMG sector significantly contributes to environmental pollution through the discharge of effluents from outdated production processes and inefficient waste disposal. The inconsistent sustainability within an exponential industrial growth has also come with severe environmental impacts, such as water scarcities, soil pollution, and so on (Holloway, 2024).

In this context, there is growing interest in GSCM practices to promote environmental performance in the RMG sector. (Shajahan et al., 2021)examine many GSCM strategies, including eco-design, sustainable sourcing, and waste minimization, that have a substantial positive impact on environmental measures. The existing studies suggest that firms that implement GSCM are not only reducing their ecological footprint but also increasing their competitive advantage (even/edge) by satisfying the growing demand, especially from consumers, for sustainability and regulatory compliance (Shajahan et al., 2021), a transition (the increase and the potential). In addition, the practice of environmental performance measurement, such as calculating carbon footprints and conducting Life Cycle Assessments (LCAs), enables companies to measure their sustainability performance and benchmark where and how to improve (Bristi, 2020).

Connecting AI and supply transition (the element is a game-changer for advancing sustainability in the RMG industry). Supply chain flexibility enabled by AI technologies can give firms greater ability to meet market demand while mitigating both scope and scale waste. For example, AI can fine-tune asset and production planning, minimizing surplus inventory and its waste (Farhana, 2022). Furthermore, when technological readiness and organizational agility are in place, enabling AI-powered, real-time data sharing across the supply chain could enhance transparency and collaboration among participants (Ahad, 2023). This approach not only improves efficiency and productivity but also helps inculcate a culture of sustainability by fostering practices that consider environmental concerns across the supply chain (Agarwal, 2022).

Furthermore, a solid foundation in technology readiness and a strong sense of agile culture are essential to implement AI in the RMG industry successfully. A Culture of Innovation and Continuous Improvement: Building a culture that embraces innovation and continuous improvement is critical for realizing the value of AI (Sreenivasan & Suresh, 2024).With technology and sustainability in harmony, RMG companies can forge a robust, sustainable supply chain that not only satisfies consumers but also supports environmentally recoverable practices (Li, 2023). Thereby, integrating GSCM practices with AI and technological readiness will help improve the sustainability of the country's RMG sector in addressing the environmental challenges it faces.

3. Conceptual Framework

The conceptual model, grounded in the Resource-Based View (RBV) and dynamic capability theories, explains how AI-based supply chain integration (AI-SCI) promotes environmental sustainability in the RMG industry in Bangladesh through both direct and indirect mechanisms. H1: AI-SCI direct effect, i.e., predictive analytics, real-time data processing, and automated decision making will facilitate operational efficiency and waste reduction, and thereby improve resource management, through more accurate demand prediction, and higher operational efficiency (Dubey, 2023).

More implicitly, this relationship is mediated by technological readiness (H5) because AI technology adoption entails investments in digital infrastructure and workforce competencies, which tend to enable the deployment of eco-efficient technologies such as AI-based water recycling systems or energy optimization algorithms (Azieva, 2021; Singh & S, 2023).

At the same time, AI-SCI contributes to supply chain agility (H3) through a capability for timely market disturbance response via real-time analytics, which subsequently facilitates sustainability (H7) through the effort to dynamically react in a range of different ways – for instance, as in sustainable sourcing or waste-minimizing production scheduling (Ciccullo, 2018; Krishnan, 2024).

Supply chain agility has a direct positive effect on environmental performance (H6), through facilitating circular practices (such as fabric recycling) and ensuring compliance with changing laws and regulations (Rehman, 2020). From the RBV perspective, AI-SCI is a strategic resource ∗. Although the application of AI for sustainability has been conceptualized as a strategic resource, we propose that firms seldom treat AI for sustainability as a strategic resource that facilitates the attainment of a sustained competitive advantage, as there is a massive gap between a firm’s IT prowess and its intentions around AI to address ecological challenges (Bag et al., 2021).

This cross-domain perspective underscores the dual function of AI-SCI involved in Bangladesh’s RMG industry—both as a direct agent to avert ecological consternation and as an indirect means to engender resilience by embracing adaptive technological and operational competencies. It provides a templatic approach to the real world of realizing industrial progression and eco-preservation in resource-scarce settings (Singh & S, 2023).

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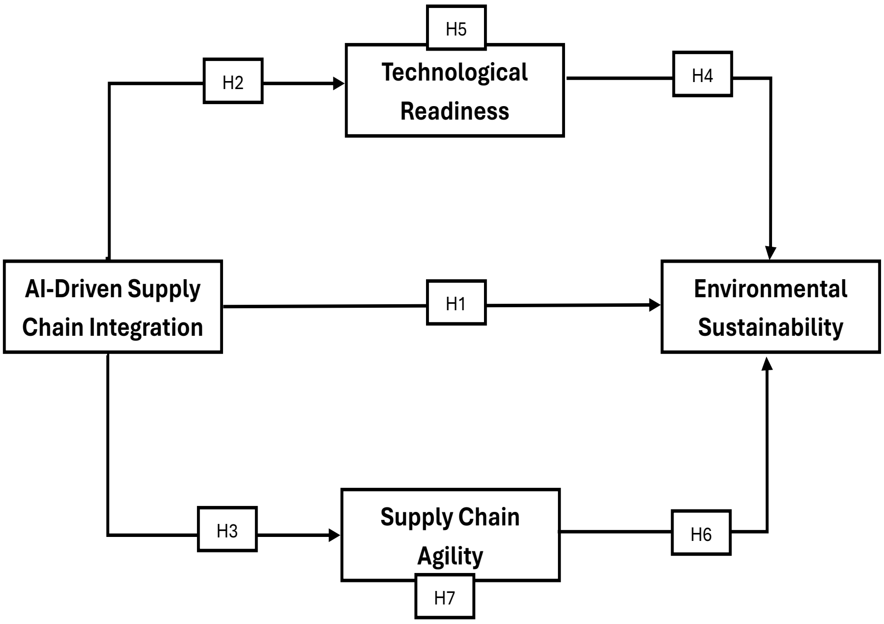

Figure 1: Conceptual Framework (Developed by Author)

4. Methodology

4.1. Research Design

The research uses a quantitative design to examine the relationships among AI-powered supply chain integration (AI-SCI), technological readiness (TR), supply chain agility (SCA), and environmental sustainability (ES) in Bangladesh's Ready-Made Garment (RMG) sector. A cross-sectional design is employed, which is suitable for collecting data at a single point in time to study the interrelationships among constructs (Hair, 2019). This model is beneficial for investigations exploring possible mediating roles of TR and SCA in the association between AI-SCI and ES. The analysis is conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), an appropriate modeling technique for complex models with mediating effects and non-normal data distributions (Henseler, 2015). PLS-SEM is also useful for studies with small-to-moderate sample sizes, as in this research (Sarstedt et al., 2014). However, the cross-sectional nature of this study limits our ability to infer causal relationships among the constructions. Future longitudinal research is recommended to establish causality.

4.2. Population and Sampling

The study employed non-probability convenience sampling due to the practical challenges of obtaining a large, randomized sample of managerial professionals in Bangladesh's RMG sector. Given the time constraints and the targeted nature of the respondents (e.g., supply chain managers, operations managers, and sustainability officers), convenience sampling allowed for efficient data collection from individuals directly involved in AI-driven supply chain integration and sustainability practices.

While this approach may introduce selection bias, the study mitigated this limitation by ensuring a sufficiently large sample (n=389) and by validating the sample's representativeness through demographic analysis (see Table 1). The sample demographics align with the sector's profile, including mid-career professionals with relevant expertise, thereby supporting the generalizability of the findings within the RMG context. Future research could enhance robustness by employing stratified or random sampling techniques.

4.3. Data Collection Procedure

A structured questionnaire was used to collect data on the study's main constructs: AI-SCI, TR, SCA, and ES. The instrument employed a five-point Likert-type scale (1=Strongly Disagree to Agree 5=Strongly) to measure respondents' attitudes and perceptions. The items for the for each construct were derived from validated scales in previous studies.

It is used to evaluate neurological impairment and is widely used to measure neurological function in various diseases. 2.2.2 AI-SCI It was modified from Wang et al. and Khan & Islam, and a modified version of the ES scale from (Rahman & F, 2023). The SCA and TR scales were based on (Pal, 2023; Wei et al., 2021), and on average.

Survey questionnaires were disseminated online (via Google Forms) and in print (hard copies distributed during workplace visits) to employees of 10 RMG companies in Dhaka, Bangladesh. Both versions of the questionnaires were conducted simultaneously in both printed and online formats. The use of the internet may have increased the survey's reach and convenience; however, face-to-face distribution may have enabled clarification of any doubts about the survey.

In this study, participation in the survey was voluntary, and respondents were informed that they could participate anonymously and that their responses would be kept confidential to control for social desirability bias (Podsakoff, 2024). The research followed ethical guidelines in the gathering and interpretation of the data. Informed consent forms outlining the study's purpose, the voluntariness of participation, and the confidentiality of responses were provided to participants. No personal data was obtained, thus guaranteeing the anonymity of the participants. Respondents' confidentiality was preserved by storing responses on encrypted servers, accessible only to the research team. These actions were carried out to ensure the anonymity and confidentiality of participants and to safeguard the ethical integrity of the study.

4.4. Measures and Validation of Instrument

The validity and reliability of the measurement tools were checked meticulously in this study. A pilot study with 30 subjects was performed to test the clarity and the reliability of the questionnaire. Results of the pilot test. All constructs had Cronbach's alphas of more than 0.70, confirming the constructs' internal consistency (Nunnally, 1978).

Second, standard method variance (CMV) was controlled with Harman's single-factor analysis. The test results showed that one factor accounted for 35.6% of the variance, which was less than 50%, suggesting that CMB was not a serious problem (Podsakoff, 2024).

Convergent validity was supported by AVEs, all of which exceeded 0.50 (Larcker & D, 1981), indicating that the items measured the constructs well. Relevant theory was also referenced through discriminant validity, and the Heterotrait-Monotrait (HTMT) ratio indicated that none of the constructs exceeded the recommended cutoff of 0.85, indicating that the constructs were distinct (Henseler, 2015). Although the outer loadings of object productions such as AI-SCI_5 (0.558) and ES_3 (0.537) were below the 0.70 threshold, they were retained to ensure adequate coverage of their construction. These items were considered theoretically important, and their removal did not substantially enhance model fit. However, the composite reliability and AVE of these constructions remained above the vet-suggested limits to maintain them.

4.5. Data Analysis

The data were analyzed in two major phases: measurement and structural. Reliability and validity were assessed using Cronbach's alpha, CR, and AVE. All the constructs showed highly reliable values (Cronbach's alphas and composite reliability> 0.70, and AVEs> 0.50).

Discriminant validity was established through the measure of the HTMT ratio, which was less than 0.85 among all constructs. PLS-SEM was applied to analyze the relationships among the constructions. The hypotheses were examined by calculating path coefficients (β), t-values, and p-values using 5000 subsampling bootstrap samples (Hair, 2019). This study also conducted a mediation analysis to examine the mediating effects of TR and SCA on the association between AI-SCI and ES. Mediation was analyzed using the approach described by Preacher and Hayes (Hayes & A, 2004), which estimates and tests confounded indirect effects via bootstrapping.

5. Analysis

5.1 Evaluation of Measurement Models

To assess a measurement model, convergent validity is evaluated through reliability and changes in average loadings. The model's fit is satisfactory. Apart from minor values, Table 2 and Figure 2 indicate that loading

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results in a 0.60 rise in recommendation value. The collective average variance of 0.50 was considered acceptable according to established learning theories and recommended studies (Sarstedt et al., 2014). Items with a loading effect below 0.50 have been excluded from the scale. The discriminant validity of the variable statements was assessed utilizing the HTMT technique. All principles were assessed to fulfill this condition once a limited number of elements were removed from the model, leading to the conclusion that they exhibited discriminant validity.

The current analysis exhibits no apparent issues with discriminant validity, as evidenced by the outcomes of both tests. Table 1 presents demographic information on respondents' gender, including frequency distributions, percentages, and cumulative percentages.

Table 1: Demographic Profile of selected variables

Demographic Variable	Category	Frequency	Percentage
Age	20–30 years	58	14.9%
	31–40 years	155	40.0%
	41–50 years	137	35.1%
	51+ years	39	10.0%
Gender	Male	272	70.0%
	Female	109	28.0%
	Other/Prefer not to say	8	2.0%
Education Level	Diploma	20	5.1%
	Bachelor’s Degree	156	40.0%
	Master’s Degree	213	54.9%
Job Position	Supply Chain Manager	116	30.0%
	Operations Manager	98	25.1%
	Sustainability Officer	78	20.0%
	IT/Technology Manager	59	15.1%
	Other (e.g., Logistics)	38	9.8%
Years of Experience	1–5 years	78	20.0%
	6–10 years	155	40.0%
	11–15 years	117	30.0%
	16+ years	39	10.0%

Table 1 presents the demographic profile of 389 respondents and the associated relevant characteristics of the study. Most respondents were males (70.0%), which corresponds to the prevailing situation in managerial positions in Bangladesh’s RMG sector, while 28.0% were females and 2.0% were other/preferred not to state. Most respondents were mid-career professionals. The age distribution was as follows: 40.0% in the 31–40 age group and 35.1% in the 41–50 age group, indicating that the respondents were skilled decision-makers in AI and sustainability. The educational composition was also 54.9% master’s degree holders and 40.0% bachelor’s degree holders, suggesting a high level of technical know-how. The job categories were Supply Chain Managers (30.0%), Operations Managers (25.1%), and Sustainability Officers (20.0%), representing respondents in positions that directly integrate AI into environmental practices. More than 70% had over 6 years’ experience, which qualified them to make judgments on supply chain agility and technology readiness. This demographic profile aligns with the study's focus on AI-powered sustainability in the RMG sector.

Table 2 presents reliability research, encompassing a comprehensive investigation of Cronbach's alpha coefficients. AI-Driven Supply Chain Integration (AI-SCI) demonstrates strong internal consistency (Cronbach’s $\alpha = 0.825$; composite reliability $rho\_c = 0.872$) and acceptable convergent validity (AVE = 0.581), though the outer loading of AI-SCI_5 (0.558) suggests potential refinement (Wang & He, 2021).

Environmental Sustainability (ES) shows robust reliability (α = 0.828; rho_c = 0.879) and convergent validity (AVE = 0.599), but ES_3's low loading (0.537) indicates measurement limitations, consistent with Martinez's (2023) critiques. Supply Chain Agility (SCA) meets reliability standards (α = 0.795; rho_c = 0.863) with strong convergent validity (AVE = 0.614), despite SCA_3's moderate loading (0.672), reflecting challenges in operationalizing agility (al, 2021). Technological Readiness (TR) emerges as the most robust construct (α = 0.858; rho_c = 0.905; AVE = 0.705), with high outer loadings (0.730–0.887), underscoring its pivotal mediating role in AI adoption (Pal, 2023). While all constructs meet reliability (α > 0.70) and convergent validity (AVE > 0.50) criteria (Larcker & D, 1981) The lower loadings for ES_3 and AI-SCI_5 highlight opportunities for scale improvement. These results validate the theoretical model, particularly the mediating roles of TR and SCA in linking AI-SCI to ES, offering empirical support for advancing sustainable practices in Bangladesh's RMG sector. Table 3 illustrates the association among the variables.

Table 3 assesses the convergent validity of the variables that have not been thoroughly investigated. The discriminant validity of the candidate variables, assessed using the Fornell-Larcker Criterion and HTMT ratio, is presented in Tables 3 and 4 (Hair, 2019; Henseler, 2015). It is generally accepted that the HTMT ratio threshold should ideally be below 0.85 in a conservative context, though values above 0.90 may also be deemed appropriate.

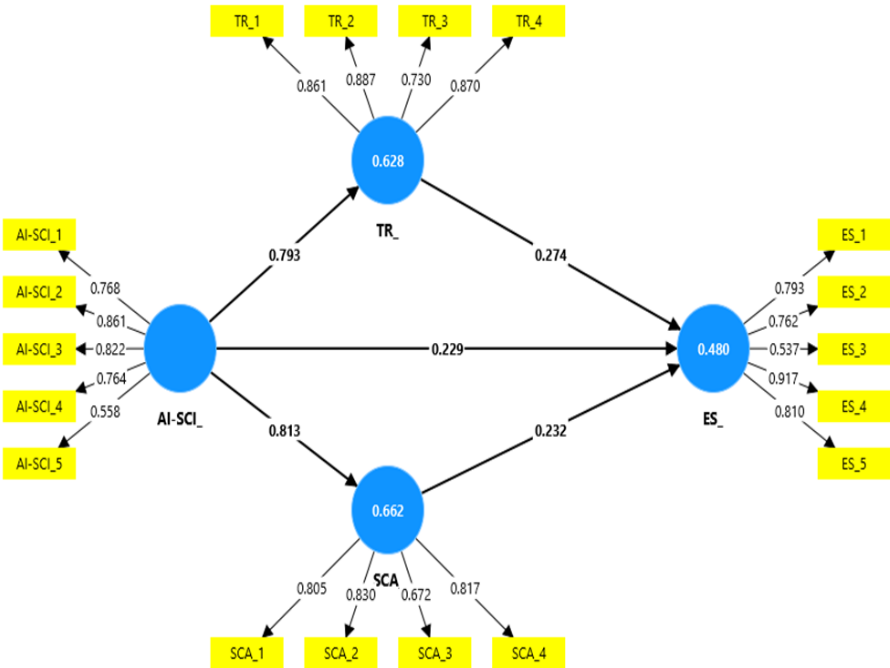

Figure 2: Measurement model of the selected variable

Table 2: Measurement model analysis (reliability/validity metrics)

Contract	Outer loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI-Driven Supply Chain Integration (Wang et al., 2023; Khan & Islam, 2023)		0.825	0.856	0.872	0.581
AI-SCI_1	0.768				
AI-SCI_2	0.861				
AI-SCI_3	0.822				
AI-SCI_4	0.764				
AI-SCI_5	0.558				

Environmental Sustainability (Ahsan & Rahman, 2023; Martinez, 2023)		0.828	0.878	0.879	0.599
ES_1	0.793				
ES_2	0.762				
ES_3	0.537				
ES_4	0.917				
ES_5	0.810				
Supply Chain Agility (Inman and Green 2021; Braunscheidel et al., 2009; Bak et al., 2020; Queiroz et al., 2021)		0.795	0.834	0.863	0.614
SCA_1	0.805				
SCA_2	0.830				
SCA_3	0.672				
SCA_4	0.817				
Technological Readiness (Singh & Patel, 2023; Khan & Rahman, 2023)		0.858	0.862	0.905	0.705
TR_1	0.861				
TR_2	0.887				
TR_3	0.730				
TR_4	0.870				

Table 3: Discriminant validity (HTMT approach).

Items	AI-SCI_	ES_	SCA_	TR_
AI-SCI_				
ES_	0.731			
SCA_	0.892	0.749		
TR_	0.863	0.752	1.024	

Table 4: Fornell-Larcker criterion

Items	AI-SCI_	ES_	SCA_	TR_
AI-SCI_	0.762			
ES_	0.634	0.774		
SCA_	0.813	0.661	0.783	
TR_	0.793	0.661	0.888	0.840

5.2. Analysis of Structural Models

Our study's latent variables and constructs are illustrated in Figure 3. The results of our analysis allow us to explain how each path in the model is found to have a positive, significant effect. It is appropriate and applicable to the aims and purposes of the study, given the unambiguous, definite pattern observed throughout the structural model, which is claimed to strengthen its validity.

Table 6 demonstrates that AI-Driven Supply Chain Integration has a significant positive correlation with Environmental Sustainability (beta = 0.229, t value = 3.716, p-value = 0.000). There is a positive correlation between AI-Driven Supply Chain Integration and Supply Chain Agility (beta = 0.813, t value = 72.416, p-value

= 0.000). Moreover, AI-Driven Supply Chain Integration has a positive relationship with Technological Readiness (beta = 0.793, t value = 56.279, p-value = 0.000). Also, Supply Chain Agility contributes to Environmental Sustainability significantly (beta = 0.232, t value = 2.559, p-value = 0.011). In addition, a positive correlation between Technological Readiness and Environmental Sustainability has been established (beta = 0.274, t value = 3.290, p-value = 0.001). The corroborating findings from several model fit indices enhance the model's resilience and make it more helpful in explaining the interwoven relationships required for the research.

Table 5 displays the R^2 values, the coefficient of determination, and the adjusted R^2 values for Environmental Sustainability (ES_), Supply Chain Agility (SCA_), and Technological Readiness (TR_) calculated with Smart PLS. These measures represent the degree of variability explained by the model. For ES_, R^2=0.480 (adjusted R^2=0.476) shows that almost one-half, or 48%, of the AI-driven supply chain integration within its SCA_ and TR_ mediators is overfed by AI sustainability rather than environmental sustainability.

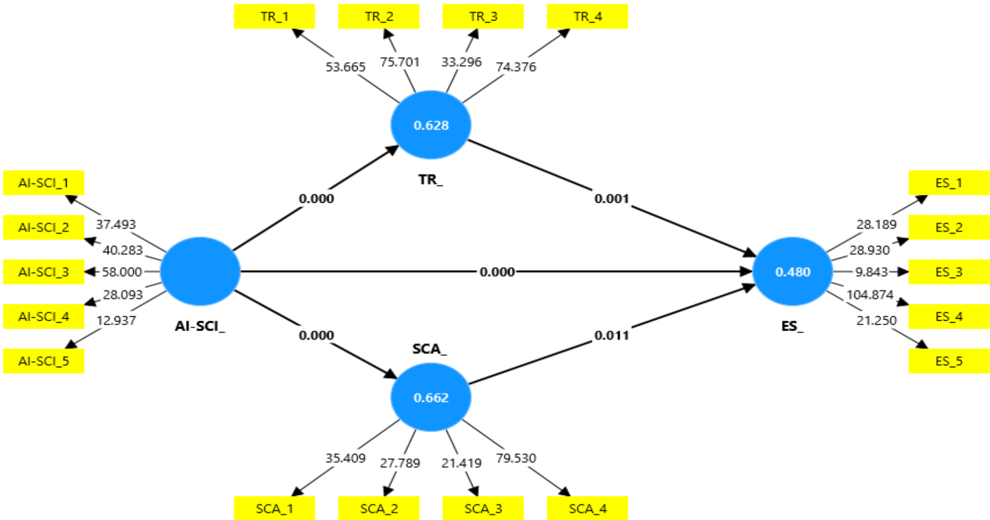

Figure 3: Structural model of selected variables

SCA_ exhibits the most significant explanatory value (R^2=0.662, adjusted R^2=0.661), meaning that 66% of the AI integration's impact on the sustainability of supply chain agility is observed. Likewise, TR_ (R^2=0.628, adjusted R^2=0.627) also contends that 63% of the variance in technological readiness is accounted for, which strengthens his mediating position. The pronounced high R^2 values for SCA_ and TR_ emphasize the strong relationship between these constructs and AI integration. In contrast, the relatively lower R^2 for ES_ suggests that other exogenous variables likely affect environmental sustainability more strongly within the RMG sector of Bangladesh, consistent with the study's mediation focus.

Table 5: R-squared and R-squared adjusted

Items	R-square	R-square adjusted
ES_	0.480	0.476
SCA_	0.662	0.661
TR_	0.628	0.627

Table 6: For direct effect

Path	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	2.5%	97.5%
AI-SCI_ -> ES_	0.229	0.062	3.716	0.000	0.107	0.346
AI-SCI_ -> SCA_	0.813	0.011	72.416	0.000	0.793	0.837
AI-SCI_ -> TR_	0.793	0.014	56.279	0.000	0.765	0.821
SCA_ -> ES_	0.232	0.091	2.559	0.011	0.053	0.411
TR_ -> ES_	0.274	0.083	3.290	0.001	0.112	0.437

Table 7 presents the f² (effect size) values to evaluate the effectiveness of the relationships among constructs in the PLS-SEM model. AI-driven Supply Chain Integration (AI-SCI) takes effect on Supply Chain Agility (SCA__) f^2 = 1.956 and technological readiness TR_ f^2 = 1.689, which means that AI-SCI influences these mediators strongly. Even so, AI-SCI has a negligible effect on Environmental Sustainability (ES_) directly f^2 = 0.032; implying that the AI-SCI impact on sustainability is mostly through … SCA_ and TR_. The small effect of ES_ on SCA_ f^2 = 0.019 and TR_ on other constructs f^2 = 0.028 denotes weaker direct relations between sustainability and agility and readiness.

These results. Manifestations underscore the picture that SCA_ and TR_ are the key mediating variables that consequently sustain the impact of AI-SCI to accomplish Environmental Sustainability in the RMG sector of Bangladesh, integrating other AI-SCI and SCA_ and TR_ and pointing toward the less obvious routes to sustainability, consistent with the emphasis of the study on mediation processes.

Table 7: F-Square: Predictive relevance (effect size)

Items	AI-SCI_	ES_	SCA_	TR_
AI-SCI_		0.032	1.956	1.689
ES_				
SCA_		0.019		
TR_		0.028		

Table 8: Q²predict, RMSE, and MAE

Items	**Q²predict**	**RMSE**	**MAE**
ES_	0.397	0.779	0.591
SCA_	0.655	0.591	0.460
TR_	0.624	0.617	0.509

The Q2 value is used to assess the predictive significance of the route model in Table 8. In terms of reflective measurement constructs, a Q2 value greater than zero indicates that the external constructs are predictive of the endogenous constructs (Geisser & S, 1974). The model demonstrates substantial predictive capability, as evidenced by moderate and high Q2 values (Table 8). The table shows the predictive performance results (Q² predict, RMSE, and MAE) related to the three constructs: Environmental Sustainability (ES), Supply Chain Agility (SCA), and Technological Readiness (TR), using Smart PLS within the scope of the study on AI-based supply chain integration in the RMG industry of Bangladesh. Es, SCA, and TR are 0.397, 0.655, and 0.624, respectively. All these values indicate that the constructions are predictive, but SCA is the strongest predictor. Based on the computed accuracy values, SCA (RMSE = 0.591, MAE = 0.460) performed the best, followed by TR (RMSE = 0.617, MAE = 0.509) and ES (RMSE = 0.779, MAE = 0.591).

These results indicate that Supply Chain Agility (SCA) and Technological Readiness (TR) serve as powerful mediators in the model of AI-enabled supply chain integration and Environmental Sustainability (ES), with TR weaker and less predictive, suggesting an opportunity for further development in the study's model.

5.3. Analysis of Mediation

This study explores the relationship between AI-Driven Supply Chain Integration and Environmental Sustainability by analyzing the mediating effects of Technological Readiness and Supply Chain Agility. The objective of the present study is to investigate the phenomenon under examination. A stringent methodology is employed to thoroughly investigate these mediating effects. Initially, as seen in Table 9, the calculation of individual indirect effects is conducted. The bootstrapping method is employed inside the Partial Least Squares (PLS) framework to rigorously assess the importance of these indirect effects. A comprehensive analysis elucidates the nature and extent of these interventions. Table 9 illustrates the correlation between AI-Driven Supply Chain Integration and Environmental Sustainability, even without the mediators Technological Readiness and Supply Chain Agility.

Table 9: For Specific Indirect Effect: Mediation

Path	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	2.5%	97.5%
AI-SCI_ -> TR_ -> ES_	0.217	0.066	3.264	0.001	0.089	0.350
AI-SCI_ -> SCA_ -> ES_	0.189	0.074	2.562	0.010	0.043	0.334

Nevertheless, the inclusion of the mediators—Technological Readiness and Supply Chain Agility—preserves the significance of this connection. This approach emphasizes the significance of several mediators, particularly Technological Readiness and Supply Chain Agility, where the relationship between AI-Driven Supply Chain Integration and Environmental Sustainability is positively mediated by Technological Readiness (beta = 0.217, t value = 3.264, p-value = 0.000) and Supply Chain Agility (beta = 0.189, t value = 2.562, p-value = 0.010). This finding provides valuable insights into the complex.

6. Discussion

The result of this study advances understanding of the impact of AI-powered supply chain integration on the environmental sustainability of the RMG sector in Bangladesh, focusing on technological readiness and supply chain agility. The findings help clarify how AI integration can aid in achieving sustainable goals while simultaneously underscoring the important mediating effects of TR and SCA. This discussion elaborated on the primary findings, their implications for the extant literature, and the drawbacks and suggestions for future studies.The study indicates a positive, statistically significant relationship between AI-Driven Supply Chain Integration and Environmental Sustainability ($\beta = 0.229$, $p < 0.000$). This underscores the importance of AI in supply chain management, as highlighted by previous studies (Islam & Z, 2023; Wang & He, 2021), which explains the role of AI in waste optimization and resource utilization. The advanced capabilities of AI technologies for real-time data processing, predictive analytics, and automation are crucial for sustainable supply chain practices, for example, by controlling inventory, preventing overstocking, and reducing waste (al, 2021).

Additionally, the study found that Supply Chain Agility ($\beta = 0.813$, $p < 0.00$) and Technological Readiness ($\beta = 0.793$, $p < 0.001$) mediate the relationship between AI-SCI and ES significantly. The most notable study on SCA suggests that AI integration tends to enhance supply chains' responsiveness to market changes, disruptions, and sustainable environmental challenges (Green & K, 2023; Suresh & N, 2009). For instance, AI can improve forecast accuracy, enabling firms to adjust production schedules to minimize excess inventory. This leads to less waste and less environmental degradation. By the same token, the mediating effect of TR illustrates how organizational readiness can be leveraged to adopt AI technologies for sustainable business practices (Pal, 2023; Rahman & A, 2023). Firms that are deemed to possess TR are more likely to use AI technologies, which boost supply chain performance and sustainability, as they become able to implement them efficiently. This aligns with the Technology-Organization-Environment (TOE) framework, which considers technological readiness as one of the determinants that can significantly impact the integration of innovations within organizations (Arpaci, 2012). The analysis also reveals the primary and secondary consequences of AI-SCI on ES. Even though the primary consequence is relatively small, the indirect consequences through SCA and TR are pretty significant, suggesting that AI-SCI's fundamental influence on ES is channeled through these constructions. This result corroborates the mediation analysis, which shows that SCA and TR, when included in the model, maintain the significance of the AI-SCI-ES relationship even in the presence of direct effects. This aligns with the theoretical framework of this study, which posits that AI-SCI impacts ES by increasing agility and technological readiness.

7. Practical Implications

Several implications relevant to managers and policymakers in the RMG industry emerge from the findings. First, there is a strong link between AI-SCI and SCA, suggesting that firms should allocate resources to AI investments to improve supply chain agility. One example of such tools is AI-enabled demand forecasting, inventory management, and logistics optimization, which can provide agility and sustainability improvements by reducing environmental impact and time-to-market (al, 2021; Bak, 2020). For instance, AI-driven demand forecasting can help companies adjust production to actual demand, thereby reducing overproduction and waste.

Second, the crucial TR on linking AI-SCI and ES suggests that organizations need to develop technical capability and an innovative culture. This includes staff training, IT infrastructure renewal, and partnering with technology vendors to facilitate AI adoption (Pal, 2023). Policy makers can facilitate these efforts by creating incentives for technological deployment and fostering collaboration between industry and academia. For instance, government grants or financial incentives might incentivize companies to invest in AI technologies that promote sustainability.

Finally, the study's emphasis on environmental sustainability underscores the need to incorporate sustainability objectives into AI-enabled supply chain strategies. Organizations should seek to integrate AI projects with broader environmental goals, including carbon emission reduction, waste minimization, and circular economy initiatives (Martinez, 2023; Rahman & F, 2023). For example, AI can optimize transportation routes, thereby reducing fuel consumption and greenhouse gas emissions.

8. Limitations and Future Research Directions

Although this study is very informative, it is not without limitations. First, the study is set within the context of Bangladesh's RMG industry, and results may not be generalizable across all industries or geographies. It might be interesting for future studies to investigate the model's generalizability across other industries (e.g., manufacturing, retail, health care). For instance, the potential of AI-SCI in the automotive or electronics field to improve environmental sustainability could be examined.

Second, because the study is based on cross-sectional data, it is impossible to ascertain whether any causal relationships exist . Longitudinal studies of these parameters might offer further insights into these dynamic interactions of AI-SCI, SCA, TR, and ES over time. One example is a long-term study examining the effects of AI adoption on supply chain agility and environmental sustainability over several years, thereby deepening understanding of these relationships. The measurement model included some items with lower outer loadings, which may reflect the nascent stage of AI-SCI research in the RMG sector. Future studies could refine these items or employ larger samples to bolster their psychometric properties.

Third, this research considers only two mediators—SCA and TR; however, other factors, such as organizational culture, leadership, and external environmental pressure, could also play a role in the AI-SCI and ES relationship. These other mediators can be tested in future research to explain sustainable supply chain practices. For example, it might be interesting to explore the role of leadership in fostering sustainability and innovation cultures.

9. Conclusion

This study highlights the importance of AI-based supply chain integration for sustainability in Bangladesh's Ready-Made Garment (RMG) industry. The results show that implementing AI solutions can improve both waste and resource management and foster better practices in these areas, thereby contributing to a more sustainable sector. Using AI, businesses can streamline not only their supply chains but also integrate their operations with larger environmental stewardship efforts. The focus of this research is on technological readiness and supply chain agility. They are the two essential keys that enable companies to deploy AI solutions in production and to quickly respond to rapidly changing market requirements and environmental regulations. When companies build their technical capacity and operational flexibility, they can create a synergistic relationship between economic and sustainability performance. The implications of this study are helpful for industry decision-makers and regulators. It underscores the speakers' belief that investment in AI, married with a company culture focused on sustainable practices, is essential. Such twin investments can help companies address environmental issues while also growing and competing globally. This study is limited to the RMG sector, but its findings apply more broadly, indicating that similar strategies would have broader applicability and similar benefits. Research Agenda for Future work should seek to extend these insights by studying the impact of AI-enabled supply chain integration on sustainability in other manufacturing sectors and other countries. Furthermore, a broader examination, for instance, of the interaction between organizational culture and leadership will be beneficial for gaining a complete understanding of the effective use of AI technologies to achieve sustainable outcomes. Finally, as with other emerging technologies, this study underscores the need to incorporate advanced technologies into supply chain practice to achieve a more sustainable future. By embracing AI-powered solutions and fostering an agile, tech-savvy culture, organizations can not only make a meaningful contribution to addressing environmental challenges but also differentiate themselves in a rapidly growing eco-friendly marketplace.

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Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent

Not applicable. This study uses publicly available, de-identified secondary data and does not involve human subjects.

participants or personal information.

Competing interests

The authors declare no competing interests.

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