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RESEARCH

Navigating Sustainability through Flexible Hyperautomation and Reverse Logistics in the B2B Sector: Implications for the Electronics Industry

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Abstract *The rising demand for sustainable practices in the electronics sector highlights the need for innovative alternatives. This study explores the impact of reverse logistics (RL) on sustainability performance (SP) among B2B electronics firms in Bangladesh, adopting a positivistic approach within the contingent resource-based view (C-RBV) framework. To test our hypotheses, we developed a single-informant questionnaire pre-tested with industry and academic experts. We distributed the questionnaire to 280 respondents via email, receiving 250 usable responses after follow-ups. Variance-based structural equation modelling was employed through WarpPLS 8.0, which utilises partial least squares algorithms. The findings indicate that reverse logistics initiatives within Bangladesh's electronics sector significantly influence sustainability efforts, especially regarding flexible hyperautomation technologies. This study enhances the C-RBV framework and provides actionable recommendations for the B2B electronics manufacturing industry in emerging economies. We acknowledge limitations and suggest future research opportunities, emphasising how reverse logistics can drive economic, environmental, and social benefits when aligned with advanced automation.*

Keywords B2B sector · Contingent resource-based view · Flexible hyperautomation technologies · Partial least squares · Reverse logistics · Sustainability

Introduction

The growing visibility of sustainability business practices is no longer merely an ethical imperative but is becoming a necessity for long-term competitiveness. Sustainability performance (SP) evaluates whether an organisation can realise economic, social, and ecological goals in harmony, and thus, companies must adopt responsible business practices in their core strategies (Ahsan, 2024). In supply chain management, sustainability is of greater priority because traditional supply chain structures tend to have to deal with inefficiency in data flow, and thus, poor decisions and wastage of materials (Hossain & Shohel Parvez, 2020; Kang et al., 2018). In supply chain management, sustainability is a fundamental concept in production management, encompassing economic, social, and environmental considerations (Emamisaleh & Rahmani, 2017; Faisal, 2010; Fernández-Miguel et al., 2025; Singh et al., 2024). The sustainability in supply chain management (SSCM) alleviates such shortcomings by establishing resilience, minimising ecological footprints, and building corporate reputation (Rahman et al., 2024; Wang & Dai, 2018). SSCM not only mitigates risks (Ayyildiz & Yildiz, 2023)

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but also enables companies to keep up with regulations and client needs, thus building their market position.

A critical component of SSCM is reverse logistics (RL), which involves the return, recovery, recycling, or disposal of used products in a way that maximises value recovery and minimises environmental harm (El Boudali et al., 2022). Supply chain performance optimisation requires an understanding of the interplay between operational performance and sustainable reverse logistics on the part of researchers and managers (Islam et al., 2025; Yang & Thoo, 2023). RL supports long-term sustainability, circular economy projects, and waste reduction by besting resource use. Apart from financial gains include cost reductions in transportation and inventory control (Can Saglam, 2023), RL improves business reputation and stakeholder confidence, hence strengthening social sustainability (Sarkis et al., 2010).

The B2B electronics market is becoming increasingly important in Bangladesh, serving as a key driver of industrial development and export diversification. With a predicted CAGR of 7.94% through 2028, the sector was valued at over USD 9.84 billion as of 2023 (Electronics ECommerce Market in Bangladesh—Data & Trends—ECDB). Exporting to more than 40 countries and lowering reliance on imported components, companies such as Walton have shown the strategic potential of reverse logistics and technology integration. Their investments in domestic R&D and vertical integration capture how Bangladeshi companies are using supply chain control and circular practices to propel sustainability and competitiveness. With industrial and B2B electronics currently making up more than thirty percent of the market, this industry provides a relevant environment for investigating how reverse logistics, automation, and sustainability results are related.

A considerable body of research has concentrated on the advantages of reinforcement learning for both the environment and the economy (Banihashemi et al., 2019; Dabees et al., 2023; Huang et al., 2015). Nonetheless, scant research examines how reverse logistics enhances sustainability performance across the three pillars: economic, environmental, and social (Banihashemi et al., 2019; Sajjanit & Rompho, 2019). This paper examines the significant gap by exploring how RL operations might foster a more equitable and effective approach to sustainability, taking into account its impact on all three pillars. Our initial research question *(RQ1) is: In what manner does the implementation of Reverse Logistics (RL) influence a company's comprehensive sustainability performance, taking into account environmental, social, and financial aspects?*

The transition to a green supply chain has rendered RL essential for sustainability transformation. Companies today acknowledge the potential of RL influenced by external factors such as governmental regulations, customer demands, and stakeholder pressures (Plaza-Úbeda et al., 2020), as well as internal drivers like cost savings and operational improvements. Recent advancements in digitisation and information and communication technology have facilitated the development of Reverse Logistics 4.0, enabling enhanced efficiency in sorting, maintenance, and recycling through digital methods (Sun et al., 2022). Autonomous robots and IoT technologies enhance reinforcement learning by streamlining processes and optimising return rates (Govindarajan & Ananthanpillai, 2021). Artificial intelligence and machine learning enhance logistics, improve transportation efficiency, and forecast component lifespan, allowing for the integration of sustainable practices in resource logistics (Chen et al., 2024; Freudenthaler et al., 2022). Recent research recognises the significance of technology-driven solutions in reverse logistics; however, the role of flexible hyperautomation in this context has not been thoroughly examined (Adler, 1988; Gebresenbet et al., 2018). Flexible automated systems let companies simplify their processes and change with the times to meet evolving market needs, therefore obtaining a major competitive advantage (Adler, 1988; Fernández-Miguel et al., 2024). Businesses can effectively change manufacturing processes, cut lead times, and cut costs by including cutting-edge robots, machine learning, and adaptive software solutions (Khang et al., 2025). This flexibility enhances operational efficiency and enables real-time adaptation to consumer preferences, ultimately leading to improved product quality and customer satisfaction (Kaswan et al., 2025; Sivakumar & Mahadevan, 2024). We introduce the idea of adaptable hyperautomation in view of the changing scene of technology and corporate operations. Based on existing flexible automation systems, this creative solution aims to solve problems presented by ever-changing surroundings. Flexible hyperautomation not only simplifies procedures but also helps companies to adapt to fast changes, therefore allowing them to effectively respond to changing market needs, improve operational resilience, and best allocate resources (Haleem et al., 2021). Flexible hyperautomation enables companies to reach more agility and responsiveness in their operations by including modern technologies including artificial intelligence, machine learning, and robotic process automation (Balasubramaniam et al., 2024).

By combining technologies including Cyber-Physical Systems, IoT, cloud platforms, artificial intelligence, and robotic process automation, Industry 4.0 (I4.0) has revolutionised supply chain processes and so increased automation and connectivity (Dalenogare et al., 2018; Galvani et al., 2025; Park, 2018). In several industry verticals, HA supports operational efficiencies, improved decisions, and business process automation (Ghobakhloo et al., 2023). HA maximises resource tracking, minimises waste, and enhances sustainability results in supply chains (Chen et al., 2023). Moreover, autonomous technologies like self-driving logistics cars maximise traffic flow and solve environmental problems (Bagloee et al., 2016). Though HA has great promise, its theoretical underdevelopment in RL is underdeveloped (Niedzielski et al., 2024). Although past research highlight HA's advantages (Madakam et al., 2022; Silva et al., 2025), empirical evidence of its influence on RL and sustainability performance (SP) is scarce. The lack of data restricts the whole implementation of HA to maximise goals for sustainability and RL. Dealing with this urgent requirement, this study probes unexplored ground by raising the RQ2 research question: *In terms of their influence on optimising reverse logistics (RL) procedures and thereby enhancing organisational sustainability performance (SP), how well can flexible hyperautomation (HA) technologies be measured?*

Two objectives have been set to handle the above described research questions. These follow:

Obj1: To examine the influence of reverse logistics practices on the sustainability performance of organisations.

Obj2: To examine the impact of flexible hyper-automation technologies on the relationship between sustainability performance and reverse logistics.

This research draws on the contingent resource-based view (C-RBV) theory to emphasise the market dynamics, regulatory requirements, and technological advancements affect the value of organisational resources (Aragón-Correa & Sharma, 2003; Brandon-Jones et al., 2014; Tiwari et al., 2024). Although it is subject to market needs, regulatory requirements, and technical advancements, the synergy between flexible hyperautomation (HA) and reverse logistics (RL) maximises resource utilisation and reduces environmental footprints. Bangladesh's electronics sector finds a suitable environment in which supply chains and legislative changes define sustainability. This paper examines how companies intentionally utilise RL and HA to enhance sustainability performance (SP) in today's rapidly evolving corporate environment. PLS-SEM analysis of valid data from 250 Bangladeshi electronics companies helps to confirm this structure empirically. The results are beneficial in several important areas. First, by assessing how businesses rearrange RL and HA to match external contingencies, they expand the use of C-RBV to sustainability research and thus contribute creatively to logistics, automation, and sustainability. Second, they specify that companies must reorganise RL and HA to adapt to external pressures and maintain long-term competitiveness in Bangladesh's electronics sector. This research adopts a systematic approach to explore how flexibility, automation, and resource-based thinking can be integrated into a single model that addresses the challenges faced in today's emerging markets. It provides valuable insights to the fields of sustainability and logistics, especially for companies undergoing digital transformations while managing sustainability demands. The study shows how adopting flexible management and flexible systems can significantly boost the strategic benefits of reverse logistics.

In the following order, the sections of the paper are organised as follows: Sect. "Review of Literature" provides a review of the literature and the theoretical background; Sect. "Research Framework and Hypothesis Development" presents the research model and hypotheses; Sects. "Research Design" and "Data Analysis and Results" describe the research design and data analysis; and the final sections discuss the implications of the research for management and theory, limitations, and potential directions for future research.

Review of Literature

This section examines the fundamental theoretical and practical foundations that underpin the interaction between reverse logistics (RL), flexible hyperautomation (HA), and sustainability performance (SP), particularly within B2B electronics companies. It builds on significant findings from B2B marketing research, highlighting how sustainability goals, digital collaboration between firms, and innovation-led supply chain strategies shape this relationship (Esangbedo et al., 2024; Ravat et al., 2024).

Underpinning Theories

Using conceptual approaches, management scenarios may be modelled and suggested techniques for enhancing the management of solid wastes and the welfare of informal waste pickers can be proposed, therefore enabling the sustainable use of shared resources (Abdel-Basset et al., 2021). The proposed theory must align with Dubin's five fundamental criteria: enhanced comprehension, engagement, variables and their interrelations, exclusion of composite variables, and incorporation of boundary-related parameters (Meredith, 1993). This paper assesses the contingent resource-based view (C-RBV) and its applications in the field, aiming to establish a theoretical framework that aligns with the demands of customers and stakeholders in B2B contexts.

Contingent Resource-Based View (C-RBV)

The contingent resource-based view (C-RBV) builds upon the resource-based view (RBV) by highlighting that the effectiveness of a firm's resources is dependent on external factors, including regulatory frameworks, technological advancements, market dynamics, and stakeholder pressures (Aragón-Correa & Sharma, 2003; Brandon-Jones et al., 2014). In contrast to the RBV, which posits that firms attain competitive advantage solely through the possession of internal resources, the C-RBV emphasises the necessity for organisations to consistently adjust their resource configurations in response to changing external conditions to maintain long-term performance (Shahzad et al., 2024). In B2B, strategic alignment of internal organisational resources, such as reverse logistics (RL) and flexible hyperautomation (HA), with external environmental variables is crucial. This alignment allows enterprises to rapidly alter their operational capacities to meet industrial customer demands and competitive market challenges. Material recovery, product returns, and recycling are strategic assets, but government laws, supply chain complexity, and changing environmental policies affect their effectiveness (Govindan & Soleimani, 2017). Companies who deliberately match their RL systems with these outside factors are more likely to be long-term sustainable (Acquaye et al., 2017). HA technologies like AI, robotics, and the IoT automate real-time tracking, predictive analytics, and waste reduction to improve RL efficiency (Huang et al., 2024). However, technological infrastructure, stakeholder expectations, and industry-wide digitalisation trends affect their sustainability (Borland et al., 2019). In Bangladesh's electronics sector, where sustainability regulations are continually evolving, firms that adapt their HA-driven RL strategies to government incentives and industry constraints are more likely to achieve better SP (Leng et al., 2025).

The C-RBV viewpoint incorporates stakeholder pressure as a significant external factor affecting sustainability performance. Companies facing stringent environmental restrictions and consumer expectations for ethical supply chains are more inclined to utilise RL and HA for sustainability improvements compared to those in less regulated contexts (Shahzad et al., 2024). Furthermore, research has shown that the incorporation of green credit policies and environmental certifications can improve the efficacy of RL and HA, underscoring the necessity for firms to strategically modify their sustainability initiatives in response to external conditions (Aladaileh et al., 2024).

C-RBV is especially pertinent to B2B marketing research since it offers understanding of how businesses use strategic capabilities for internal efficiency and to improve interactions between different departments and co-create customer value (Malik et al., 2018). This methodology offers a more dynamic and accurate perspective on sustainability performance in the Bangladeshi electronics sector. It provides both theoretical and managerial perspectives on how companies might organise their reverse logistics and automation strategies in reaction to evolving external demands.

Flexible Hyperautomation (HA) Technologies

Flexible hyperautomation signifies a sophisticated advancement in automation, integrating artificial intelligence (AI), machine learning (ML), internet of things (IoT), robotic process automation (RPA), and business process monitoring (BPM). In B2B markets, HA technologies improve operational efficiencies and enhance interorganisational relationships by fostering greater responsiveness, transparency, and customisation capabilities. Currently, flexible hyperautomation combines these technologies to facilitate proactive and continuous optimisation of business processes, significantly enhancing efficiency, accuracy, and cost-effectiveness (Zhao et al., 2022). Flexible hyperautomation in reverse logistics has shown considerable potential by automating essential processes such as product sorting, refurbishment, recycling, and disposal. AI-powered systems efficiently classify returned items such as electronics, furniture, and clothing, significantly decreasing manual sorting time, enhancing accuracy, and optimising returns management. Research indicates that as much as 70% of reinforcement learning tasks may be automated via artificial intelligence, leading to significant efficiency improvements (Agrawal et al., 2020). Flexible hyperautomation enhances sustainability through the promotion of data-driven decision-making, resource optimisation, and agile responses to environmental challenges (Haleem et al., 2021). The integration of these technologies allows firms to establish closed-loop supply chains and promote circular economy principles, thus enhancing sustainability outcomes across economic, environmental, and social dimensions (Lin & Chu, 2024; Rehman Khan et al., 2022).

Flexible hyperautomation also uses IoT sensors and ML algorithms to forecast logistics performance, optimise transportation routes, control inventories effectively, and extend product lifecycles through focused maintenance strategies (Hossain et al., 2025; Murat & Hamada, 2023). Driven by Internet of Things (IoT), insights to maximise transportation routes, decrease energy usage in storage facilities, and extend product lifecycles through focused repairs and refurbishing (Bashir et al., 2023). RPA, which automates repetitive processes including administrative bookkeeping and inventory management, hence enhancing production and accuracy in back-office operations (Haleem et al., 2021; Ylä-Kujala et al., 2023). Particularly in small and medium-sized businesses, BPM concepts also help companies in structuring, standardising, and constantly upgrading logistics operations, hence reinforcing sustainability and competitiveness (Moreira & Dallavalle, 2024).

Thus, HA promotes operational sustainability and functions as a strategic marketing resource, enhancing collaboration and value-driven connections with B2B clients. Table 1 presents a summary of various technologies as delineated in current academic literature.

Reverse Logistics (RL)

Reverse logistics (RL) pertains to the reverse movement of products from consumers back to suppliers (Huscroft et al., 2013). In B2B relationships, RL functions as both a logistical element and a strategic component that facilitates value co-creation, inter-firm trust, and customer loyalty (Kalwey et al., 2025; Ravi, 2014). Reverse logistics activities concentrate on the retrieval of products from customers to recover value via remanufacturing, refurbishing, recycling, or environmentally responsible disposal. Conversely, forward logistics pertains to the distribution of products to consumers (Agrawal et al., 2015).

Effectively implemented RL programmes enhance sustainable development and provide a competitive edge by boosting profitability, reducing operational costs, and elevating customer satisfaction (Banihashemi et al., 2019; Stock et al., 2006). Reverse logistics provides significant benefits by reclaiming value from returned or used products, extending product lifespan, and reducing the necessity for new raw material acquisitions (Ali et al., 2018; Janse et al., 2010; Shamsuddoha et al., 2022). This conserves resources and minimises the expenditure of manpower and time. Additionally, RL can facilitate product enhancements and innovation through the integration of customer feedback and the analysis of return reasons (Aitken & Harrison, 2013). Consequently, RL extends beyond fundamental operational roles, becoming an essential relational and marketing asset for organisations seeking to maintain competitive advantage via distinct value propositions in B2B markets.

Table 1 HA technologies

HA Technologies	Sources
Machine Learning and (ML)	Haleem et al. (2021), Madakam et al. (2022)
Artificial Intelligence (AI)	Haleem et al. (2021), Madakam et al. (2022)
Internet-of-Things (IoT)	Haleem et al. (2021), Souri et al. (2024)
Business Process Monitoring (BPM)	Lasso et al. (2020), Zhao et al. (2022), Szelągowski et al. (2022)
Robotic Process Automation (RPA)	Haleem et al. (2021), Madakam et al. (2022), Kavitha (2023)

Product disposition is a critical component of reverse logistics, involving the identification of the optimal end-of-life solution for returned products (Hazen et al., 2012). Common disposition strategies encompass reuse, repair, remanufacturing, recycling, and, when required, disposal (Fleischmann et al., 1997; Pokharel & Mutha, 2009). A separate study looked at how alternative RL disposal methods affected operational and financial performance (Skinner et al., 2008). Table 2 lists the precise reverse logistics methods that were considered in this study.

Sustainability Performance (SP)

Adoption and implementation of successful management methods meant to support sustainable development across all spheres of an organisation's operations is known as sustainability performance (SP) (Kuei & Lu, 2013; Pandya et al., 2024). Businesses negotiate challenging stakeholder expectations in manufacturing and supply chain management including those from regulatory authorities, suppliers, consumers, and competitors, therefore requiring a multifarious approach (Agrawal & Singh, 2019; Ahmed et al., 2020). Dealing with these expectations calls for consideration of sustainability across three linked dimensions: economic, environmental, and social, together referred to as the triple bottom line (TBL) (Elkington, 1998; Rauniar & Cao, 2025). Within the framework of B2B marketing, sustainability goes beyond internal efficiency or legal compliance to reflect a strategic strategy for generating and presenting long-term value in buyer–supplier partnerships (Foerstl et al., 2015).

Organisations are increasingly refocusing their strategies on sustainability-oriented objectives as sustainable practices are seen as a critical factor in achieving long-term competitive advantage (Banihashemi et al., 2019). Research by Ye et al. (2013) shown that reverse logistics enhances both environmental and economic performance among Chinese manufacturers; analogous results were found in a later study on Taiwanese enterprises, further validating the advantageous effects of reverse logistics in these domains. Despite being less examined, RL possesses potential for advancing social sustainability by ameliorating labour circumstances, bolstering business reputation, and augmenting customer pleasure (Sarkis et al., 2010). Strategic decisions regarding reuse, recycling, and disposal are crucial in influencing Triple Bottom Line outcomes, highlighting their significance in sustainable supply chain management (Jindal & Sangwan, 2013).

Moreover, including cutting-edge technologies like flexible hyper-automation into eco-friendly supply chains

Table 2 RL strategies

RL strategies	RL disposition option	Sources
Reuse	It requires only minor inspection, cleaning, and maintenance without disassembly, reprocessing, and reassembly activities	Fleischmann et al. (2000), Matsumoto (2010)
Repair	It denotes the process of repairing and servicing products and returning them to customers	Fleischmann et al. (2000)
Remanufacturing	It involves recovering materials from high-value products while preserving the identity and functionality of the original materials	Blackburn et al. (2004), Eltayeb et al. (2011)
Recycling	It is related to material recovery from products with low value and involves processes to extract reusable materials from used products. The identity and functionality of the original product materials are lost	Blackburn et al. (2004), Khor et al. (2016)
Disposal	This option is selected when products cannot be sold or reused, and other disposal methods are not viable	Khor et al. (2016)

enables B2B companies to reach better operational transparency, resource economy, and predictive agility. These features encourage relational quality and long-term strategic alliances, therefore improving the perceived value given to clients and partners. Therefore, sustainability performance in the B2B sector is closely linked with companies' capacity to strategically use innovations in logistics and automation, so generating value not only through operational excellence but also by improved inter-organisational relationships and shared sustainability commitments (Ghazimatin et al., 2023).

The three pillars of sustainability, environmental, social, and economic, are intricately interconnected, often existing in a harmonious balance but sometimes facing potential conflicts. This is where the concept of holistic sustainability comes into play. It emphasises the need to view these pillars not as isolated components but as interdependent factors driving long-term success (Harik et al., 2015) Each pillar is necessary but not sufficient on its own; organisations must address all three to truly advance sustainability (Braccini & Margherita, 2018). This study considers all three dimensions of TBL, viewed from a B2B marketing lens, to measure sustainability performance. The conceptual model underpinning this research is depicted in Fig. 1.

Research Framework and Hypothesis Development

This section develops the research model, drawing insights from the contingent resource-based view (C-RBV). Subsequently, a set of hypotheses is formulated to establish connections among flexible hyperautomation (HA) technologies, reverse logistics (RL), and sustainable performance (SP) constructs. These hypotheses investigate the moderating impact of flexible hyperautomation technologies on enhancing the effect of reverse logistics methods on sustainable performance and reveal the direct relationships between reverse logistics and sustainable performance constructs.

Reverse Logistics (RL) and Sustainability Performance (SP)

RL enhances organisational performance and customer satisfaction, resulting in a triple bottom line (Agrawal et al., 2016). The concept is closely linked to the circular economy, as it aids in the restoration and circularity of materials vital for sustainable development (Julianelli et al., 2020). Companies can reach economic sustainability and help the triple bottom line by evaluating and suggesting sustainable RL methods (Mishra et al., 2022). By lowering procurement, inventory, distribution, and transportation (Dabees et al., 2024), effective and sustainable RL practices enable companies to get a competitive edge. To improve economic and environmental outcomes while reducing ecological hazards, green supply chain management (GSCM) uses eco-friendly approaches like RL (Pai et al., 2025). RL's use of recycled materials and enhanced waste management practices can help reduce the negative effects of the building sector on the environment (Pimentel et al., 2022). With regard to social sustainability, RL shows a favourable correlation (Younis et al., 2016). RL helps to decrease waste and simplify manufacturing processes, both of which could improve the standing of a company. Adopting sustainable solutions helps companies to stay flexible and creative, therefore enabling them to satisfy the needs of next generations (Alnoor et al., 2019). Using real-world business cases to underline the possible social advantages, Sarkis et al. (2010) highlighted RL for social sustainability. Although certain studies incorporate social criteria in evaluating RL performance, the majority emphasise economic and environmental outcomes, frequently neglecting the social aspect (Ngadiman et al., 2022). The effectiveness of RL disposition decisions is

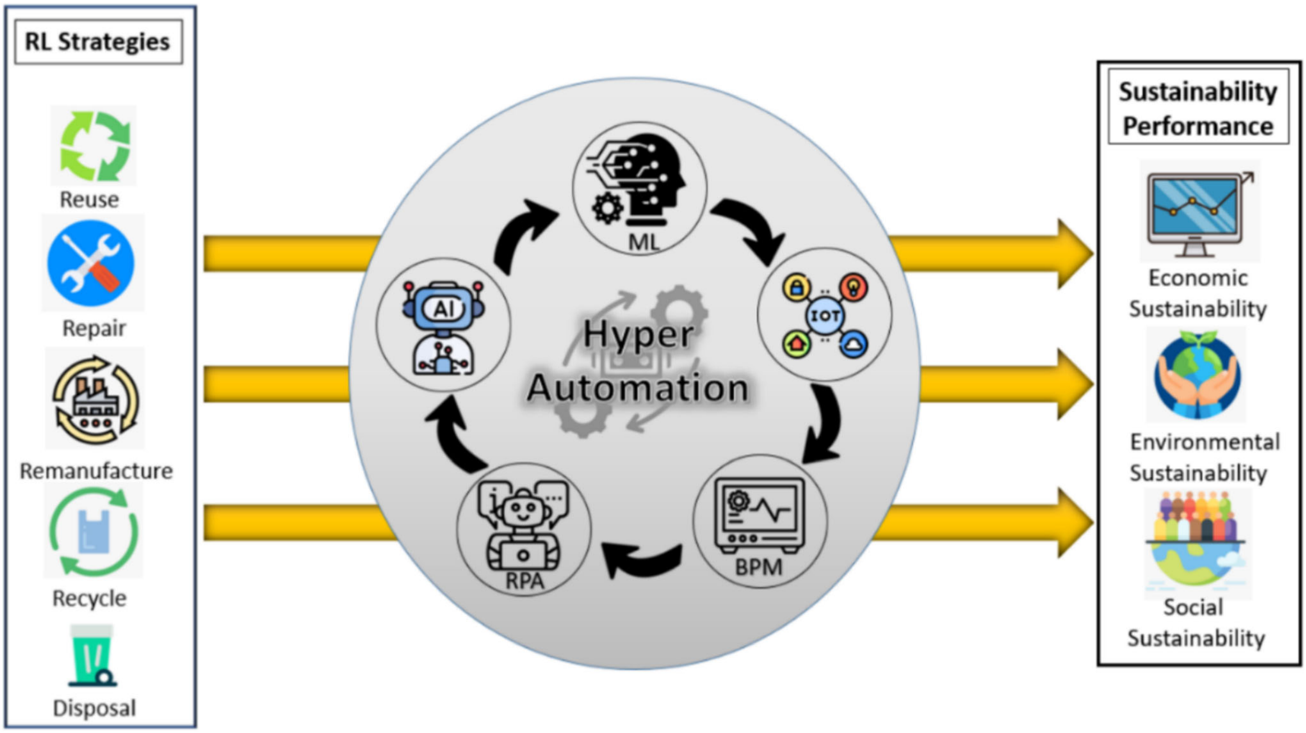

Fig. 1 Conceptual model of HA implementation

positively correlated with triple bottom line performance, which includes economic, environmental, and social dimensions (Agrawal & Singh, 2019). In light of what is known about the connection between RL and SP in the literature, we thus put out proposed hypothesis to test:

H1a RL has a positive and significant impact on economic sustainability (EcS).

H1b RL has a positive and significant impact on environmental sustainability (EnS).

H1c RL has a positive and significant impact on social sustainability (ScS).

Integration between Flexible Hyper-automation (HA) Technologies, Reverse Logistics (RL), and Sustainability Performance (SP)

Flexible hyperautomation is a new topic that combines advanced technologies such as AI, machine learning, and process automation to automate complex business processes (Zhao et al., 2022). The rise of digital technologies and the adoption of e-commerce have shifted supply chain operations from traditional flow management to mass customisation. To keep up with the growing digitalisation of business, executives need to think seriously about flexible hyper-automation (George et al., 2023). A new level of automation that draws on prior industrial revolutions, flexible hyper-automation is emerging from the progress of Industry 4.0 (Niedzielski et al., 2024). By means of technological innovation and digital technologies, Industry 4.0 (I4.0) has notably revolutionised logistics and spawned the idea of Logistics 4.0, which seeks to make supply chains more efficient, flexible, and linked (Dallasega et al., 2022; Hrouga & Sbihi, 2023). The application of I4.0 technologies in the field of logistics has been investigated and it has been discovered that technologies including the internet of things (IoT), big data, and cloud computing are very applicable in logistics centres (Miškić et al., 2023). Moreover, the incorporation of flexible hyperautomation and Industry 4.0 technologies (Haleem et al., 2021) in reverse logistics processes is essential for the effective functioning of contemporary supply chains.

Companies that want to cut costs need to keep an eye on every process and function to make sure they stay profitable and competitive. A good logistics system makes a business run better generally. Self-driving cars in logistics networks make delivery more flexible and improve the efficiency of transportation (Deineko et al., 2022; Nand et al., 2023). Adding technology and electricity to the freight sector can also make it more profitable and lower costs, which makes sustainable transportation more likely (Ghandriz et al., 2020). With the help of data, intelligent automation solutions can solve the problems in internal supply chains and make them work better by being faster, more flexible, more efficient, and of higher quality.

A comprehensive scientometric review of reverse logistics and sustainability performance has highlighted key research areas and emerging trends, including evaluating the impact of reverse logistics on various sustainability dimensions and examining the role of game theory, artificial intelligence, and the circular economy (Shahidzadeh & Shokouhyar, 2024; Yang & Thoo, 2023). However, the theoretical foundations for flexible hyperautomation are still developing, and its conceptualisation and practical implementation require further exploration (Niedzielski et al., 2024). To the authors' knowledge, no study has investigated the integration between HA technologies, RL, and SP. Based on the available literature on HA, RL, and SP, this study supports the premise that with the presence of existing HA technologies, RL may offer tremendous potential for achieving SP. So, the second hypothesis of this study is stated as follows:

H2a HA has a positive and significant impact on RL and EcS.

H2b HA has a positive and significant impact on RL and EnS.

H2c HA has a positive and significant impact on RL and ScS.

Control Variables

We included two more contextual factors as control variables to account for the differences in various electronics companies. First of all, a main predictor of variance is considered to be firm size (FS). Shah and Ward (2007) underline how important company size is for developing an always improving culture. Companies in this research are categorised by Tortorella et al. (2019) as either those with less than 500 or those with more than 500 employees. Although bigger companies could have resource advantages, they nevertheless have to actively grow and modify their capacity to get outstanding results on sustainability. Second, it is well known that the wider acceptance of flexible hyperautomation technologies depends mostly on technological intensity (TI). Regardless of their particular industry, companies with higher degrees of technological intensity are usually more suited for innovation (Zawislak et al., 2018). With regard to this criterion, we took into account three groups: high, medium, and low intensity, corresponding to the degree of technological integration of the company. Dziurski (2022) research on coopetition tactics in high-, medium-, and low-tech sectors reveals that corporate groups in all three types of sectors apply coopetition marked by great cooperation and low competitiveness. Figure 2 here shows the study model of this work.

Research Design

This work used two successive steps of a two-stage mixed approach (Hwami & Jacobs, 2023; Schilke, 2014). The data collected from both phases were evaluated using both quantitative and qualitative techniques (Soundy et al., 2021). Exploratory interviews were carried out in the first phase to better grasp industry techniques for enhancing reverse logistics operations and methods for attaining sustainable success. The second step involved utilising a survey form to conduct a cross-sectional study. The independent and dependent structures as well as the suggested hypotheses were examined using the survey results.

Key Informant Validation and Sampling Strategy

This study followed a two-stage methodology for gathering and validating important informant data on reverse logistics (RL), flexible hyperautomation (HA), and sustainability performance (SP) within Bangladesh's B2B electronics sector in order to guarantee methodological rigour and contextual relevance.

Phase 1: Expert Interviews and Instrument Development

Thirteen semi-structured interviews with domain experts (Appendix A) helped to validate the conceptual framework and hone the survey instrument. This group comprised eight senior electronics specialists and five university academics knowledgeable in reverse logistics, automation, and sustainability. With between 9 and 18 years of pertinent experience, these experts occupied important positions including General Manager, Chief Operations Officer, and Supply Chain Manager. Two phases of the interviews provided insightful analysis of the newest trends in reverse logistics (RL) and human automation (HA) technologies and how they affect sustainability results.

A formal survey was shaped in great part by the qualitative comments from these sessions. Four primary elements comprised the finished questionnaire: demographic information and control factors; the degree of HA adoption; application of RL techniques; and impressions of sustainability performance. Participants assessed each statement using a 7-point Likert scale, with 1 signifying strong disagreement and 7 denoting strong agreement. Prior to formal distribution, the questionnaire was evaluated by both academics and industry practitioners to ascertain clarity and relevance.

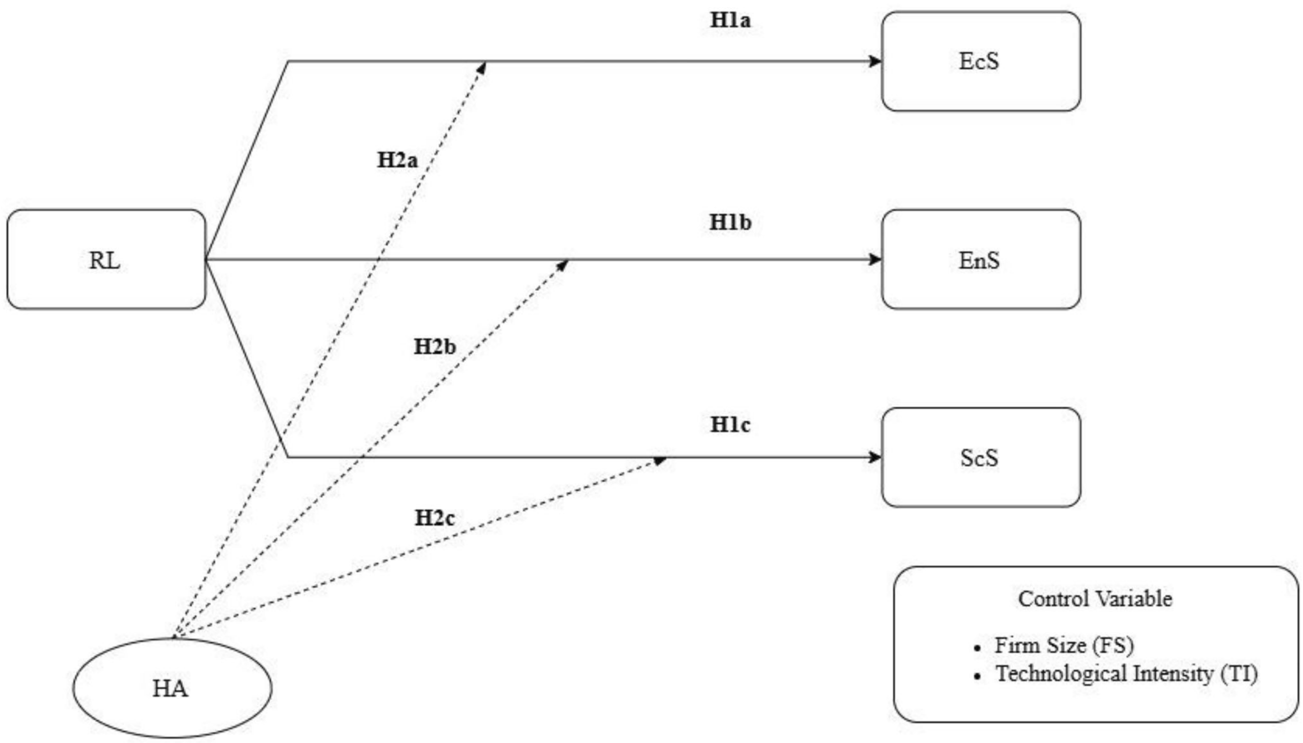

Fig. 2 Research model

Phase 2: Survey Implementation and Sampling

In the second phase, the finalised survey was distributed to a sample of 280 B2B electronics firms, identified through Dun and Bradstreet databases and public company listings. Contact details for 180 electronics firms were obtained from Dun & Bradstreet, a widely recognised commercial database (Powell et al., 2011). A screening question was included to confirm that only individuals directly involved in RL or HA initiatives would complete the survey. Data were collected electronically from April to August 2023, resulting in 250 valid responses a response rate of 70%, which is considered robust for organisational studies.

Demographic and role-specific information was gathered to establish respondent expertise and ensure data quality (see Table 3). Senior managers comprised 63.6% of the sample, with mid-level and general managers comprising 15.2% and 6.4%, respectively. A significant majority (85.31%) had over a decade of experience, and 68.43% reported more than 20 years in the field, indicating a high level of professional insight. The sample included 192 male and 58 female participants.

Organisational characteristics were also considered. Of the participating firms, 35.16% were large enterprises (500 + employees), while 64.84% were SMEs. Regarding technological orientation, 30.75% belonged to high or medium–high tech segments, whereas 69.25% were from low or medium–low tech industries. All companies operated within the B2B electronics manufacturing or component recovery sectors, aligning them well with the study's focus on RL and HA adoption.

This two-phase methodological design, combining expert input with comprehensive survey implementation, ensures that the data are empirically grounded and reflect informed perspectives from experienced decision-makers in the electronics sector.

Nonresponse Bias Test

Nonresponse bias can be a concern in survey-based studies, as differences between respondents and nonrespondents may affect the validity of results (Lavrakas, 2008). While some level of nonresponse bias is unavoidable, its impact depends on the proportion of nonrespondents and variations in response rates within the sampled population. Two analytical methods were applied to evaluate this bias. Initially, adjusting for nonresponse bias involved comparing early and late replies (Armstrong & Overton, 1977). Responses were sorted according to the weekdays received and divided into equal-sized groups. A t-test at the 95% confidence level revealed no significant differences between these groups, indicating response timing did not bias the results. We next asked 25 randomly chosen nonrespondents to respond one sample question from each of

Table 3 Sampling profile

Criteria	Respondents categories	Respondents (In percentage)
Position in the Company	General Manager	6.40
	Senior Manager	63.60
	Manager	15.20
	Junior Manager	14.80
Experience (Years)	Above 20	68.43
	10–19	16.88
	Below 10	14.69
Firm Size	Large (More than 500 employees)	35.16
	Small and Medium (Less than 500 employees)	64.84
Technological Industry	High and medium–high	30.75
	Low and medium–low	69.25

the theoretical framework sections (Iqbal et al., 2021). A follow-up t-test conducted at a 95% confidence level revealed no significant differences between respondents and nonrespondents. Levene's variance test was conducted to evaluate homogeneity, revealing no statistically significant differences in the results. Consequently, the analyses indicate that nonresponse bias is not expected to be a significant concern in this study.

Common Method Bias

This study's reliance on a single-respondent survey introduces a potential risk of common method bias (CMB) (Podsakoff & Organ, 1986). To address this issue, various procedural measures were implemented (MacKenzie et al., 2012).

Qualitative conversations were used to check how clear the questions were, which led to the necessary changes. To make items clearer, questions were made easier to understand and didn't use double-barreled wording (Krosnick, 1991), which can lead to CMB by making people focus different parts of a question (Podsakoff et al., 2003). Furthermore, removed in favour of evaluating only current conditions to improve response accuracy were retrospective enquiries, which can cause cognitive strain. Beyond these technical steps, common method variance (CMV) was found using statistical tests. Applying Harman's single-factor test, a single component explained less than 25% of the entire variance, far below the 50% criterion, thereby suggesting that CMB was not a major concern (Kock, 2021). Because Harman's test has some flaws (Hulland et al., 2018; Podsakoff et al., 2003), the correlation marker method was used to look at CMB (Lindell & Whitney, 2001). This method looks at how an unrelated variable affects correlations that are changed by CMB. It found almost no difference between adjusted and unadjusted correlations, which confirmed that CMV effects were not important (Williams et al., 2010). These checks on the methods and statistics show that common method bias does not pose a major threat to the truth of the study's results.

Data Analysis and Results

Many latent factors can be confirmed using numerous statistical techniques. Structural equation modelling (SEM), a statistical technique, allows researchers to create and test models displaying the relationships between observed and concealed elements (Cao, 2023). Since SEM analysis is a complex and advanced statistical method that allows the investigation of correlations between measured and latent variables, most academics want SEM analysis (Gupta & Shankar, 2022). Combining elements of factor analysis and regression, SEM lets researchers simultaneously investigate correlations between variables (Ghaithan et al., 2021; Iqbal et al., 2021). With partial least squares SEM (PLS-SEM) and covariance-based SEM (CB-SEM), the most widely used approaches among the several techniques available for SEM (Rigdon et al., 2017). PLS maximises the correlation between predictor and predicted variables and catches their most variance. This work applied PLS-SEM data analysis method among the other SEM techniques using WarpPLS, a commonly used statistical tool in structural equation modelling. Several main benefits guided the decision on this approach (Dubey et al., 2018; Gupta et al., 2019; Talapatra et al., 2020). Initially, PLS-SEM adeptly handles numerous variables at once, rendering it particularly appropriate for intricate models. Secondly, it demonstrates exceptional capability in examining and confirming connections within complex structures. Third, the approach effectively handles partial and non-normally distributed data, guaranteeing resilience across a variety of datasets. Ultimately, PLS-SEM proves to be especially advantageous in situations where the emphasis is on achieving high predictive accuracy.

WarpPLS 8.0 was utilised to overcome the limitations linked to conventional PLS-SEM, which may exhibit bias when depending on composite-based instead of factor-based estimations (Kock, 2023). Using WarpPLS 8.0, researchers hope to close the difference between factor-based and composite-based SEM methods (Sharma & Aggarwal, 2019).

Measures

The conceptual model we proposed employed a multi-item variable assessment aimed at enhancing accuracy, ensuring greater diversity among survey participants, and reducing measurement error (Churchill, 1979). To make the latent constructs more concrete, twenty-two items were looked at: five items for HA, five items for RL improving operations, and twelve items for sustainability performance, with four items each for economic, environmental, and social sustainability. Fifteen experts from many fields of business and the school verified every item before it was included into the finished text. Using five industry and academic specialists with great knowledge and experience in this subject, item sorting, and pre-testing were done following Anderson and Gerbing's approach (Anderson & Gerbing, 1988). This investigation considered all the professional points of view. Their suggestions helped to simplify the language so as to raise the questions' clarity. Two multilingual people fluent in both languages first wrote the measures in English then Bangla. Later retranslation of the Bangla version into English guarantees that idioms between the two languages are corrected (Brislin, 1970). In Appendix B, you can find a complete list of all the measure tools that are used for the latent components that are being studied.

Reflective Measurement Model Validation and Reliability

The models used in this study for all of the variables were reflective. Several important metrics were checked to make sure that the measurement model was correct and reliable. First, standard procedures were used to figure out the factor loadings for each survey question, as well as the scale composite reliability (SCR) and average variance extracted (AVE) for each construct (Ting et al., 2017). The findings of the confirmatory factor analysis (CFA) are displayed in Table 4. In order for measurement items to be considered for inclusion in the PLS-SEM analysis, Hair et al. (2017) state that factor loading values greater than 0.5 are required. Reject them if that is not the case. The factor loading values of all the measuring items are greater than 0.5. Table 4 shows that the SCR value was higher than the AVE value, which was higher than the recommended cutoff of 0.5 (Tan et al., 2018). For every construct, Cronbach's alpha was also calculated; all values shown great internal consistency and dependability (Molina et al., 2007).

The challenges pertaining to our structural model were subsequently addressed through the application of a discriminant validity assessment. As noted by (Henseler et al., 2015), the HTMT (heterotrait-monotrait ratio of correlations) method and the Fornell and Larcker (1981) criterion were employed to ascertain the divergent validity of the measures. The square root values of AVE were incorporated into the leading diagonal elements in Table 5, following the guidance provided by Fornell and Larcker (1981) for the construction of the innercorrelation matrix. The discriminant validity of each construct was confirmed by the fact that the square root of the AVE was greater than its correlations with other constructs (Fornell & Larcker, 1981).

The discriminant validity of the ideas was then additionally investigated applying the HTMT criterion. Table 6 shows that, given results of less than 0.85 (Henseler et al., 2015), all reflective constructs show appropriate discriminant validity. Using Simpson's paradox ratio (SPR), R-squared contribution ratio (RSCR), and statistical suppression ratio (SSR), causality was investigated in order to evaluate the model's correctness even further.

The values for these indices are displayed in Table 7, and they are all well within the permissible range. Approximately 75% of path-related occurrences correspond to the model's assumptions with no indication of bidirectional causality between constructs (Kock, 2019a) because the NLBCDR value of 0.750 exceeds the 0.7 criterion. Our proposed model does not have any problems with causation, according to these results. Additional results for model fit and quality indices are provided in Table 8.

Hypothesis Testing

PLS-SEM (WarpPLS 8.0) was used to validate the study's proposed hypotheses. The PLS-SEM study's *p*-values and path coefficient (β) are shown in Table 9 and Fig. 3. Regarding reverse logistics (RL), the findings indicate that the industries have positively and significantly impacted the implementation of RL, or the acceptance of Hypotheses Hla, H1b, and H1c, in the areas of economic sustainability (EcS) ($\beta = 0.51$, $p < 0.01$), environmental sustainability (EnS) ($\beta = 0.51$, $p < 0.01$), and social sustainability (ScS) ($\beta = 0.44$, $p < 0.01$). Reverse logistics is crucial for social, economic, and environmental sustainability because it

Table 4 Measures of constructs and factor loadings

Construct	Item	Factor Loading	Variance	Error	SCR	AVE	Cronbach's Alpha
HA technologies	HA1	0.910	0.828	0.172	0.947	0.782	0.930
	HA2	0.900	0.810	0.190			
	HA3	0.802	0.643	0.357			
	HA4	0.909	0.826	0.174			
	HA5	0.895	0.801	0.199			
RL	RL1	0.961	0.924	0.076			
0.980							
	0.909	0.975					
	RL2	0.966	0.933	0.067			
	RL3	0.921	0.848	0.152			
	RL4	0.955	0.912	0.088			
	RL5	0.963	0.927	0.073			
EcS	EcS1	0.828	0.686	0.314	0.887	0.662	0.829
	EcS2	0.782	0.612	0.388			
	EcS3	0.813	0.661	0.339			
	EcS4	0.830	0.689	0.311			
EnS	EnS1	0.792	0.627	0.373	0.905	0.708	0.855
	EnS2	0.951	0.904	0.096			
	EnS3	0.650	0.423	0.578			
	EnS4	0.938	0.880	0.120			
ScS	ScS1	0.700	0.490	0.510	0.884	0.660	0.820
	ScS2	0.933	0.870	0.130			
	ScS3	0.668	0.446	0.554			
	ScS4	0.913	0.834	0.166			

Table 5 Discriminant validity

	RL	HA technologies	ScS	EnS	EcS
RL	0.953				
HA technologies	− 0.047	0.884			
ScS	0.409	0.058	0.812		
EnS	0.492	0.144	0.575	0.842	
EcS	0.472	0.143	0.524	0.688	0.813

Table 6 HTMT values

	HA technologies	RL	EcS	EnS	ScS
HA technologies	–	–	–	–	–
RL	0.051	–	–	–	–
EcS	0.177	0.524	–	–	–
EnS	0.179	0.530	0.809	–	–
ScS	0.087	0.464	0.636	0.685	–

Table 7 Causality assessment indices

Parameters	Values
Simpson's paradox ratio (SPR)	0.917
R-squared contribution ratio (RSCR)	0.974
Statistical suppression ratio (SSR)	0.917
Nonlinear bivariate causality direction ratio (NLBCDR)	0.750

lowers costs, creates value, and encourages recycling, repair, and reuse. This result validates previous findings (Can Saglam, 2023; El Boudali et al., 2022).

Concerning RL's sustainability performance with flexible hyperautomation (HA) technologies, the findings indicate that the adoption of H2b and H2c is positively impacted by HA implementation, with a substantial and favourable impact on environmental ($\beta = 0.16$, $p < 0.01$) and social ($\beta = 0.18$, $p < 0.01$) sustainability performance. However, H2a, H2b, and H2c are accepted since the Sustainability of RL is significantly affected by the introduction of HA.

Flexible hyperautomation helps industries to integrate business information systems, increase automation experience, and increase productivity. Additionally, it makes it possible to automate decision-making procedures using methods based on algorithms. These results confirm the importance of RL in advancing economic, environmental, and social objectives, aligning with previous research in the field (Haleem et al., 2021).

The control variables firm size (FS) on EcS ($\beta = 0.07$; $p > 0.05$), EnS ($\beta = 0.04$; $p > 0.05$), ScS ($\beta = 0.05$; $p > 0.05$) and technological intensity (TI) on EcS ($\beta = 0.05$; $p > 0.05$), EnS ($\beta = 0.05$; $p > 0.05$), ScS ($\beta = 0.11$; $p > 0.05$) did not show evidence of support in Table 10. These data immediately imply that the size or intensity of an industry's sustainability performance has no bearing on its performance in the electronics industry.

We also examine the effect sizes of constructs in Table 11. RL's effect sizes on EcS and the other two variables (EnS and ScS) are large (f2 = 0.727) and modest (f2 = 0.316 and 0.180, respectively). According to Cohen (1988), small, medium, and high effect sizes are represented, respectively, by $f2 \geq 0.02$, $f2 \geq 0.15$, and $f2 \geq 0.35$.

The endogenous constructs' coefficient of determination (R2) was analysed to look at the theoretical model's capacity for explanation in more detail. HA and RL are significant factors in achieving Sustainability (EcS, EnS, and ScS), based on the computed value of R^2. HA and RL account for about 28.1%, 24.1%, and 21.9% of the variation in economic, environmental, and social sustainability, respectively, according to the value of R^2. According to (Dubey et al., 2023), that demonstrates a significant amount of the structural model's explanatory power. Furthermore, the predictability values (Q^2) of the explanatory variables are given; they have previously attracted much interest from scholars employing PLS-SEM methods (Chin, 1998). The endogenous constructs' Q^2 values were discovered to be larger than zero. They are 0.286, 0.286, and 0.222 for all sustainability performances (EcS, EnS, and ScS, respectively). These results collectively highlight the critical role of reverse logistics and flexible hyper-automation in promoting sustainability within the B2B electronics sector, providing empirical support for the study's conceptual framework and hypotheses. The values of R^2 and Q^2 are presented in Table 12.

Discussions

This study investigated the role of reverse logistics (RL) and flexible hyperautomation (HA) technologies in enhancing sustainability performance (SP) within the Bangladeshi B2B electronics industry. Applying the contingent resource-based view (C-RBV), the research emphasises how strongly external contingencies including legislative frameworks, technology advances, and market dynamics affect the efficacy of RL and HA. Unlike conventional viewpoints that mostly see internal resources as fixed, the C-RBV stresses the need of dynamic alignment of organisational capabilities with changing external conditions.

Table 8 Model fit and quality indices

Parameters	Values	Acceptable range	References
Average path coefficient (APC)	0.195, $P < 0.001$	$P < 0.05$	Dubey et al. (2022)
Average R-squared (ARS)	0.247, $P < 0.001$	$P < 0.05$	Dubey et al. (2022)
Average block VIF (AVIF)	1.011	0 < AVIF < = 5	Kock (2019b)
Tenenhaus GoF (GoF)	0.455	large > = 0.36	Tenenhaus et al. (2005)

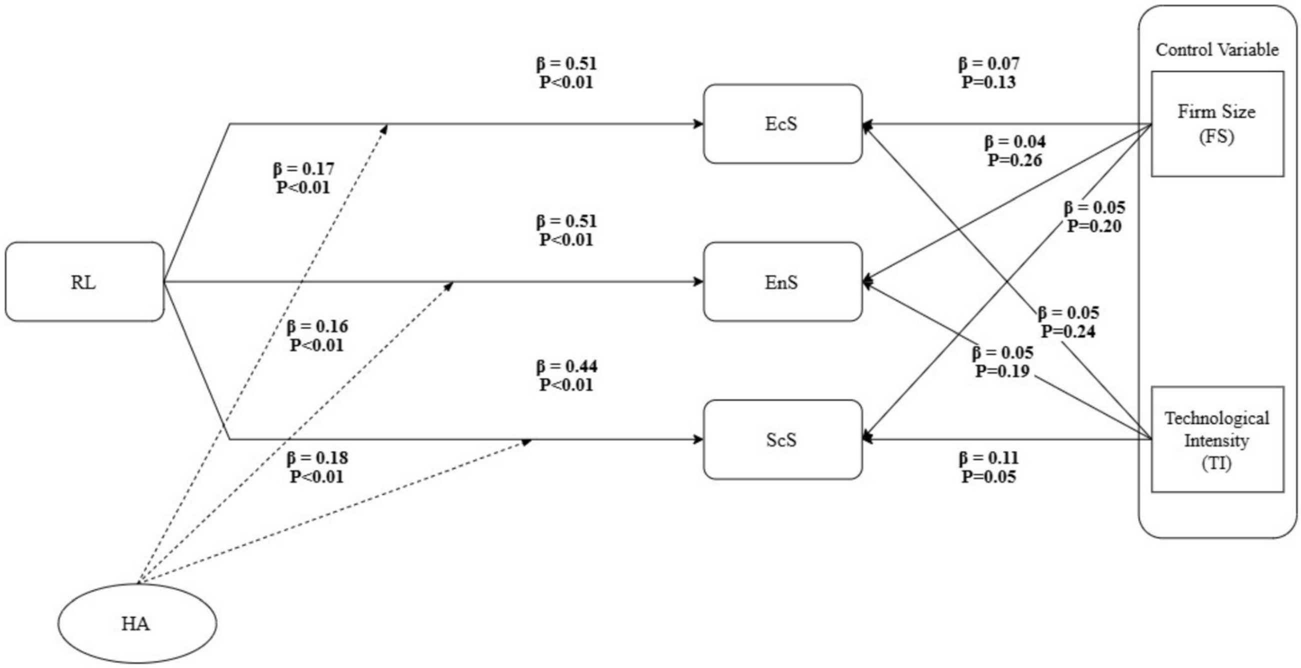

Fig. 3 PLS model

Table 9 Hypothesis testing results

Hypothesis	Path coefficient (β value)	*P*- value	Result
H1a: RL has a positive and significant impact on Economic Sustainability (EcS)	0.51	$P < 0.01$	Accepted
H1b: RL has a positive and significant impact on Environmental Sustainability (EnS)	0.51	$P < 0.01$	Accepted
H1c: RL has a positive and significant impact on Social Sustainability (ScS)	0.44	$P < 0.01$	Accepted
H2a: HA has a positive and significant impact on RL & EcS	0.17	$P < 0.01$	Accepted
H2b: HA has a positive and significant impact on RL & EnS	0.16	$P < 0.01$	Accepted
H2c: HA has a positive and significant impact on RL & ScS	0.18	$P < 0.01$	Accepted

Particularly in the social, environmental, and economic areas, the empirical results show a clear influence of RL methods on sustainable performance. Specifically, RL demonstrated a robust positive relationship with economic sustainability ($\beta = 0.51$, $p < 0.01$), environmental sustainability ($\beta = 0.51$, $p < 0.01$), and social sustainability

Table 10 Control variables impact

	PLS path	Path coefficient (β value)	*P*- value	Result
FS	FS—> EcS	0.07	$P = 0.13$	Not significant
	FS—> EnS	0.04	$P = 0.26$	Not significant
	FS—> ScS	0.05	$P = 0.20$	Not significant
TI	TI—> EcS	0.05	$P = 0.24$	Not significant
	TI—> EnS	0.05	$P = 0.19$	Not significant
	TI—> ScS	0.11	$P = 0.055$	Not Significant

Table 11 Effect size

Path	f^2	Effect size
RL—> EcS	0.251	Medium
RL—> EnS	0.256	Medium
RL—> ScS	0.184	Medium

Table 12 Co-efficient of variation (R^2) and predictability (Q^2)

Endogenous variable	R^2	Q^2
ScS	0.281	0.286
EnS	0.241	0.286
EcS	0.219	0.222

($\beta = 0.44$, $p < 0.01$). These findings coincide with earlier studies underlining RL's ability to improve profitability, lower environmental impact, and strengthen good stakeholder relationships (Banihashemi et al., 2019; Can Saglam, 2023; Mishra et al., 2023). As fundamental practices for businesses striving to reach competitive sustainability, the results highlight the strategic relevance of RL activities encompassing reuse, remanufacturing, recycling, and responsible disposal.

This study empirically substantiates the moderating effect of flexible hyperautomation technologies on enhancing the link between RL and sustainability performance. The findings show that economic ($\beta = 0.17$, $p < 0.01$), environmental ($\beta = 0.16$, $p < 0.01$), and social ($\beta = 0.18$, $p < 0.01$) sustainability outcomes of RL are greatly enhanced by using HA technology. Reduced waste and resource inefficiencies can be achieved through the utilisation of HA technologies like RPA, AI-driven analytics, machine learning, the internet of things (IoT), and reverse logistics (Guillot et al., 2024; Haleem et al., 2021). Therefore, logistics plans should prioritise technological integration, as HA and RL working together produce better sustainability results than either could on its own.

The main contribution made in this research is the identification of systemic flexibility as one of the enabling factors of successful integration of RL and HA. By integrating modular RL processes and scalable automation technologies, the organisations will be more prepared to adjust their sustainability efforts to external disruptions (new regulations or market demand changes). The flexible management strategies (such as decentralisation of decisions and adaptive leadership) have become the necessary ones in helping the technology transitions needed to support automated, sustainability-oriented logistics. Within Bangladeshi B2B contexts, the results, therefore, confirm the significance of organisational adaptability as a strategic tool and as a viable need to ensure continued performance. The next sections address the study's theoretical and managerial implications, in addition to these results.

Theoretical Implications

This work develops theory in numerous respects. First, it expands the contingent resource-based view (C-RBV) by empirically proving, especially in a developing economy environment, the alignment of reverse logistics (RL) and flexible hyperautomation (HA) with external contingencies such as regulation and technological readiness determines their effectiveness.

Second, by characterising RL and HA as strategic relational capacities, the research supports B2B marketing theory. The results imply that companies enhance operational results and boost inter-firm links and consumer value in industrial markets when they apply these competencies to meet sustainability objectives. Lastly, the empirical evidence supporting the complementarity between RL and HA enriches the dynamic-capabilities perspective. The interaction between these capabilities highlights the importance of synergistic resource bundles in achieving superior sustainability performance in volatile, technology-driven environments. This integrated view opens new avenues for research on how organisations combine physical, technological, and human capabilities to build sustainable, adaptive, and resilient supply chains, particularly within emerging-economy contexts where institutional conditions differ significantly from developed markets.

Managerial Implications

Especially in emerging nations like Bangladesh, the results of this study offer managers in the B2B electronics sector practical direction. The study emphasises for industry executives the need of strategic investments in RL and HA in order to acquire a sustained competitive edge in social, environmental, and economic aspects. Advanced technologies include artificial intelligence, RPA, IoT, and BPM should be used by businesses to maximise resource efficiency, simplify RL procedures, and coordinate supply chains. Organisations should prioritise flexibility by adopting modular processes and cross functional teams. Training programmes and decentralised decision making help ensure that technology complements human expertise rather than replacing it. These insights can help policymakers create tailored regulatory incentives to encourage reverse logistics and flexible hyperautomation adoption and a sustainable sector change. This study's empirically validated measuring scales provide a strong framework for examining organisational practices connected to RL and

HA, allowing industry experts and researchers to compare and evaluate.

Conclusions

Concluding Summary

All things considered, the findings of this study meet their aims and clarify the complex dynamics among RL, HA technologies, and SP in the framework of the B2B electronics sector in Bangladesh. This paper develops a thorough theoretical framework using the Contingent Resource-Based View (C-RBV), which explains how external environmental factors in shaping sustainability outcomes determines the strategic deployment of organisational resources including flexible hyperautomation and reverse logistics. We hope that the issues and results of this study will lead to more real-world research that will help us understand the small differences in how businesses work, what tools they have, and how they do things. Our study aims to encourage future academics to support innovation, teamwork, and ongoing improvement as means for businesses to create a more sustainable future. We believe that these practices can help firms balance social responsibility and environmental stewardship with economic success.

Limitations and Future Research Directions

It is important to note that this study has some flaws, even though it does provide useful information about how to combine reverse logistics (RL) and flexible hyper-automation (HA) to improve sustainability in Bangladesh's B2B electronics industry. First, the analysis was based on cross-sectional survey data from 250 Bangladeshi electronics companies, potentially limiting generalisability. Future research could adopt longitudinal or cross-industry approaches to verify findings across diverse contexts and temporal variations. Second, the study did not investigate barriers or challenges to jointly implementing RL and HA technologies. Future research should examine specific organisational, technological, and regulatory challenges that could affect successful integration. Third, the subjective nature of survey-based measures may introduce potential biases; thus, incorporating objective measures or mixed-method approaches in future studies could enhance validity. Lastly, future research might expand the range of measurement items or variables to enrich further the understanding of RL and HA integration and their impacts on sustainability outcomes.

Appendix A Sample for Interviews

Participant	Gender	Organization type	Experience (years)	Position
1	M	University	> 15	Professor
2	M	University	> 17	Professor
3	F	University	> 16	Professor
4	F	University	> 15	Professor
5	M	University	> 18	Professor
6	M	Electronics	> 10	Operations Manager
7	F	Electronics	> 10	Senior Manager (Manufacturing)
8	M	Electronics	> 14	Supply Chain Manager
9	M	Electronics	> 9	Production Manager
10	F	Electronics	> 14	General Manager
11	M	Electronics	> 16	Chief Operations Officer
12	F	Electronics	> 15	Country Manager
13	M	Electronics	> 13	Quality controller

Appendix B. Measurement Scales

Construct	Items	Statement	Adapted from
HA	HA1	Our firm employs AI for product design, logistical optimization, and personalized marketing	Lasso et al. (2020), Zhao et al. (2022), Szelągowski et al. (2022), Souri et al. (2024), Ghobakhloo et al. (2023),Haleem et al. (2021), Madakam et al. (2022), Kavitha (2023)
	HA2	We employ ML to achieve more accurate predictions and assessments of product behavior, design flaws, and potential production issues	
	HA3	We employ RPA to track shipments, identify and address delays, and automate notifications	
	HA4	We employ BPM to create consistent and efficient workflows across departments	
	HA5	We employ IoT to issues, reduce troubleshooting time, and improve service efficiency	
RL strategies	RL1	Reusing operational parts from electronics nearing the end of life in new product assemblies	Khor et al. (2016), Fleischmann et al. (2000), Matsumoto (2010), Blackburn et al. (2004), Eltayeb et al. (2011), Paras & Pal (2020), Silva et al. (2022), Pandit (2021), Banihashemi et al. (2019)
	RL2	Providing repairs under warranty for product malfunctions	
	RL3	Manufacturers gather discarded goods, swap out damaged parts, and remanufacture them into goods that are comparable to new ones	
	RL4	Encouraging responsible customer behavior and involvement in electronics recycling initiatives	
	RL5	Enhancing accountability and tracking every step of the disposal process	
EcS	EcS1	Reducing cost in logistics operation	Jindal & Sangwan (2016), Khor et al. (2016), Agrawal et al. (2016), Huang et al. (2015), Thore & Tarverdyan (2022)
	EcS2	Improvement in Profitability	
	EcS3	Improvement in Quality	
	EcS4	Achieving growth in market share	
EnS	EnS1	Reduction of hazardous and toxic Materials	Khor et al. (2016), Agrawal et al. (2016), Ahmed et al. (2016), Qian et al. (2021)
	EnS2	Reduction in pollution	
	EnS3	Reduction of wastes	
	EnS4	Reduced energy and resources	
ScS	ScS1	Improved the firm's corporate image	Ahmed et al. (2016), Wanjiku (2019), Mensah (2021)
	ScS2	Improved customer satisfaction	
	ScS3	Improved health and safety of employees	
	ScS4	Improved social commitment	

Author Contribution SHR and MIH: Conceptualisation, Methodology, Investigation, Data Curation, Writing (Original Draft Preparation). HMB (Corresponding Author): Supervision, Project Administration, Resources, Writing (Review & Editing). PS and MAR: Formal Analysis, Helping in Writing (Visualisation).

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Declarations

Competing Interests The authors declare no competing interests.

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Key Questions for Further Reflection

1. How can firms in emerging economies design strategies that align reverse logistics (RL) and hyper-automation (HA) under varying regulatory and market contingencies?
2. How can small and medium-sized enterprises (SMEs) scale hyper-automation solutions while maintaining flexibility and sustainability goals?
3. What specific policy frameworks could encourage reverse logistics & hyper-automation synergy at a national level, promoting responsible innovation and waste recovery?
4. What new managerial competencies and training approaches are required to lead organisations through automation-driven sustainability transitions?

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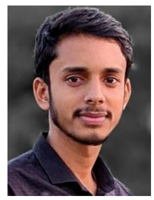

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