Big Data Analytics Capability and Supply Chain Sustainability: Analyzing the Moderating Role of Green Supply Chain Management Practices

Journal:	*Benchmarking: an International Journal*
Manuscript ID	BIJ-10-2024-0852.R2
Manuscript Type:	Original Article
Keywords:	Big data analytics capability (BDAC), dynamic capability view (DCV), sustainable supply chain performance (SSCP), green supply chain management (GSCM)

Big Data Analytics Capability and Supply Chain Sustainability: Analyzing the Moderating Role of Green Supply Chain Management Practices

Abstract

Purpose: This research develops a theoretical framework to understand the role of big data analytics capability (BDAC) in enhancing supply chain sustainability and examines the moderating effect of green supply chain management (GSCM) practices on this relationship.

Design/Methodology: Guided by the dynamic capability view (DCV), we formulated a theoretical model and research hypotheses. Using partial-least-square-based structural equation modeling (PLS-SEM), we analyzed data collected from 159 survey responses from Bangladeshi ready-made garments (RMG).

Findings: The statistical analysis revealed that BDAC positively impacts all three dimensions of supply chain sustainability: economic, social, and environmental. Additionally, GSCM practices significantly moderate the relationship between BDAC and supply chain sustainability.

Value/Originality: This study advances the current understanding of supply chain sustainability by integrating BDAC with GSCM practices. It is among the first to empirically investigate the combined effects of BDAC on the three dimensions of sustainability—economic, social, and environmental—while also exploring the moderating role of GSCM practices. By employing the DCV, this research offers a robust theoretical framework that highlights the dynamic interplay between technological and environmental capabilities in achieving sustainable supply chain performance.

Implications: This study makes unique contributions to the operations and supply chain management literature by providing empirical evidence and theoretical insights that extend beyond the focus on single sustainability dimensions. The findings offer valuable guidelines for policymakers and managers aiming to enhance supply chain sustainability through BDAC and GSCM practices.

Keywords: Big data analytics capability (BDAC), dynamic capability view (DCV), sustainable supply chain performance (SSCP), green supply chain management (GSCM).

Type: Research paper

1.0 Introduction

In recent years, the imperative for sustainability within supply chains (SCs) has grown exponentially due to the significant environmental impacts of SC activities, including production, distribution, transportation, and disposal (Bag et al., 2023; Yan et al., 2024). This urgency is driven by increasing global awareness and regulatory pressures, necessitating a shift towards sustainable supply chain management (SSCM) (Le, 2023; Jum'a et al., 2024). SSCM seeks to integrate sustainable practices into SC operations, aiming to balance economic, social, and environmental performance (Cetindamar et al., 2022). By doing so, SSCM not only addresses environmental challenges but also enhances corporate reputation, reduces costs, and meets regulatory requirements. The pursuit of sustainable supply chain performance (SSCP) is now a critical goal for organizations, particularly in emerging economies where the balance between industrial growth and environmental stewardship is precarious (Naseer et al., 2023; Raj et al., 2023).

The triple bottom line (TBL) framework, which encompasses economic, social, and environmental dimensions, serves as a cornerstone for understanding sustainability in SCs (Carter & Rogers, 2008). Unlike traditional SC management, which primarily focuses on financial outcomes, SSCM emphasizes the need for a holistic approach that addresses broader sustainability issues (Yousefi & Tosarkani, 2023). This paradigm shift highlights the importance of developing capabilities that enable organizations to adapt and thrive in an increasingly complex and dynamic environment (Huang et al., 2024).

With the advent of advanced technologies, big data analytics (BDA) has become a pivotal factor in optimizing SC performance and achieving competitive advantages (Liu et al., 2023; Gopal et al., 2024). Big data (BD), characterized by its volume, variety, velocity, veracity, and value, generates vast amounts of information that can be leveraged through BDA (Rashid et al., 2024). BDA enables firms to process vast amounts of data, uncover hidden patterns, and make data-driven decisions that enhance operational efficiency (Morimura & Sakagawa, 2023). Studies show that BDA positively impacts supply chain performance through enhanced resilience and innovation (Arias-Pérez et al., 2022; Bahrami & Shokouhyar, 2022). Developing BDA capabilities (BDAC) enables firms to execute algorithms faster with larger datasets, improving decision-making and forecasting market preferences (Choi & Park, 2022). BDAC allows organizations to convert data into actionable insights, enhancing SC performance and decision-making (Xu & Pero, 2023). Prominent corporations like Walmart, Uber, Netflix, Google, Amazon, and Facebook have leveraged BDA to benefit their SC functions (Belhadi et al., 2023). The implementation of BDA in supply chains contributes to improved service supply chain innovation capabilities and overall performance (Sahoo et al., 2023).

Despite the recognized potential of BDAC, there remains a gap in understanding how it influences the three pillars of supply chain sustainability—economic, social, and environmental performance. Though few scholars have looked into the impact of BDAC on a single dimension of SC sustainability, empirical research on their impact across the three dimensions of sustainability is lacking. For instance, some scholars have explored BDAC's impact on environmental sustainability (Dubey et al., 2019; Nisar et al., 2020; Zhu et al., 2022; Belhadi et al., 2023; Sahoo et al., 2023), and others have examined its relationship with economic performance (Dubey et al., 2020; Arias-Pérez et al., 2022; Bahrami, & Shokouhyar, 2022; Behl, 2022; Morimura & Sakagawa, 2023; Gopal et al., 2024), however, comprehensive studies on BDAC's combined

effects on all three dimensions are limited. To address this gap, we pose our first research question (RQ1):

RQ1: What are the impacts of BDAC on the three dimensions of supply chain sustainability?

Boyd et al. (2012) assert that models analyzing direct effects are crucial but insufficient for understanding real-world complexities. Research indicates that BDAC performance depends on various contextual factors (Dubey et al., 2019; Tipu & Fantazy, 2023; Yamin, 2024). Thus, we explore conditions that enhance BDAC effectiveness. Green supply chain management (GSCM) practices have been widely used as a significant influencing element in SC and operations management literature (Sarkis et al., 2011; Khan et al., 2023; Rahman et al., 2023). Sahoo et al. (2023) highlight the importance of selecting appropriate practices for a competitive edge in SCM. Behl et al. (2024) note that GSCM practices can reduce carbon footprints, waste, and hazardous substances in manufacturing, thereby contributing to sustainability. Rashid et al. (2024) suggest that GSCM can enhance technological solutions' effectiveness. Therefore, we propose that GSCM practices may moderate BDAC's impact on SSCP. However, empirical studies on this moderating role are lacking. Thus, we pose our second research question (RQ2):

RQ2: What are the moderating effects of GSCM on the links between BDAC and SSCP?

To explore BDAC's influence on the three sustainability aspects, we develop a theoretical framework based on the dynamic capability view (DCV). The DCV emphasizes firms' adaptation, integration, and reconfiguration of internal and external competencies, such as BDA and GSCM, to achieve sustained competitive advantage and supply chain sustainability (Teece, 2007). Using a survey-based questionnaire, we collected 159 responses from the Bangladesh ready-made garments (RMG) industry. Our findings enrich the BDAC literature by integrating the DCV to explain how BDAC and GSCM jointly contribute to SC sustainability. Additionally, it provides a nuanced understanding of contextual conditions that enhance BDAC's effectiveness in achieving sustainability goals. Practitioners can leverage these insights to strategically implement BDAC and GSCM practices, improving operational efficiency and environmental performance.

Our document is structured as follows: Section 2 presents the research background and theoretical foundations. Section 3 discusses theoretical model development. Section 4 covers the research methodology, including sample selection, data collection, and non-response bias. Section 5 details the data analysis and results. Section 6 discusses overall findings and future research directions.

2.0 Theoretical background

2.1 DCV

DCV is an extension of the resource-based view (RBV) theory, addressing criticisms that RBV often fails to explain how and under what conditions resources can grant competitive advantages (Eisenhardt & Martin, 2000). DCV provides insights into how organizations can achieve competitive advantages in evolving environments by integrating, reorganizing, and developing internal and external capabilities (Teece et al., 1997; Ghasemzadeh et al., 2022). According to Teece et al. (1997), dynamic capabilities are defined as a company's ability to adapt to rapidly changing environments by sensing opportunities and threats, seizing opportunities, and transforming resources to maintain a competitive edge.

Dynamic capabilities encompass three primary dimensions: sensing, seizing, and transforming. Sensing involves identifying and assessing opportunities and threats in the market. Seizing refers to mobilizing resources to capture opportunities and mitigate threats. Transforming entails reconfiguring and realigning resources to sustain competitiveness (Teece, 2007).

In this context, BDAC is regarded as a dynamic capability that enables organizations to reconfigure firm-level resources in response to evolving market conditions and technological advancements (Dubey et al., 2019; Bahrami & Shokouhyar, 2022; Sahoo et al., 2023). By effectively processing, analyzing, and visualizing data, BDAC provides valuable insights that enhance decision-making, planning, and execution (Xu & Pero, 2023). Moreover, BDAC fosters a culture of innovation and learning by allowing organizations to experiment with various analytical techniques and continuously refine their processes (Belhadi et al., 2023).

Given these arguments, DCV serves as an appropriate theoretical lens for understanding the role of BDAC in achieving business competitiveness in dynamic environments. In this study, we argue that by leveraging BDAC as a dynamic capability, organizations can remain agile, competitive, and resilient, ultimately contributing to SSCP.

2.2 BDAC

As businesses have become more technologically advanced, their SCs generate vast amounts of data (Cheng et al., 2023; Riggs et al., 2023). Jum'a et al. (2024) highlight that big data serves as a novel method for organizing and analyzing this information, providing valuable insights for SC participants. Belhadi et al. (2023) define big data as extensive, diverse observational data that supports various decision-making processes. While almost all firms now have access to big data, traditional methods often fall short of effectively analyzing and deriving meaningful conclusions from such large datasets (Bagherpasandi et al., 2024). To address this, organizations require real-time capabilities that can handle larger and more complex data sets, leading to commercial benefits. This necessitates the development of new data architectures, analytical techniques, and tools (Bag et al., 2023).

Researchers have acknowledged that the success of big data projects depends not just on data availability, analytical tools, and process utilization but on a broader range of factors (Bahrami & Shokouhyar, 2022; Ma & Chang, 2024). To capture this complexity, the concept of big BDAC was introduced (Rashid et al., 2024). BDAC is generally defined as an organization's ability to effectively leverage data management, infrastructure, and talent to derive actionable insights, transforming the business into a competitive force (Riggs et al., 2023). With BDAC, organizations can process, analyze, and visualize data, thereby improving planning, decision-making, and mission execution (Shi et al., 2023; Gupta et al., 2024).

Nisar et al. (2023) assert that applying BDAC in supply chains can mitigate various organizational uncertainties, such as those related to capacity, supplier availability, and customer demands. Moreover, BDAC can foster process-oriented dynamic capabilities within organizations, leading to enhanced firm performance. By adopting a holistic view of BDAC that encompasses all relevant organizational resources, firms can maximize the strategic value of big data, gaining a sustainable competitive advantage in today's data-driven business environment (Jum'a et al., 2024).

2.3 GSCM

In recent years, there has been a growing emphasis on integrating environmental sustainability into SCM, giving rise to the concept of GSCM. GSCM refers to the incorporation of eco-friendly practices in supply chain operations, encompassing procurement, production, distribution, and end-of-life management (Feng et al., 2022). This approach aims to minimize the environmental footprint of SCs by reducing waste, emissions, and energy consumption while enhancing resource efficiency and sustainability (Sarkis et al., 2011).

GSCM practices include a wide range of activities such as green procurement, eco-design, reverse logistics, and sustainable packaging (Behl et al., 2024). Green procurement involves selecting suppliers based on their environmental performance and encouraging them to adopt sustainable practices. Eco-design focuses on creating products that have minimal environmental impact throughout their lifecycle, from raw material extraction to disposal. Reverse logistics involves the process of reclaiming products for reuse, recycling, or proper disposal, thereby reducing waste and conserving resources. Sustainable packaging aims to use materials that are recyclable or biodegradable, reducing the environmental burden of packaging waste (Sarkis et al., 2011; Behl et al., 2024).

The adoption of GSCM practices is driven by various factors, including regulatory pressures, stakeholder expectations, and the desire for competitive advantage (Karmaker et al., 2023). Governments worldwide have implemented stringent environmental regulations that compel organizations to adopt sustainable practices. Additionally, consumers and other stakeholders are increasingly demanding environmentally responsible products and practices, prompting companies to integrate sustainability into their SC strategies (Akram et al., 2024). Firms that successfully implement GSCM can achieve significant benefits such as cost savings, improved brand image, and enhanced compliance with environmental standards (Dzikriansyah et al., 2023; Balkumar et al., 2024).

Moreover, GSCM can significantly influence SC sustainability by integrating the TBL principles, which focus on economic, social, and environmental performance (Huang et al., 2024). By reducing environmental impact and promoting social responsibility, GSCM helps organizations achieve a balanced approach to sustainability, which is essential for long-term success and resilience in the competitive market (Khan et al., 2023). In conclusion, GSCM represents a strategic approach to achieving SC sustainability by integrating environmental considerations into SCM. The adoption of green practices not only helps organizations comply with regulatory requirements and meet stakeholder expectations but also provides a competitive edge by enhancing operational efficiency and brand reputation (Hunag et al., 2024).

2.4 SSCP

SSCP is an integral concept in contemporary SCM, emphasizing the need for a holistic approach that balances economic, social, and environmental performance. The TBL framework underpins SSCP, advocating that businesses should not only focus on profitability but also consider their social and environmental responsibilities (Elkington, 1998). The pursuit of SSCP is becoming increasingly critical as organizations strive to meet the demands of various stakeholders, including customers, regulators, and the broader community, while also ensuring long-term sustainability and competitiveness (Yousefi & Tosarkani, 2023).

2.4.1 Economic Performance

The economic dimension of SSCP pertains to the financial health and efficiency of SC operations. This includes cost reduction, improved profitability, and value creation throughout the SC (Cetindamar et al., 2022). Effective SC management practices can lead to significant economic benefits by optimizing resource utilization, enhancing operational efficiency, and reducing waste. Economic sustainability in supply chains ensures long-term financial viability and competitive advantage, which is crucial for organizational success in a dynamic market environment (Khan et al., 2023; Huang et al., 2024).

2.4.2 Social Performance

The social dimension of SSCP focuses on the impact of SC activities on various stakeholders, including employees, communities, and customers. It encompasses aspects such as labor practices, human rights, community engagement, and customer satisfaction (Karmaker et al., 2023). Ensuring fair labor practices, promoting diversity and inclusion, and engaging in ethical sourcing are key components of social sustainability. By addressing social concerns, organizations can build stronger relationships with stakeholders, enhance brand reputation, and foster customer loyalty, which is essential for sustainable business operations (Dubey et al., 2019; Saha et al., 2023).

2.4.3 Environmental Performance

The environmental dimension of SSCP involves minimizing the ecological footprint of SC activities. This includes reducing resource consumption, waste, and emissions throughout the SC (Nisar et al., 2020). Environmental sustainability practices in supply chains often involve adopting green technologies, implementing energy-efficient processes, and promoting the circular economy. By integrating environmental considerations into SCM, organizations can mitigate environmental risks, comply with regulatory requirements, and contribute to global sustainability goals (Zhu et al., 2022; Sahoo et al., 2023). This not only enhances environmental performance but also drives innovation and operational efficiencies (Gallo et al., 2023).

3.0 Theoretical Framework and Hypothesis

The DCV constitutes the basis of our theoretical framework (Figure 1). Drawing on the DCV theory, this study posits that BDAC serves as a critical dynamic capability, enabling firms to reconfigure their resources and processes in response to evolving market conditions and technological advancements (Dubey et al., 2019; Bahrami & Shokouhyar, 2022). BDAC allows organizations to effectively process, analyze, and utilize vast amounts of data, which can enhance their economic, social, and environmental performance—key dimensions of SSCP (Dubey et al., 2020; Riggs et al., 2023). Additionally, GSCM practices are hypothesized to play a moderating role in this relationship. By integrating environmental considerations into supply chain operations, we argue that GSCM practices can amplify the positive impact of BDAC on SSCP. This integration is theorized to enhance the firm's ability to achieve sustainability goals, comply with regulatory requirements, and meet stakeholder expectations, thereby ensuring long-term competitiveness and resilience.

3.1 Impact of BDAC on Economic Performance

In the contemporary business environment, maintaining profitability is paramount for the long-term survival and competitiveness of firms (Jeble et al., 2018). Economic performance (ECOP) is typically assessed through indicators such as profitability, competitiveness, cost reduction, and brand equity (Behl, 2022). The existing literature underscores the significant role of BDAC in enhancing ECOP. Bag et al. (2023) state that effective BDAC enables firms to optimize resource allocation, reduce costs, and improve overall profitability through better demand forecasting, inventory management, and production planning. Furthermore, Morimura and Sakagawa (2023) argue that BDAC provides real-time insights into market trends and consumer behavior, allowing for more informed and timely decisions that drive economic benefits. Additionally, BDAC supports the development of predictive analytics, which can anticipate market fluctuations and optimize pricing strategies (Dubey et al., 2020). From the DCV perspective, BDAC can be seen as a dynamic capability that allows firms to reconfigure their resources and processes to adapt to changing market conditions and achieve superior ECOP (Bahrami & Shokouhyar, 2022; Sahoo et al., 2023). Therefore, we hypothesize:

H1: BDAC has a positive impact on ECOP

3.2 Impact of BDAC on Social Performance

In today's socially conscious business environment, organizations are increasingly expected to go beyond economic success and demonstrate a commitment to social responsibility. Ensuring positive social performance (SP) is crucial for firms to maintain strong stakeholder relationships and foster customer loyalty (Choi & Park, 2022). BDAC can significantly enhance SP by enabling firms to analyze extensive data related to employee welfare, working conditions, and community impact (Dubey et al., 2019). Choi and Park (2022) argue that BDAC facilitates better labor practices and more ethical sourcing decisions, ensuring compliance with social standards and regulations. Moreover, BDAC allows organizations to monitor real-time customer feedback and preferences, leading to enhanced customer satisfaction and loyalty through tailored products and services (Jeble et al., 2018). Through the DCV lens, BDAC helps firms sense social trends and stakeholder needs, seize opportunities to improve social impact, and transform organizational practices to align with social sustainability goals (Dubey et al., 2019; Bahrami & Shokouhyar, 2022). Therefore, we hypothesize:

H2: BDAC has a positive impact on SP

3.3 Impact of BDAC on Environmental Performance

The increasing visibility of global warming effects, driven by carbon emissions, has spurred discussions on environmental concerns from local government bodies to international forums such as the United Nations. As a result, businesses face growing pressure to operate sustainably and comply with regulatory requirements (Rashid et al., 2024). Achieving high environmental performance (EP) is essential for firms to reduce their ecological footprint and contribute to global sustainability goals. Scholars widely highlight the critical role of BDAC in achieving EP. Sahoo et al. (2023) argue that BDAC can enhance EP by enabling firms to adopt data-driven approaches for environmental management. BDAC allows for the monitoring and optimization of energy use, waste management, and emission control through advanced analytics and real-time data processing (Nisar et al., 2020). From the DCV perspective, BDAC provides the dynamic capability to sense environmental challenges, seize opportunities for green innovation, and transform organizational processes to achieve sustainable environmental outcomes (Dubey et al., 2019). By integrating BDAC into their environmental strategies, firms can enhance their ecological performance, comply with environmental standards, and drive innovation for sustainability (Bag et al., 2023; Gallo et al., 2023). Therefore, we hypothesize:

H3: BDAC has a positive impact on EP

3.4 Moderating Effect of GSCM

BDAC provides valuable insights through the processing of vast amounts of data from various sources, thereby enabling better decision-making and strategic planning (Sahoo et al., 2023; Fantazy & Tipu, 2024). Nisar et al. (2023) note that organizations need to implement sustainable practices to effectively leverage the insights gained from BDAC for achieving sustainable advantages. Karmaker et al. (2023) report that the integration of GSCM with data-driven technologies can enable organizations to utilize data-driven insights to optimize resource allocation, improve operational efficiency, and reduce costs, thereby enhancing ECOP. Similarly, GSCM practices foster ethical sourcing, fair labor practices, and community engagement, which, when combined with BDAC insights, can significantly enhance SP by building stronger relationships with stakeholders and enhancing brand reputation (Rashid et al., 2024). Furthermore, GSCM practices focus on reducing the environmental impact of SC activities (Feng et al., 2022). By utilizing BDAC, firms can identify inefficiencies and adopt green technologies, energy-efficient processes, and circular economy models, thereby improving EP (Cheng et al., 2023). Thus, we posit that organizations with strong GSCM practices can more effectively utilize the insights provided by BDAC to achieve SSCP. Therefore, we hypothesize:

H4a: GSCM positively moderates the link between BDAC and ECOP

H4b: GSCM positively moderates the link between BDAC and SP

H4c: GSCM positively moderates the link between BDAC and EP.

The theoretical model is presented in Figure 1.

4.0 Research Methodology

This study employs a two-stage mixed methodology, which has proven effective in previous research (Schilke, 2014; Dubey et al., 2019). The first stage involves developing survey instruments with measurement items extracted from the existing literature, followed by pre-testing with scholars to ensure validity and reliability. In the second stage, a cross-sectional survey was conducted to collect data from diverse sample respondents within the Bangladeshi RMG sector.

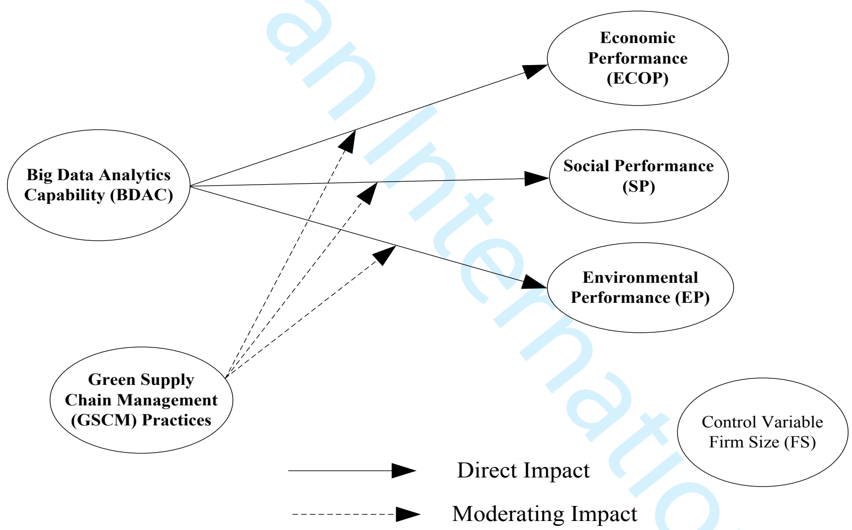

Figure 1. Theoretical Model

4.1 Survey Instrument Development

A survey-based questionnaire was developed to test the proposed model. Measurement items for each construct were sourced from previous relevant literature, with adjustments made to align the items with the context of BDAC. All constructs, both exogenous and endogenous, were operationalized as reflective constructs (see Table I). The survey questionnaire was pre-tested with three experienced academic scholars specializing in data analytics and sustainability performance. They evaluated the questionnaire for the suitability of the measurements, clarity of the questions, and potential ambiguities (DeVellis, 1991). Based on their feedback, adjustments were made to enhance the questionnaire's effectiveness and alignment with the model requirements. All measuring scales utilized a seven-point Likert scale, ranging from “1 = strongly disagree” to “7 = strongly agree.”

To control for potential variations in resources, capabilities, and organizational structures, firm size (FS) was included as a control variable. Larger firms may possess more advanced technological infrastructures and greater financial capacity to implement SC management practices, which could skew results if not controlled (Dubey et al., 2019). Firm size was categorized based on the number of employees: firms with ≤500 employees were classified as small, and firms with >500 employees were classified as large.

4.2 Data Collection

Data were collected using a cross-sectional survey from firms registered with the Bangladesh Garment Manufacturers and Exporters Association (BGMEA). The Bangladeshi RMG sector was selected due to its significant global presence and its impact on both economic development and sustainability challenges. As one of the largest apparel exporters worldwide, Bangladesh’s RMG industry faces pressing issues related to SC sustainability (Saha et al., 2024), making it an ideal context to explore the role of BDAC and the moderating influence of GSCM.

The organizational unit served as our unit of analysis, and the survey was designed for a single respondent. To ensure a representative sample, we employed a simple random sampling technique (Dillman, 2011). The BGMEA database, which includes detailed information on registered RMG firms, served as our sampling frame. A total of 760 firms were selected from this database to participate in the study. The selection process aimed to cover a diverse range of firms in terms of size, market presence, and commitment to integrating technological innovations with sustainable practices. Senior supply chain executives (e.g., purchasing managers, inventory managers, materials managers, procurement managers, sourcing managers, distribution managers, supply chain managers, logistics managers, planning managers, and directors of operations) were targeted as respondents. These individuals were chosen due to their comprehensive knowledge and expertise in SC management practices, information flow, and the adoption of data-driven technologies.

Questionnaires were e-mailed to the selected respondents through Google Forms. To enhance the response rate, we followed up with multiple reminders, typically three times. In total, we received 159 comprehensive and usable responses, resulting in a response rate of 20.92%. This response rate is deemed sufficient for PLS-SEM analysis (Dubey et al., 2020; Saha et al., 2023). We ensured the eligibility of respondents by excluding participants who were not from the RMG sector or lacked relevant experience. Additionally, incomplete responses were not included in the analysis. The sampling and response details are presented in Table II.

Table I. Measures

Construct	Type	Measures	Sources
Big data analytics capability (BDAC)	Reflective	We employ data visualization methods for comprehending intricate information extracted from extensive data sources (BDAC1)	(Dubey et al., 2019; Bahrami & Shokouhyar, 2022; Fantazy & Tipu, 2024)
		We utilize advanced analytical tools (such as optimization, regression, or simulation) to analyze data (BDAC2)	
		We integrate data from multiple sources (including company reports and social media) for comprehensive data analysis (BDAC3)	
Green supply chain management (GSCM)	Reflective	Our firm invests in technologies that enhance energy efficiency across the SC (GSCM1)	(Karmaker et al., 2023; Behl et al., 2024; Huang et al., 2024)
		Our firm implements strategies for recycling, reusing, and safe disposal of products at the end of their lifecycle (GSCM2)	
		Our firm conducts regular audits to ensure compliance with environmental standards and regulations (GSCM3)	
Economic Performance (ECOP)	Reflective	Our firm achieves higher gross profit margins by decreasing materials purchasing costs (ECOP1)	(Jeble et al., 2018; Jum'a et al., 2024)
		Our firm enhances net income margins by reducing energy consumption expenses (ECOP2)	
		Our firm increases operational efficiency by optimizing logistics and transportation costs (ECOP3)	
		Our firm improves cost-efficiency by minimizing fees associated with waste discharge (ECOP4)	
Social Performance (SP)	Reflective	Our firm believes in gender equality (SP1)	(Jeble et al., 2018; Jum'a et al., 2024)
		Our firm places significant emphasis on employee safety and occupational health (SP2)	
		Our firm adheres to international labor standards and conventions (SP3)	

Environmental Performance (EP)	Reflective	Our firm has implemented measures to reduce air emissions (EP1)	(Jeble et al., 2018; Jum'a et al., 2024)
		Our firm has adopted practices for recycling wastewater (EP2)	
		Our firm has taken steps to prevent the discharge of solid waste (EP3)	

4.3 Non-response Bias

Given the survey-based data collection process, we checked for non-response bias following Armstrong and Overton's (1977) guidelines. Collected data were categorized into early and late responses, as early respondents are thought to have greater interest in and understanding of the topic. Then, we conducted a t-test following Armstrong and Overton's (1977) recommendations and found no statistically significant difference between early and late responses. As bias did not influence our research, the two data sets were merged to test our model.

Table II. An overview of the sampling

Criteria	Genre	Number	Responses rate
Gender	Male	125	78.61%
	Female	34	21.39%
Firm size	Small (<500 employees)	24	15.09%
	Large (500-5000 employees)	135	84.91%
Experience	6-11 years	91	57.23%
	12-16 years	56	35.23%
	17-24 years	12	07.54%
Designation	Director of Operations	38	23.91%
	Planning Manager	12	07.54%
	Procurement Manager	17	10.69%
	Materials Manager	9	05.66%
	Supply Chain Manager	58	36.48%
	Logistics Manager	18	11.32%
	Other Manager	7	04.40%

5.0 Data Analysis and Result

To test our theoretical model, we employed WarpPLS 8.0 software, which utilizes the partial least squares-based structural equation modeling (PLS-SEM) technique (Kock, 2019). PLS-SEM is particularly suited for our study due to its predictive orientation (Peng & Lai, 2012) and its ability to handle complex models with smaller sample sizes effectively (Hair et al., 2016). Besides, PLS-SEM is robust to non-normal data distributions and does not require strict assumptions about the underlying data distribution, enhancing its applicability across diverse research domains (Peng & Lai, 2012; Dubey et al., 2020). Furthermore, PLS-SEM allows for the simultaneous evaluation of both measurement and structural models. This dual capability is a powerful tool for theory development and hypothesis testing, enabling us to rigorously assess the predictive accuracy of our independent latent variables (Henseler et al., 2015). Unlike covariance-based SEM (CB-SEM), PLS-SEM considers measurement errors, thus providing more accurate and reliable results (Dubey et al., 2020; Kock, 2019). Therefore, by employing WarpPLS 8.0, we aim to leverage these strengths to comprehensively evaluate the relationships and hypotheses proposed in our study, ensuring robust and reliable results.

5.1 Measurement Model

We used confirmatory factor analysis (CFA) to assess the convergent and discriminant validity of our measurement model. Following Fornell and Larcker's (1981) recommendations, we reported composite reliability (SCR) values, factor loadings for each measurement item (λ), and the average variance extracted (AVE) values (Table III). As shown in Table III, all factor loadings for the measurement items exceed the threshold limit of 0.5 and the SCR and AVE values also surpass their respective cut-off points (i.e., SCR $\geq$ 0.7, AVE $\geq$ 0.5), suggesting high convergent validity of our constructs (Fornell & Larcker, 1981). We further calculated Cronbach's alpha (α) values for each construct to evaluate the reliability of our measurement model (Table III). All α values were above the acceptable threshold of 0.7, confirming the high internal consistency and reliability of the constructs (Hair et al., 2017).

Table III. Convergent validity test (SCR, Cronbach's Alpha (α) and AVE)

Construct	Items	Factor loadings (λ)	Variance (λ^2)	Error ($1-\lambda^2$)	SCR	AVE
Big Data Analytics Capability (BDAC) (α=0.947)	BDAC1	0.95	0.90	0.10	0.97	0.91
	BDAC2	0.96	0.92	0.08		
	BDAC3	0.94	0.88	0.12		
Green supply chain management (GSCM) (α=0.840)	GSCM1	0.88	0.77	0.23	0.90	0.76
	GSCM2	0.87	0.76	0.24		
	GSCM3	0.86	0.74	0.26		
Economic Performance (ECOP) (α=0.822)	ECOP1	0.83	0.69	0.31	0.88	0.65
	ECOP2	0.77	0.59	0.41		
	ECOP3	0.80	0.64	0.36		
	ECOP4	0.82	0.67	0.33		
Social Performance (SP) (α=0.727)	SP1	0.80	0.64	0.36	0.85	0.65
	SP2	0.83	0.69	0.31		
	SP3	0.78	0.61	0.39		
Environmental Performance (EP) (α=0.735)	EP1	0.82	0.67	0.33	0.85	0.66
	EP2	0.88	0.77	0.23		
	EP3	0.72	0.52	0.48		

Then, we tested the discriminant validity following Fornell and Larcker's (1981) suggestions (Table IV). Fornell and Larcker (1981) stated that a construct shows higher discriminant validity if its square root of AVE is greater than all other constructs' correlation values. Table IV indicates that all the square root values of AVE meet the required condition, which provides significant evidence of the discriminant validity of the constructs.

Table IV. Discriminant Validity Test

	BDAC	GSCM	SP	EP	ECOP
BDAC	*0.95*				
GSCM	0.09	*0.87*			
SP	0.44	0.02	*0.80*		
EP	0.48	0.10	0.56	*0.81*	
ECOP	0.48	0.11	0.55	0.66	*0.81*

Note: Italic represents the root-square of AVE of a construct

5.2 Common Method Bias (CMB)

Survey-based data may be subject to common method biases (CMB) due to consistency in responses and implicit social desirability (Podsakoff et al., 2003). Recognizing potential biases in data obtained from a single source utilizing a survey-based instrument, as noted by Ketokivi and Schroeder (2004), we conducted two tests to assess CMB. Firstly, we performed Harman's single-factor test, following Kock's (2015) guidelines. The analysis revealed that only 37.56% of the total variance could be attributed to a single factor. Kock (2015) suggested that if the explanatory power of the single construct of the total variance is more than 50%, then it indicates the presence of CMB in the dataset. Thus, CMB is not a major concern in our dataset. Secondly, we conducted the full collinearity test to evaluate vertical and lateral collinearity, generating variance inflation factors (VIFs) for all latent variables using WarpPLS (Kock, 2017). A VIF greater than 3.3 suggests pathological collinearity and potential CMB contamination (Kock, 2017). All VIF values in our analysis were below 3.3, indicating negligible CMB impact.

Furthermore, we checked causality issues before proceeding to the hypothesis testing. We analyzed four indices: Simpson's paradox ratio (SPR), R-squared contribution ratio (RSCR), Statistical suppression ratio (SSR), and Nonlinear bivariate causality direction ratio (NLBCDR) (Table V), following Kock's (2022) suggestions. In our analysis, the NLBCDR value is found to be 0.833, which is above its cut-off value of 0.7 (Kock, 2022). Table V demonstrates that other indices are also in the allowable range, indicating that causality is not a significant concern in our study.

Table V. Causality Assessment Indices

Indices	Values
SPR	1.000, acceptable if >= 0.7
RSCR	1.000, acceptable if >= 0.9
SSR	1.000, acceptable if >= 0.7
NLBCDR	0.833, acceptable if >= 0.7

5.3 Hypothesis Testing

Our study hypotheses have been tested by PLS-SEM (WarpPLS 8.0). The PLS utilizes a bootstrapping technique to determine the standard errors and significance of parameter estimations (Chin, 1998). Table VI presents the results of the structural path analysis obtained from the PLS algorithm, showing standardized path coefficients (β) and corresponding p-values. For instance, $\beta = 0.50$, $p < 0.01$, indicates strong support for H1 (BDAC→ECOP), demonstrating that BDAC is a strong predictor of the ECOP. Similarly, H2 (BDAC→SP) ($\beta = 0.45$, $p < 0.01$) and H3 (BDAC→EP) ($\beta = 0.49$, $p < 0.01$) are statistically significant at the 0.01 level. Next, we evaluated the moderation effect of GSCM on the paths joining BDAC and EP (H4a), BDAC and SP (H4b), and BDAC and ECOP (H4c). The results show that all the moderation impacts of GSCM (H4a, H4b, and H4c) are significant at the 0.05 level (Table VI). We also assessed the impact of the control variable, firm size (FS), on our model. However, FS was not found to have a significant impact on the endogenous variables.

Table VI. Structural Estimates

Hypothesis	Effect of	Effect on	β	p-value	Results
H1	BDAC	ECOP	0.50	<.01	Supported
H2	BDAC	SP	0.45	<.01	Supported
H3	BDAC	EP	0.49	<.01	Supported
H4a	GSCM	BDAC-ECOP	0.15	<.05	Supported
H4b	GSCM	BDAC-SP	0.17	<.05	Supported
H4c	GSCM	BDAC-EP	0.25	<.05	Supported
control variables	FS	ECOP	0.02	0.39	Not significant
	FS	SP	0.03	0.35	Not significant
	FS	EP	0.07	0.18	Not significant

We then assessed the explanatory power of our model by estimating the R^2 values of the endogenous variables. The R^2 values for ECOP, SP, and EP are 0.27, 0.22, and 0.26, respectively (Table VII), indicating moderately strong explanatory power (Chin, 1998). We also determined the f^2 values to analyze the effect size of BDAC on ECOP, SP, and EP (Cohen, 1988). The effect sizes are 0.249, 0.200, and 0.236 (Table VII), respectively, indicating large effect sizes (Cohen, 1988). Furthermore, we calculated Stone-Geisser's Q^2 values to evaluate the predictive capability of our model. We found the Q^2 values for ECOP, SP, and EP are 0.229, 0.261, and 0.276, respectively (Table VII), suggesting the allowable predictive relevance (Peng & Lai, 2012).

Table VII. Coefficient of variation (R^2), predictability (Q^2) and effect size (f^2)

Construct	R^2	Q^2	f^2 in relation to BDAC
ECOP	0.27	0.229	0.249
SP	0.22	0.261	0.200
EP	0.25	0.276	0.236

5.4 Model Fit and Indices

We calculated the average path coefficient (APC), average R-squared (ARS), and Average block VIF (AVIF) to check the fitness and quality of our model (Kock, 2011; Behl et al., 2022). All the values were found to be in the allowable range (Table VIII). The AVIF value below 3.3 indicates the absence of multicollinearity issues in the dataset (Kock, 2011). We also calculated Tenenhaus GoF to measure the goodness of fit, following the suggestions of Tenenhaus et al. (2005). Tenenhaus GoF is found to be 0.449, which is considered medium (Tenenhaus et al., 2005). Based on these findings, we can conclude that our model fits our data well.

Table VIII. Model Fitness and quality indices parameter

Fitness and quality indices	Values
Average path coefficient (APC)	0.226 (P<0.001)
Average R-squared (ARS)	0.251 (P<0.001)
Average block VIF (AVIF)	1.007 (acceptable if <= 5, ideally <= 3.3)
Tenenhaus GoF	0.449 (small >= 0.1, medium >= 0.25, large >= 0.36)

6.0 Discussion

The results of this study provide significant insights into the relationships among BDAC, GSCM practices, and SC sustainability across economic, social, and environmental dimensions. The findings indicate that BDAC positively influences SC sustainability, addressing our first RQ. Specifically, BDAC was found to be a strong predictor of economic ($\beta = 0.50$, $p < 0.01$), social ($\beta = 0.45$, $p < 0.01$), and environmental performance ($\beta = 0.49$, $p < 0.01$). This outcome aligns with existing literature, which has consistently highlighted the transformative potential of BDA in SC management. For instance, Dubey et al. (2024) and Li et al. (2024) note that BDAC enables firms to process vast amounts of data, leading to improved decision-making, enhanced operational efficiency, and greater agility in responding to market changes. Our study not only confirms these findings but also extends them by empirically validating the positive impact of BDAC on all three dimensions of the TBL. While previous studies have often focused on individual aspects of sustainability, such as economic or environmental performance (Zhu et al., 2022; Morimura & Sakagawa, 2023; Gopal et al., 2024), our research offers a more comprehensive view by examining the combined effects of BDAC across economic, social, and environmental dimensions simultaneously.

Economically, our findings support earlier work by Chong et al. (2023), who highlighted the role of BDAC in optimizing inventory levels, reducing costs, and improving demand forecasting accuracy, which, in turn, enhances financial performance. However, our study contributes to the literature by demonstrating that BDAC's economic benefits also have a cascading effect on social and environmental performance. Socially, our results resonate with the findings of Dubey et al. (2019), who argued that BDAC enhances transparency and traceability in SC, improving labor practices and ensuring compliance with social standards. Yet, our study goes further by showing that these social improvements are also linked to broader supply chain sustainability goals. Environmentally, the positive influence of BDAC on sustainability is consistent with Sahoo et al. (2023), who noted its role in supporting sustainable practices such as monitoring and reducing carbon footprints, managing waste more effectively, and optimizing resource use.

The moderating role of GSCM practices was also confirmed, addressing our second RQ. The moderation effects of GSCM on the relationships between BDAC and ECOP (H4a), SP (H4b), and EP (H4c) were significant at the 0.05 level. This finding is consistent with the DCV, which posits that firms can achieve sustained competitive advantage through the integration and reconfiguration of internal and external competencies (Teece et al., 1997; Ghasemzadeh et al., 2022; Tipu & Fantazy, 2023). While prior studies, such as those by Dzikriansyah et al. (2023) and Huang et al. (2024), have explored the individual impacts of GSCM on sustainability, our research extends this body of work by illustrating how GSCM practices enhance the effectiveness of BDAC in achieving sustainability across multiple dimensions. This integrated approach provides new insights into how firms can leverage dynamic capabilities to navigate complex sustainability challenges.

The DCV emphasizes that it is not just the possession of resources like BDAC that leads to competitive advantage but how firms dynamically integrate, build, and reconfigure these resources in response to changing environments. In this context, GSCM practices serve as complementary capabilities that, when combined with BDAC, enhance a firm's ability to adapt and respond to environmental pressures and opportunities. This synergy between BDAC and GSCM practices highlights a critical extension of the DCV framework, suggesting that the dynamic reconfiguration of technological and operational capabilities is key to achieving and sustaining competitive advantage in today's rapidly evolving market. For example, Teece (2007) highlights that dynamic capabilities enable firms to create, extend, and modify their resource base to address rapidly changing environments. Our findings suggest that by integrating BDAC with GSCM practices, firms are better positioned to reconfigure their operations to achieve higher levels of sustainability. BDAC provides the technological capabilities to analyze and utilize data for better decision-making, while GSCM practices offer the procedural and operational changes needed to implement sustainable practices. This combination allows firms to continuously adapt their supply chain strategies, processes, and practices to meet sustainability goals, thus achieving a sustained competitive advantage.

6.1 Theoretical Implications

This study makes several theoretical contributions to the fields of DCV, BDAC, GSCM, and supply chain sustainability, advancing the understanding of how these constructs interact to shape sustainable SC outcomes. First, this research extends the DCV by demonstrating the synergistic effects of integrating BDAC with GSCM practices to achieve SC sustainability. While the DCV traditionally emphasizes a firm's ability to integrate, build, and reconfigure internal and external competencies in response to environmental changes (Teece, 2007), this study breaks new ground by empirically illustrating how the combination of BDAC and GSCM creates a dynamic interplay that enhances a firm's adaptability and sustainability performance. Previous studies have examined BDAC and GSCM independently (Jeble et al., 2018; Huang et al., 2024), but the interaction between these capabilities within the DCV framework has remained underexplored. By showing how BDAC and GSCM jointly contribute to sustainability across economic, social, and environmental dimensions, this study enriches the DCV by highlighting the importance of integrating complementary capabilities to achieve sustained competitive advantage in an era increasingly defined by sustainability challenges.

Second, the study empirically validates the positive impact of BDAC on the three dimensions of supply chain sustainability—economic, social, and environmental performance—within the context of the TBL framework. This finding not only corroborates existing research that emphasizes the role of BDAC in enhancing operational efficiency and resilience (e.g., Dubey et al., 2020; Liu et al., 2023) but also extends this body of literature by demonstrating the broad applicability of BDAC across multiple dimensions of sustainability. By adopting a comprehensive TBL perspective, this study addresses the call for research that moves beyond the economic benefits of BDAC to explore its role in achieving balanced economic, social, and environmental objectives in SC management.

Third, the study highlights the moderating role of GSCM practices in enhancing the impact of BDAC on SC sustainability. This insight contributes to the literature on SSCM by underscoring the necessity of integrating green practices into data-driven decision-making processes. While prior research has largely focused on the independent effects of GSCM on sustainability (Dzikriansyah et al., 2023; Hejazi et al., 2023), this study reveals that GSCM practices are most effective when combined with advanced technological capabilities like BDAC. This finding advances SSCM theory by illustrating how the alignment of technological and sustainable practices can amplify the positive outcomes of each, thereby offering a more integrated approach to achieving long-term sustainability in SCs.

6.2 Managerial Implications

The findings of this study have several practical implications for SC managers and policymakers. For SC managers, the positive impact of BDAC on SC sustainability underscores the importance of investing in data-driven analytical capabilities. Firms should focus on developing robust data analytics infrastructure, acquiring skilled personnel, and fostering a data-driven culture to harness the full potential of BDAC. By leveraging big data, managers can improve decision-making, enhance operational efficiency, and achieve SSCP.

The significant moderation effects of GSCM practices suggest that firms should integrate green SC management practices with their data analytics initiatives. Managers should adopt practices such as sustainable sourcing, waste reduction, and carbon footprint minimization to enhance the effectiveness of their BDAC efforts. By aligning GSCM practices with data-driven strategies, firms can achieve a competitive edge while contributing to environmental sustainability.

For policymakers, the study highlights the importance of promoting policies that encourage the adoption of BDAC and GSCM practices in the supply chain sector. Governments and regulatory bodies should provide incentives for firms to invest in big data analytics and implement green practices. Policies that support training and development programs in data analytics and sustainability can help build the necessary skills and capabilities within the industry. Additionally, policymakers should encourage collaboration between industry and academia to foster innovation and disseminate best practices in sustainable SC management.

7.0 Conclusion

This study has developed and tested a theoretical framework grounded on DCV theory to explore the role of BDAC in enhancing SC sustainability while examining the moderating effects of GSCM practices. Utilizing data from 159 respondents in the Bangladeshi RMG sector, the findings reveal that BDAC significantly improves economic, social, and environmental performance. Additionally, GSCM practices significantly strengthen the positive impacts of BDAC on these dimensions of sustainability. These results underscore the importance of integrating BDAC with GSCM practices to achieve comprehensive SC sustainability. The study contributes to the DCV by illustrating how the reconfiguration and integration of BDAC and GSCM can lead to sustained competitive advantage and improved sustainable performance in supply chains.

7.1 Limitations and Future Scopes

Despite the valuable insights provided by this study, several limitations should be acknowledged. First, the cross-sectional nature of the data limits the ability to infer causality between BDAC, GSCM practices, and SC sustainability outcomes. Future research could employ longitudinal designs to better capture the dynamic effects of these variables over time.

Second, the study focuses solely on the Bangladeshi RMG sector, which may limit the generalizability of the findings to other industries or geographical contexts. Future studies could explore these relationships in different sectors and regions to enhance external validity.

Third, while this research uses survey data from senior SC executives, incorporating multiple respondents from each firm or triangulating survey data with qualitative interviews could provide a more comprehensive understanding.

Lastly, we applied the DCV perspectives to frame our research; however, future studies may apply other theoretical frameworks to offer a more comprehensive explanation. Researchers could explore additional organizational capabilities or assets that complement BDAC. Moreover, incorporating theoretical perspectives such as the knowledge-based view, contingency theory, information processing theory, organizational learning, and organizational culture might yield valuable extensions to our study.

References

Akram, H. W., Ahmad, A., Abbas, H., & Akhter, S. (2024). A bibliometric analysis of the genesis, journey, and current status of green supply chain management in the digital economy. Benchmarking: An International Journal.

Arias-Pérez, J., Coronado-Medina, A., & Perdomo-Charry, G. (2022). Big data analytics capability as a mediator in the impact of open innovation on firm performance. Journal of Strategy and Management, 15(1), 1-15.

Armstrong, J. S., & Overton, T. S. (1977). Estimating Non-response Bias in Mail Surveys. Journal of Marketing Research, 14(3), 396–402.

Bag, S., Rahman, M. S., Srivastava, G., Shore, A., & Ram, P. (2023). Examining the role of virtue ethics and big data in enhancing viable, sustainable, and digital supply chain performance. Technological Forecasting and Social Change, 186, 122154.

Bagherpasandi, M., Salehi, M., Hajiha, Z., & Hejazi, R. (2024). Presenting a model for enhancing the performance of sustainable supply chain management using a data-driven approach. Benchmarking: An International Journal, (ahead-of-print).

Bahrami, M., & Shokouhyar, S. (2022). The role of big data analytics capabilities in bolstering supply chain resilience and firm performance: a dynamic capability view. Information Technology & People, 35(5), 1621-1651.

Balkumar, K., Gedam, V. V., Himateja, M., Anbuudayasankar, S. P., Narassima, M. S., Ganesh, K., Dwarakanath, M., & Pazhani, S. (2024). Prevalence and future trend in green supply chain management (GSCM): a systematic literature review. Benchmarking: An International Journal, 31(6), 2002-2033.

Behl, A. (2022). Antecedents to firm performance and competitiveness using the lens of big data analytics: a cross-cultural study. Management Decision, 60(2), 368-398.

Behl, A., Gaur, J., Pereira, V., Yadav, R., & Laker, B. (2022). Role of big data analytics capabilities to improve the sustainable competitive advantage of MSME service firms during COVID-19– A multi-theoretical approach. Journal of Business Research, 148, 378-389.

Behl, A., Sampat, B., Gaur, J., Pereira, V., Laker, B., Shankar, A., ... & Roohanifar, M. (2024). Can gamification help green supply chain management firms achieve sustainable results in servitized ecosystem? An empirical investigation. Technovation, 129, 102915.

Belhadi, A., Kamble, S. S., Gunasekaran, A., Zkik, K., & Touriki, F. E. (2023). A Big Data Analytics-driven Lean Six Sigma framework for enhanced green performance: a case study of a chemical company. Production Planning & Control, 34(9), 767-790.

Boyd, B. K., Takacs Haynes, K., Hitt, M. A., Bergh, D. D., & Ketchen Jr, D. J. (2012). Contingency hypotheses in strategic management research: Use, disuse, or misuse? Journal of Management, 38(1), 278-313.

Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: moving toward new theory. International Journal of Physical Distribution & Logistics Management, 38(5), 360-387.

Cetindamar, D., Shdifat, B., & Erfani, E. (2022). Understanding Big Data Analytics Capability and Sustainable Supply Chains. Information Systems Management, 39(1), 19–33.

Cheng, J., Singh, H. S. M., Zhang, Y. C., & Wang, S. Y. (2023). The impact of business intelligence, big data analytics capability, and green knowledge management on sustainability performance. Journal of Cleaner Production, 429, 139410.

Chong, C. L., Abdul Rasid, S. Z., Khalid, H., & Ramayah, T. (2023). Big data analytics capability for competitive advantage and firm performance in Malaysian manufacturing firms. International Journal of Productivity and Performance Management.

Chin, W. W. (1998). Commentary: Issues and Opinion on Structural Equation Modeling. MIS Quarterly, 22(1), 07-16.

Choi, H. Y., & Park, J. (2022). Do data-driven CSR initiatives improve CSR performance? The importance of big data analytics capability. Technological Forecasting and Social Change, 182, 121802.

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences, 2nd Edn. Hillsdale, NJ: Erlbaum.

DeVellis, R.F., 1991. Scale Development: Theory and Applications. Sage Publications, Newbury Park, CA.

Dillman, D. A. (2011). Mail and Internet surveys: The tailored design method--2007 Update with new Internet, visual, and mixed-mode guide. John Wiley & Sons.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Luo, Z., Wamba, S. F., & Roubaud, D. (2019). Can big data and predictive analytics improve social and environmental sustainability? Technological Forecasting and Social Change, 144, 534-545.

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., ... & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organizations. International Journal of Production Economics, 226, 107599.

Dubey, R., Bryde, D. J., Graham, G., Foropon, C., Kumari, S., & Gupta, O. (2024). The role of alliance management, big data analytics, and information visibility on new-product development capability. Annals of Operations Research, 1-25.

Dzikriansyah, M. A., Masudin, I., Zulfikarijah, F., Jihadi, M., & Jatmiko, R. D. (2023). The role of green supply chain management practices on environmental performance: A case of Indonesian small and medium enterprises. Cleaner Logistics and Supply Chain, 6, 100100.

Eisenhardt, K.M. and Martin, J.A. (2000). Dynamic capabilities: what are they? Strategic Management Journal, 21 (10/11), 1105-1121.

Elkington, J. (1998). Partnerships from cannibals with forks: The triple bottom line of 21st-century business. Environmental Quality Management, 8(1), 37-51.

Fantazy, K., & Tipu, S. A. A. (2024). Linking big data analytics capability and sustainable supply chain performance: mediating role of knowledge development. Management Research Review, 47(4), 512-536.

Feng, Y., Lai, K. H., & Zhu, Q. (2022). Green supply chain innovation: Emergence, adoption, and challenges. International Journal of Production Economics, 248, 108497.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39.

Gallo, H., Khadem, A., & Alzubi, A. (2023). The Relationship between Big Data Analytic-Artificial Intelligence and Environmental Performance: A Moderated Mediated Model of Green Supply Chain Collaboration (GSCC) and Top Management Commitment (TMC). Discrete Dynamics in Nature and Society, 2023(1), 4980895.

Ghasemzadeh, P., Rezayat Sorkhabadi, S. M., Kebriaeezadeh, A., Nazari, J. A., Farzaneh, M., & Mehralian, G. (2022). How does organizational learning contribute to corporate social responsibility and innovation performance? The dynamic capability view. Journal of Knowledge Management, 26(10), 2579-2601.

Gopal, P. R. C., Rana, N. P., Krishna, T. V., & Ramkumar, M. (2024). Impact of big data analytics on supply chain performance: an analysis of influencing factors. Annals of Operations Research, 333(2), 769-797.

Gupta, Y., Khan, F. M., Kumar, A., Luthra, S., & Queiroz, M. M. (2024). Mobilizing big data analytics capabilities to improve performance of tourism supply chains: the moderating role of dynamic capabilities. The International Journal of Logistics Management, 35(2), 649-679.

Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012). The Use of Partial Least Squares Structural Equation Modeling in Strategic Management Research: A Review of Past Practices and Recommendations for Future Applications. Long Range Planning, 45(5), 320–340.

Hair, J. F., Sarstedt, M., Matthews, L. M., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: part I – method. European Business Review, 28(1), 63–76.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. Industrial Management & Data Systems, 117(3), 442-458.

Hejazi, M. T., Al Batati, B., & Bahurmuz, A. (2023). The influence of green supply chain management practices on corporate sustainability performance. Sustainability, 15(6), 5459.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135.

Huang, X., Ullah, M., Wang, L., Ullah, F., & Khan, R. (2024). Green supply chain management practices and triple bottom line performance: Insights from an emerging economy with a mediating and moderating model. Journal of Environmental Management, 357, 120575.

Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D., & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. International Journal of Logistics Management, 29(2), 513–538.

Jum'a, L., Zimon, D., & Madzik, P. (2024). Impact of big data technological and personal capabilities on sustainable performance on Jordanian manufacturing companies: the mediating role of innovation. Journal of Enterprise Information Management, 37(2), 329–354.

Karmaker, C. L., Al Aziz, R., Ahmed, T., Misbauddin, S. M., & Moktadir, M. A. (2023). Impact of Industry 4.0 technologies on sustainable supply chain performance: The mediating role of green supply chain management practices and circular economy. Journal of Cleaner Production, 419, 138249.

Ketokivi, M.A. and Schroeder, R.G. (2004). Perceptual measures of performance: fact or fiction? Journal of Operations Management, 22 (3), 247-264.

Khan, S. A. R., Yu, Z., & Farooq, K. (2023). Green capabilities, green purchasing, and triple bottom line performance: Leading toward environmental sustainability. Business Strategy and Environment, 32(4), 2022-2034.

Kock, N. (2011). A mathematical analysis of the evolution of human mate choice traits: Implications for evolutionary psychologists. Journal of Evolutionary Psychology, 9(3), 219–247.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1-10.

Kock, N. (2017). Common Method Bias: A Full Collinearity Assessment Method for PLS-SEM. In: Latan, H., Noonan, R. (eds) Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications (pp. 245–257), Springer, Cham.

Kock, N. (2019). From composites to factors: Bridging the gap between PLS and covariance-based structural equation modelling. Information Systems Journal, 29(3), 674–706.

Kock, N. (2022). Using causality assessment indices in PLS-SEM. Data Analysis Perspectives Journal, 3(5), 1-6.

Le, T. T. (2023). Linking big data, sustainable supply chain management and corporate performance: the moderating role of circular economy thinking. The International Journal of Logistics Management, 34(3), 744-771.

Li, W., Waris, I., & Bhutto, M. Y. (2024). Understanding the nexus among big data analytics capabilities, green dynamic capabilities, supply chain agility, and green competitive advantage: the moderating effect of supply chain innovativeness. Journal of Manufacturing Technology Management, 35(1), 119-140.

Liu, H., Lu, F., Shi, B., Hu, Y., & Li, M. (2023). Big data and supply chain resilience: role of decision-making technology. Management Decision, 61(9), 2792-2808.

Ma, L., & Chang, R. (2024). How big data analytics and artificial intelligence facilitate digital supply chain transformation: the role of integration and agility. Management Decision, (ahead-of-print).

Morimura, F., & Sakagawa, Y. (2023). The intermediating role of big data analytics capability between responsive and proactive market orientations and firm performance in the retail industry. Journal of Retailing and Consumer Services, 71, 103193.

Naseer, S., Song, H., Adu-Gyamfi, G., Abbass, K., & Naseer, S. (2023). Impact of green supply chain management and green human resource management practices on the sustainable performance of manufacturing firms in Pakistan. Environmental Science and Pollution Research, 30(16), 48021-48035.

Nisar, Q. A., Nasir, N., Jamshed, S., Naz, S., Ali, M., & Ali, S. (2020). Big data management and environmental performance: role of big data decision-making capabilities and decision-making quality. Journal of Enterprise Information Management, 34(4), 1061–1096.

Nisar, Q. A., Haider, S., Ameer, I., Hussain, M. S., Gill, S. S., & Usama, A. (2023). Sustainable supply chain management performance in post COVID-19 era in an emerging economy: a big data perspective. International Journal of Emerging Markets, 18(12), 5900-5920.

Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. Journal of Operations Management, 30(6), 467–480.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. Journal of Applied Psychology, 88(5), 879–903.

Raj, R., Kumar, V., & Verma, P. (2023). Big data analytics in mitigating challenges of sustainable manufacturing supply chain. Operations Management Research, 16(4), 1886-1900.

Rashid, A., Baloch, N., Rasheed, R., & Ngah, A. H. (2024). Big data analytics-artificial intelligence and sustainable performance through green supply chain practices in manufacturing firms of a developing country. Journal of Science and Technology Policy Management.

Riggs, R., Roldán, J. L., Real, J. C., & Felipe, C. M. (2023). Opening the black box of big data sustainable value creation: the mediating role of supply chain management capabilities and circular economy practices. International Journal of Physical Distribution & Logistics Management, 53(7/8), 762-788.

Saha, P., Talapatra, S., Belal, H. M., Jackson, V., Mason, A., & Durowoju, O. (2023). Examining the viability of lean production practices in the Industry 4.0 era: an empirical evidence based on B2B garment manufacturing sector. Journal of Business & Industrial Marketing, 38(12), 2694-2712.

Saha, P., Belal, H. M., & Talapatra, S. (2024). Driving Towards Sustainable Development Goals (SDGs) in the Ready-Made Garments (RMG) Sector: The Role of Digital Capabilities and Operational Transparency. IEEE Transactions on Engineering Management, (ahead-of-print).

Sahoo, S., Upadhyay, A., & Kumar, A. (2023). Circular economy practices and environmental performance: Analysing the role of big data analytics capability and responsible research and innovation. Business Strategy and the Environment, 32(8), 6029-6046.

Sarkis, J., Zhu, Q., & Lai, K. H. (2011). An organizational theoretic review of green supply chain management literature. International Journal of Production Economics, 130(1), 1-15.

Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. Strategic Management Journal, 35(2), 179–203.

Shi, H., Feng, T., & Zhu, Z. (2023). The impact of big data analytics capability on green supply chain integration: an organizational information processing theory perspective. Business Process Management Journal, 29(2), 550-577.

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and micro foundations of (sustainable) enterprise performance. Strategic Management Journal, 28 (13), 1319-1350.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y. M., & Lauro, C. (2005). PLS path modeling. Computational statistics & data analysis, 48(1), 159-205.

Tipu, S. A. A., & Fantazy, K. (2023). Examining the relationships between big data analytics capability, entrepreneurial orientation, and sustainable supply chain performance: the moderating role of trust. Benchmarking: An International Journal.

Xu, J., & Pero, M. E. P. (2023). A resource orchestration perspective of organizational big data analytics adoption: evidence from supply chain planning. International Journal of Physical Distribution & Logistics Management, 53(11), 71-97.

Yamin, M. A. Y. (2024). The role of HR practices, big data analytics capabilities, and supply chain resilience in achieving firm disaster immunity: the moderating effect of a data-driven culture. Benchmarking: An International Journal.

Yan, X., Chen, X., Lu, C., Liu, W., Shi, X., & Gong, Y. (2024). Strategy for sustainable supply chain transformation: a resource orchestration perspective. Industrial Management & Data Systems, (ahead-of-print).

Yousefi, S., & Tosarkani, B. M. (2023). Exploring the role of blockchain technology in improving sustainable supply chain performance: a system-analysis-based approach. IEEE Transactions on Engineering Management, 71, 4389-4405.

Zhu, C., Du, J., Shahzad, F., & Wattoo, M. U. (2022). Environment sustainability is a corporate social responsibility: measuring the nexus between sustainable supply chain management, big data analytics capabilities, and organizational performance. Sustainability, 14(6), 3379.

Big Data Analytics Capability and Supply Chain Sustainability: Analyzing the Moderating Role of Green Supply Chain Management Practices

Abstract

Purpose: This research develops a theoretical framework to understand the role of big data analytics capability (BDAC) in enhancing supply chain sustainability and examines the moderating effect of green supply chain management (GSCM) practices on this relationship.

Design/Methodology: Guided by the dynamic capability view (DCV), we formulated a theoretical model and research hypotheses. We used partial-least-square-based structural equation modeling (PLS-SEM) to analyze data collected from 159 survey responses from Bangladeshi ready-made garments (RMG).

Findings: The statistical analysis revealed that BDAC positively impacts all three dimensions of supply chain sustainability: economic, social, and environmental. Additionally, GSCM practices significantly moderate the relationship between BDAC and supply chain sustainability.

Value/Originality: This study advances the current understanding of supply chain sustainability by integrating BDAC with GSCM practices. It is among the first to empirically investigate the combined effects of BDAC on the three dimensions of sustainability—economic, social, and environmental—while also exploring the moderating role of GSCM practices. By employing the DCV, this research offers a robust theoretical framework highlighting the dynamic interplay between technological and environmental capabilities in achieving sustainable supply chain performance.

Implications: This study makes unique contributions to the operations and supply chain management literature by providing empirical evidence and theoretical insights that extend beyond the focus on single sustainability dimensions. The findings offer valuable guidelines for policymakers and managers to enhance supply chain sustainability through BDAC and GSCM practices.

Keywords: Big data analytics capability (BDAC), dynamic capability view (DCV), sustainable supply chain performance (SSCP), green supply chain management (GSCM).

Type: Research paper

1.0 Introduction

In recent years, the imperative for sustainability within supply chains (SCs) has grown exponentially due to the significant environmental impacts of SC activities, including production, distribution, transportation, and disposal (Bag et al., 2023; Shrivastava, 2023; Yan et al., 2024).

This urgency is driven by increasing global awareness and regulatory pressures, necessitating a shift towards sustainable supply chain management (SSCM) (Le, 2023; Srivastava & Bag, 2023; Jum'a et al., 2024). SSCM seeks to integrate sustainable practices into SC operations to balance economic, social, and environmental performance (Cetindamar et al., 2022). By doing so, SSCM addresses environmental challenges, enhances corporate reputation, reduces costs, and meets regulatory requirements. Pursuing sustainable supply chain performance (SSCP) is now a critical goal for organizations, particularly in emerging economies where the balance between industrial growth and environmental stewardship is precarious (Naseer et al., 2023; Raj et al., 2023).

The triple bottom line (TBL) framework encompasses economic, social, and environmental dimensions, is a cornerstone for understanding sustainability in SCs (Carter & Rogers, 2008). Unlike traditional SC management, which primarily focuses on financial outcomes, SSCM emphasizes the need for a holistic approach that addresses broader sustainability issues (Yousefi & Tosarkani, 2023). This paradigm shift highlights the importance of developing capabilities that enable organizations to adapt and thrive in an increasingly complex and dynamic environment (Huang et al., 2024).

With the advent of advanced technologies, big data analytics (BDA) has become a pivotal factor in optimizing SC performance and achieving competitive advantages (Liu et al., 2023; Kumar et al., 2023; Gopal et al., 2024). Big data (BD), characterized by its volume, variety, velocity, veracity, and value, generates vast amounts of information that can be leveraged through BDA (Rashid et al., 2024). BDA enables firms to process vast amounts of data, uncover hidden patterns, and make data-driven decisions that enhance operational efficiency (Morimura & Sakagawa, 2023). Studies show that BDA positively impacts supply chain performance through enhanced resilience and innovation (Arias-Pérez et al., 2022; Bahrami & Shokouhyar, 2022). Developing BDA capabilities (BDAC) enables firms to execute algorithms faster with larger datasets, improving decision-making and forecasting market preferences (Choi & Park, 2022). BDAC allows organizations to convert data into actionable insights, enhancing SC performance and decision-making (Xu & Pero, 2023). Prominent corporations like Walmart, Uber, Netflix, Google, Amazon, and Facebook have leveraged BDA to benefit their SC functions (Belhadi et al., 2023). Implementing BDA in supply chains improves service supply chain innovation capabilities and overall performance (Sahoo et al., 2023).

Despite the recognized potential of BDAC, there remains a gap in understanding how it influences the three pillars of supply chain sustainability—economic, social, and environmental performance. Though few scholars have looked into the impact of BDAC on a single dimension of SC sustainability, empirical research on their impact across the three dimensions of sustainability is lacking. For instance, some scholars have explored BDAC's impact on environmental sustainability (Dubey et al., 2019; Nisar et al., 2020; Zhu et al., 2022; Belhadi et al., 2023; Sahoo et al., 2023), and others have examined its relationship with economic performance (Dubey et al., 2020; Arias-Pérez et al., 2022; Bahrami, & Shokouhyar, 2022; Behl, 2022; Morimura & Sakagawa, 2023; Gopal et al., 2024), however, comprehensive studies on BDAC's combined

effects on all three dimensions are limited. To address this gap, we pose our first research question (RQ1):

RQ1: What are the impacts of BDAC on the three dimensions of supply chain sustainability?

Boyd et al. (2012) assert that models analyzing direct effects are crucial but insufficient for understanding real-world complexities. Research indicates that BDAC performance depends on various contextual factors (Dubey et al., 2019; Tipu & Fantazy, 2023; Yamin, 2024). Thus, we explore conditions that enhance BDAC effectiveness. Green supply chain management (GSCM) practices have been widely used as a significant influencing element in SC and operations management literature (Sarkis et al., 2011; Khan et al., 2023; Rahman et al., 2023). Sahoo et al. (2023) highlight the importance of selecting appropriate practices for a competitive edge in SCM. Behl et al. (2024) note that GSCM practices can reduce carbon footprints, waste, and hazardous substances in manufacturing, contributing to sustainability. Rashid et al. (2024) suggest that GSCM can enhance technological solutions' effectiveness. Therefore, we propose that GSCM practices may moderate BDAC's impact on SSCP. However, empirical studies on this moderating role are lacking. Thus, we pose our second research question (RQ2):

RQ2: What are the moderating effects of GSCM on the links between BDAC and SSCP?

We develop a theoretical framework based on the dynamic capability view (DCV) to explore BDAC's influence on the three sustainability aspects. The DCV emphasizes firms' adaptation, integration, and reconfiguration of internal and external competencies, such as BDA and GSCM, to achieve sustained competitive advantage and supply chain sustainability (Teece, 2007). We collected 159 responses from the Bangladesh ready-made garments (RMG) industry using a survey-based questionnaire. Our findings enrich the BDAC literature by integrating the DCV to explain how BDAC and GSCM jointly contribute to SC sustainability. Additionally, it provides a nuanced understanding of contextual conditions that enhance BDAC's effectiveness in achieving sustainability goals. Practitioners can leverage these insights to implement BDAC and GSCM practices strategically, improving operational efficiency and environmental performance.

Our document is structured as follows: Section 2 presents the research background and theoretical foundations. Section 3 discusses theoretical model development. Section 4 covers the research methodology, including sample selection, data collection, and non-response bias. Section 5 details the data analysis and results. Section 6 discusses overall findings and future research directions.

2.0 Theoretical background

2.1 DCV

DCV is an extension of the resource-based view (RBV) theory, addressing criticisms that RBV often fails to explain how and under what conditions resources can grant competitive advantages (Eisenhardt & Martin, 2000). DCV provides insights into how organizations can achieve competitive advantages in evolving environments by integrating, reorganizing, and developing internal and external capabilities (Teece et al., 1997; Ghasemzadeh et al., 2022). According to

Teece et al. (1997), dynamic capabilities are defined as a company's ability to adapt to rapidly changing environments by sensing opportunities and threats, seizing opportunities, and transforming resources to maintain a competitive edge.

Dynamic capabilities encompass three primary dimensions: sensing, seizing, and transforming. Sensing involves identifying and assessing opportunities and threats in the market. Seizing refers to mobilizing resources to capture opportunities and mitigate threats. Transforming entails reconfiguring and realigning resources to sustain competitiveness (Teece, 2007).

In this context, BDAC is regarded as a dynamic capability that enables organizations to reconfigure firm-level resources in response to evolving market conditions and technological advancements (Dubey et al., 2019; Bahrami & Shokouhyar, 2022; Sahoo et al., 2023). By effectively processing, analyzing, and visualizing data, BDAC provides valuable insights that enhance decision-making, planning, and execution (Xu & Pero, 2023). Moreover, BDAC fosters innovation and learning by allowing organizations to experiment with various analytical techniques and continuously refine their processes (Belhadi et al., 2023).

Given these arguments, DCV serves as an appropriate theoretical lens for understanding the role of BDAC in achieving business competitiveness in dynamic environments. In this study, we argue that organizations can remain agile, competitive, and resilient by leveraging BDAC as a dynamic capability, ultimately contributing to SSCP.

2.2 BDAC

As businesses have become more technologically advanced, their SCs generate vast amounts of data (Cheng et al., 2023; Riggs et al., 2023). Jum'a et al. (2024) highlight that big data is a novel method for organizing and analyzing this information, providing valuable insights for SC participants. Belhadi et al. (2023) define big data as extensive, diverse observational data that supports various decision-making processes. While almost all firms now have access to big data, traditional methods often fall short of effectively analyzing and deriving meaningful conclusions from large datasets (Bagherpasandi et al., 2024). To address this, organizations require real-time capabilities to handle larger and more complex data sets, leading to commercial benefits. This necessitates the development of new data architectures, analytical techniques, and tools (Bag et al., 2023).

Researchers have acknowledged that the success of big data projects depends not just on data availability, analytical tools, and process utilization but on a broader range of factors (Bahrami & Shokouhyar, 2022; Ma & Chang, 2024). The big BDAC concept was introduced to capture this complexity (Rashid et al., 2024). BDAC is generally defined as an organization's ability to effectively leverage data management, infrastructure, and talent to derive actionable insights, transforming the business into a competitive force (Riggs et al., 2023). With BDAC, organizations can process, analyze, and visualize data, thereby improving planning, decision-making, and mission execution (Shi et al., 2023; Gupta et al., 2024).

Nisar et al. (2023) assert that applying BDAC in supply chains can mitigate various organizational uncertainties related to capacity, supplier availability, and customer demands. Moreover, BDAC can foster process-oriented dynamic capabilities within organizations, enhancing firm performance. By adopting a holistic view of BDAC that encompasses all relevant organizational resources, firms can maximize the strategic value of big data, gaining a sustainable competitive advantage in today's data-driven business environment (Jum'a et al., 2024).

2.3 GSCM

In recent years, there has been a growing emphasis on integrating environmental sustainability into SCM, giving rise to the concept of GSCM. GSCM refers to incorporating eco-friendly practices in supply chain operations, encompassing procurement, production, distribution, and end-of-life management (Feng et al., 2022). This approach aims to minimize SCs' environmental footprint by reducing waste, emissions, and energy consumption while enhancing resource efficiency and sustainability (Sarkis et al., 2011).

GSCM practices include various activities such as green procurement, eco-design, reverse logistics, and sustainable packaging (Behl et al., 2024). Green procurement involves selecting suppliers based on their environmental performance and encouraging them to adopt sustainable practices. Eco-design focuses on creating products with minimal environmental impact throughout their lifecycle, from raw material extraction to disposal. Reverse logistics involves the process of reclaiming products for reuse, recycling, or proper disposal, thereby reducing waste and conserving resources. Sustainable packaging aims to use recyclable or biodegradable materials, reducing the environmental burden of packaging waste (Sarkis et al., 2011; Behl et al., 2024). Proactive GSCM practices ensure regulatory compliance, enhance reputation, and drive economic benefits by improving environmental performance, attracting eco-conscious consumers and investors (Althaqafi, 2023; Tsai et al., 2023; Wiredu et al., 2023).

GSCM practices are adopted by various factors, including regulatory pressures, stakeholder expectations, and the desire for competitive advantage (Karmaker et al., 2023). Governments worldwide have implemented stringent environmental regulations that compel organizations to adopt sustainable practices. Additionally, consumers and other stakeholders increasingly demand environmentally responsible products and practices, prompting companies to integrate sustainability into their SC strategies (Akram et al., 2024). Firms that successfully implement GSCM can achieve significant benefits such as cost savings, improved brand image, and enhanced compliance with environmental standards (Dzikriansyah et al., 2023; Balkumar et al., 2024).

Moreover, GSCM can significantly influence SC sustainability by integrating the TBL principles, which focus on economic, social, and environmental performance (Huang et al., 2024). By reducing environmental impact and promoting social responsibility, GSCM helps organizations achieve a balanced approach to sustainability, which is essential for long-term success and resilience in the competitive market (Khan et al., 2023). In conclusion, GSCM represents a strategic approach to achieving SC sustainability by integrating environmental considerations into SCM. The adoption of green practices not only helps organizations comply with regulatory requirements and meet stakeholder expectations and provides a competitive edge by enhancing operational efficiency and brand reputation (Hunag et al., 2024).

2.4 SSCP

SSCP is an integral concept in contemporary SCM, emphasizing the need for a holistic approach that balances economic, social, and environmental performance. The TBL framework underpins SSCP, advocating that businesses should focus on profitability and consider their social and environmental responsibilities (Elkington, 1998). The pursuit of SSCP is becoming increasingly critical as organizations strive to meet the demands of various stakeholders, including customers, regulators, and the broader community, while ensuring long-term sustainability and competitiveness (Yousefi & Tosarkani, 2023). Moreover, SSCP drive innovation, encouraging the development of new products and processes that are both eco-friendly and cost-effective (Holling & Backhaus, 2023; Kumar et al., 2023).

2.4.1 Economic Performance

The economic dimension of SSCP pertains to the financial health and efficiency of SC operations. This includes cost reduction, improved profitability, and value creation throughout the SC (Cetindamar et al., 2022). Effective SC management practices can lead to significant economic benefits by optimizing resource utilization, enhancing operational efficiency, and reducing waste. Economic sustainability in supply chains ensures long-term financial viability and competitive advantage, crucial for organizational success in a dynamic market environment (Khan et al., 2023; Huang et al., 2024). SSCP boost economic performance by reducing energy and water costs, enhancing efficiency, and leveraging digital technologies for better resource management & driving profitability (Abuzawida et al., 2023; Al-Khatib, 2023; Asante-Darko & Osei, 2023; Billah et al., 2023; Xu et al., 2023).

2.4.2 Social Performance

The social dimension of SSCP focuses on the impact of SC activities on various stakeholders, including employees, communities, and customers. It encompasses labor practices, human rights, community engagement, and customer satisfaction (Karmaker et al., 2023). Ensuring fair labor practices, promoting diversity and inclusion, and engaging in ethical sourcing are key components of social sustainability. By addressing social concerns, organizations can build stronger relationships with stakeholders, enhance brand reputation, and foster customer loyalty, which is essential for sustainable business operations (Dubey et al., 2019; Saha et al., 2023). Ensuring safe working conditions and responsible sourcing are essential for social sustainability. Promoting diversity and societal responsibility strengthens relationships with stakeholders. Prioritizing product safety, social capital comprising networking, trustworthiness, and information exchange plays a significant role in developing sustainable supply chains (Al-Tarawneh et al., 2024; Khokhar et al., 2020; Wijaya & Said, 2024).ss

2.4.3 Environmental Performance

The environmental dimension of SSCP involves minimizing the ecological footprint of SC activities. This includes reducing resource consumption, waste, and emissions throughout the SC (Nisar et al., 2020). Environmental sustainability practices in supply chains often involve adopting green technologies, implementing energy-efficient processes, and promoting the circular economy. By integrating environmental considerations into SCM, organizations can mitigate environmental risks, comply with regulatory requirements, and contribute to global sustainability goals (Zhu et al., 2022; Sahoo et al., 2023). This enhances environmental performance and drives innovation and operational efficiencies (Gallo et al., 2023).

3.0 Theoretical Framework and Hypothesis

The DCV constitutes the basis of our theoretical framework (Figure 1). Drawing on the DCV theory, this study posits that BDAC serves as a critical dynamic capability, enabling firms to reconfigure their resources and processes in response to evolving market conditions and technological advancements (Dubey et al., 2019; Bahrami & Shokouhyar, 2022). BDAC allows organizations to effectively process, analyze, and utilize vast amounts of data, enhancing their economic, social, and environmental performance—key dimensions of SSCP (Dubey et al., 2020; Riggs et al., 2023). Additionally, GSCM practices are hypothesized to play a moderating role in this relationship. By integrating environmental considerations into supply chain operations, we argue that GSCM practices can amplify the positive impact of BDAC on SSCP. This integration is theorized to enhance the firm's ability to achieve sustainability goals, comply with regulatory requirements, and meet stakeholder expectations, ensuring long-term competitiveness and resilience.

3.1 Impact of BDAC on Economic Performance

In the contemporary business environment, maintaining profitability is paramount for firms' long-term survival and competitiveness (Jeble et al., 2018). Economic performance (ECOP) is typically assessed through profitability, competitiveness, cost reduction, and brand equity (Behl, 2022). The existing literature underscores the significant role of BDAC in enhancing ECOP. Bag et al. (2023) state that effective BDAC enables firms to optimize resource allocation, reduce costs, and improve overall profitability through demand forecasting, inventory management, and production planning. Furthermore, Morimura and Sakagawa (2023) argue that BDAC provides real-time insights into market trends and consumer behavior, allowing for more informed and timely decisions that drive economic benefits. Large firms benefit from value-added advantages, while small firms experience increased sales through product innovation. BDA improves investment efficiency, allowing for timely and informed decision-making, and enhances forecasting accuracy by utilizing high-frequency data. In the financial sector, BDA supports risk management and decision-making, promoting strategic agility and sustainable performance in dynamic markets (Ansari & Ghasemaghaei, 2023; Boreik et al., 2023; Conti et al., 2023; Reddy & Reddy, 2023). Additionally, BDAC supports the development of predictive analytics, which can anticipate market fluctuations and optimize pricing strategies (Dubey et al., 2020). From the DCV perspective, BDAC can be seen as a dynamic capability that allows firms to reconfigure their resources and processes to adapt to changing market conditions and achieve superior ECOP (Bahrami & Shokouhyar, 2022; Sahoo et al., 2023). Therefore, we hypothesize:

H1: BDAC has a positive impact on ECOP

3.2 Impact of BDAC on Social Performance

In today's socially conscious business environment, organizations are increasingly expected to go beyond economic success and demonstrate a commitment to social responsibility. Ensuring positive social performance (SP) is crucial for firms to maintain strong stakeholder relationships and foster customer loyalty (Choi & Park, 2022). BDAC can significantly enhance SP by enabling firms to analyze extensive data on employee welfare, working conditions, and community impact (Dubey et al., 2019). Choi and Park (2022) argue that BDAC facilitates better labor practices and more ethical sourcing decisions, ensuring compliance with social standards and regulations. Moreover, BDAC allows organizations to monitor real-time customer feedback and preferences, enhancing customer satisfaction and loyalty through tailored products and services (Jeble et al., 2018). Big Data enables the personalization of services and products, enhancing user satisfaction and engagement while improving social competence in digital learning environments (Sfetcu, 2024). Big data analytics provides insights into human behavior and market trends, benefiting marketing and customer understanding and planning future initiatives. Additionally, it reveals patterns in social interactions that correlate with academic success and foster innovation performance, especially in high-tech firms (Elfeky et al., 2023; Sfetcu, 2024; Wang et al., 2023). Through the DCV lens, BDAC helps firms sense social trends and stakeholder needs, seize opportunities to improve social impact and transform organizational practices to align with social sustainability goals (Dubey et al., 2019; Bahrami & Shokouhyar, 2022). Therefore, we hypothesize:

H2: BDAC has a positive impact on SP

3.3 Impact of BDAC on Environmental Performance

The increasing visibility of global warming effects, driven by carbon emissions, has spurred discussions on environmental concerns from local government bodies to international forums such as the United Nations. As a result, businesses face growing pressure to operate sustainably and comply with regulatory requirements (Rashid et al., 2024). High environmental performance (EP) is essential for firms to reduce their ecological footprint and contribute to global sustainability goals. Scholars widely highlight the critical role of BDAC in achieving EP. Sahoo et al. (2023) argue that BDAC can enhance EP by enabling firms to adopt data-driven approaches for environmental management. BDAC allows for the monitoring and optimizing energy use, waste management, and emission control through advanced analytics and real-time data processing (Nisar et al., 2020; Zrigui et al., 2023) . Real-time waste monitoring with BDA helps companies identify opportunities to reduce waste, minimize landfill use, and promote recycling or reuse(Namoun et al., 2022; Niska & Serkkola, 2018). Big data optimizes routes, schedules, and inventory management, reducing fuel use, emissions, storage needs, and transportation of surplus goods for an environment-friendly logistics process (Li, 2023; Moldagulova et al., 2020; Pujiarto et al., 2021). From the DCV perspective, BDAC provides the dynamic capability to sense environmental challenges, seize opportunities for green innovation, and transform organizational processes to achieve sustainable environmental outcomes (Dubey et al., 2019). By integrating BDAC into their environmental strategies, firms can enhance their ecological performance, comply with environmental standards, and drive innovation for sustainability (Bag et al., 2023; Gallo et al., 2023). Therefore, we hypothesize:

H3: BDAC has a positive impact on EP

3.4 Moderating Effect of GSCM

BDAC provides valuable insights by processing vast amounts of data from various sources, thereby enabling better decision-making and strategic planning (Sahoo et al., 2023; Fantazy & Tipu, 2024). Nisar et al. (2023) note that organizations must implement sustainable practices to leverage BDAC's insights to achieve sustainable advantages effectively. Karmaker et al. (2023) report that integrating GSCM with data-driven technologies can enable organizations to utilize data-driven insights to optimize resource allocation, improve operational efficiency, and reduce costs, thereby enhancing ECOP. Similarly, GSCM practices foster ethical sourcing, fair labor practices, and community engagement, which, when combined with BDAC insights, can significantly enhance SP by building stronger relationships with stakeholders and enhancing brand reputation (Rashid et al., 2024). Furthermore, GSCM practices focus on reducing the environmental impact of SC activities (Feng et al., 2022). By utilizing BDAC, firms can identify inefficiencies and adopt green technologies, energy-efficient processes, and circular economy models, thereby improving EP (Cheng et al., 2023). Thus, we posit that organizations with strong GSCM practices can more effectively utilize the insights provided by BDAC to achieve SSCP. Therefore, we hypothesize:

H4a: GSCM positively moderates the link between BDAC and ECOP

H4b: GSCM positively moderates the link between BDAC and SP

H4c: GSCM positively moderates the link between BDAC and EP.

The theoretical model is presented in Figure 1.

4.0 Research Methodology

This study employs a two-stage mixed methodology, proven effective in previous research (Schilke, 2014; Dubey et al., 2019). The first stage involves developing survey instruments with measurement items extracted from the existing literature, followed by pre-testing with scholars to ensure validity and reliability. In the second stage, a cross-sectional survey was conducted to collect data from diverse sample respondents within the Bangladeshi RMG sector. Analytical methods are selected to systematically and thoroughly collect, analyze, and interpret data, which is essential for obtaining reliable and valid results. These methods help form a holistic picture of the study and understand the correlation of all variables within the research framework (Khoa et al., 2023; Practices, 2024). This systematic approach ensures that the research findings are robust and can be generalized to a broader context.

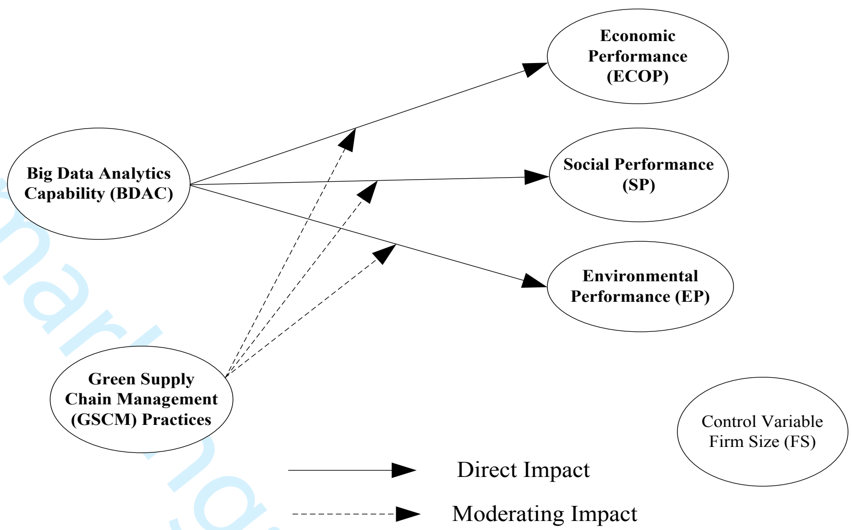

Figure 1. Theoretical Model

4.1 Survey Instrument Development

A survey-based questionnaire was developed to test the proposed model. Measurement items for each construct were sourced from previous relevant literature, with adjustments made to align the items with the context of BDAC. All exogenous and endogenous constructs were operationalized as reflective constructs (see Table I). The survey questionnaire was pre-tested through eight interviews involving five industry experts and three academicians specializing in data analytics and sustainability performance. They evaluated the questionnaire for the suitability of the measurements, clarity of the questions, and potential ambiguities (DeVellis, 1991). Based on their feedback, adjustments were made to enhance the questionnaire's effectiveness and alignment with the model requirements. All measuring scales utilized a seven-point Likert scale, ranging from "1 = strongly disagree" to "7 = strongly agree."

Firm size is a key control variable in corporate finance and governance research due to its substantial influence on financial performance and behavior. Although factors like industry type, firm age, and ownership structure are also relevant, they are often controlled differently or deemed less impactful (Yadav et al., 2021). Prioritizing firm size simplifies analysis and enhances the robustness of findings, especially under data constraints. So to control for potential variations in resources, capabilities, and organizational structures, firm size (FS) was included as a control variable. Larger firms may possess more advanced technological infrastructures and greater financial capacity to implement SC management practices, which could skew results if not controlled (Dubey et al., 2019). Firm size was categorized based on the number of employees: firms with ≤500 employees were classified as small, and firms with >500 employees were classified as large.

4.2 Data Collection

Data were collected using a cross-sectional survey from firms registered with the Bangladesh Garment Manufacturers and Exporters Association (BGMEA). The Bangladeshi RMG sector was selected due to its significant global presence and impact on economic development and sustainability challenges. As one of the largest apparel exporters worldwide, Bangladesh's RMG industry faces pressing issues related to SC sustainability (Saha et al., 2024), making it an ideal context to explore the role of BDAC and the moderating influence of GSCM.

The organizational unit served as our unit of analysis, and the survey was designed for a single respondent. To ensure a representative sample, we employed a simple random sampling technique (Dillman, 2011). The BGMEA database, which includes detailed information on registered RMG firms, served as our sampling frame. 760 firms were selected from this database to participate in the study. The selection process aimed to cover a diverse range of firms in size, market presence, and commitment to integrating technological innovations with sustainable practices. Senior supply chain executives (e.g., purchasing managers, inventory managers, materials managers, procurement managers, sourcing managers, distribution managers, supply chain managers, logistics managers, planning managers, and operations directors) were targeted as respondents. These individuals were chosen due to their comprehensive knowledge and expertise in SC management practices, information flow, and the adoption of data-driven technologies.

Questionnaires were e-mailed to the selected respondents through Google Forms. We followed up with multiple reminders, typically three times to enhance the response rate. In total, we received 159 comprehensive and usable responses, resulting in a response rate of 20.92%.In Bangladeshi corporate offices, employees often face extended working hours, leading to fatigue and a lack of motivation to participate in additional tasks such as surveys. Furthermore, the absence of financial incentives or adequate remuneration for their participation diminishes their interest and willingness to engage, resulting in a notably low response rate for such surveys. However, this response rate is deemed sufficient for PLS-SEM analysis (Dubey et al., 2020; Saha et al., 2023). We ensured the eligibility of respondents by excluding participants who were not from the RMG sector or lacked relevant experience. Additionally, incomplete responses were not included in the analysis.

The demographic profiles of the 159 respondents were analyzed, focusing on key attributes such as firm size, experience, gender distribution, and professional designation. The gender distribution revealed a male-to-female ratio of 125:34. Regarding firm size, most respondents were associated with large firms (135, 84.91%), while a considerably smaller proportion were from small firms (24, 15.09%). All respondents held managerial or higher-level positions. Among these, Supply Chain Managers constituted the largest group (58, 36.48%), followed by Directors of Operations (38, 23.91%), Logistics Managers (18, 11.32%), Procurement Managers (17, 10.69%), Planning Managers (12, 7.54%), Materials Managers (9, 5.66%), and Other Managers (7, 4.40%). In terms of professional experience, the majority of respondents had 6–11 years of experience (91, 57.23%), followed by those with 12–16 years (56, 35.23%) and 17–24 years (12, 7.54%). This analysis highlights significant variation in demographic and professional attributes among the respondents. The sampling and response details are presented in Table II.

Table I. Measures

Construct	Type	Measures	Sources
Big data analytics capability (BDAC)	Reflective	We employ data visualization methods for comprehending intricate information extracted from extensive data sources (BDAC1)	(Dubey et al., 2019; Bahrami & Shokouhyar, 2022; Fantazy & Tipu, 2024)
		We utilize advanced analytical tools (such as optimization, regression, or simulation) to analyze data (BDAC2)	
		We integrate data from multiple sources (including company reports and social media) for comprehensive data analysis (BDAC3)	
Green supply chain management (GSCM)	Reflective	Our firm invests in technologies that enhance energy efficiency across the SC (GSCM1)	(Karmaker et al., 2023; Behl et al., 2024; Huang et al., 2024)
		Our firm implements strategies for recycling, reusing, and safe disposal of products at the end of their lifecycle (GSCM2)	
		Our firm conducts regular audits to ensure compliance with environmental standards and regulations (GSCM3)	
Economic Performance (ECOP)	Reflective	Our firm achieves higher gross profit margins by decreasing materials purchasing costs (ECOP1)	(Jeble et al., 2018; Jum'a et al., 2024)
		Our firm enhances net income margins by reducing energy consumption expenses (ECOP2)	
		Our firm increases operational efficiency by optimizing logistics and transportation costs (ECOP3)	
		Our firm improves cost-efficiency by minimizing fees associated with waste discharge (ECOP4)	
Social Performance (SP)	Reflective	Our firm believes in gender equality (SP1)	(Jeble et al., 2018; Jum'a et al., 2024)
		Our firm places significant emphasis on employee safety and occupational health (SP2)	

		Our firm adheres to international labor standards and conventions (SP3)	
Environmental Performance (EP)	Reflective	Our firm has implemented measures to reduce air emissions (EP1)	(Jeble et al., 2018; Jum'a et al., 2024)
		Our firm has adopted practices for recycling wastewater (EP2)	
		Our firm has taken steps to prevent the discharge of solid waste (EP3)	

4.3 Non-response Bias

Given the survey-based data collection process, we checked for non-response bias following Armstrong and Overton's (1977) guidelines. Collected data were categorized into early and late responses, as early respondents are thought to have greater interest in and understanding of the topic. Then, we conducted a t-test following Armstrong and Overton's (1977) recommendations and found no statistically significant difference between early and late responses. As bias did not influence our research, the two data sets were merged to test our model.

Table II. An overview of the sampling

Criteria	Genre	Number	Responses rate
Gender	Male	125	78.61%
	Female	34	21.39%
Firm size	Small (<500 employees)	24	15.09%
	Large (500-5000 employees)	135	84.91%
Experience	6-11 years	91	57.23%
	12-16 years	56	35.23%
	17-24 years	12	07.54%
Designation	Director of Operations	38	23.91%
	Planning Manager	12	07.54%
	Procurement Manager	17	10.69%
	Materials Manager	9	05.66%
	Supply Chain Manager	58	36.48%
	Logistics Manager	18	11.32%
	Other Manager	7	04.40%

5.0 Data Analysis and Result

To test our theoretical model, we employed WarpPLS 8.0 software, which utilizes the partial least squares-based structural equation modeling (PLS-SEM) technique (Kock, 2019). PLS-SEM is particularly suited for our study due to its predictive orientation (Peng & Lai, 2012) and its ability to effectively handle complex models with smaller sample sizes (Hair et al., 2016). Besides, PLS-SEM is robust to non-normal data distributions and does not require strict assumptions about the underlying data distribution, enhancing its applicability across diverse research domains (Peng &

Lai, 2012; Dubey et al., 2020). Furthermore, PLS-SEM allows for the simultaneous evaluation of measurement and structural models. This dual capability is a powerful tool for theory development and hypothesis testing, enabling us to rigorously assess the predictive accuracy of our independent latent variables (Henseler et al., 2015). Unlike covariance-based SEM (CB-SEM), PLS-SEM considers measurement errors, thus providing more accurate and reliable results (Dubey et al., 2020; Kock, 2019; Tiwari et al., 2024). Therefore, by employing WarpPLS 8.0, we aim to leverage these strengths to comprehensively evaluate the relationships and hypotheses proposed in our study, ensuring robust and reliable results.

5.1 Measurement Model

We used confirmatory factor analysis (CFA) to assess our measurement model's convergent and discriminant validity. Following Fornell and Larcker's (1981) recommendations, we reported composite reliability (SCR) values, factor loadings for each measurement item (λ), and the average variance extracted (AVE) values (Table III). As shown in Table III, all factor loadings for the measurement items exceed the threshold limit of 0.5 and the SCR and AVE values also surpass their respective cut-off points (i.e., SCR ≥ 0.7, AVE ≥ 0.5), suggesting high convergent validity of our constructs (Fornell & Larcker, 1981). We further calculated Cronbach's alpha (α) values for each construct to evaluate the reliability of our measurement model (Table III). All α values were above the acceptable threshold of 0.7, confirming the constructs' high internal consistency and reliability (Hair et al., 2017).

Table III. Convergent validity test (SCR, Cronbach's Alpha (α) and AVE)

Construct	Items	Factor loadings (λ)	Variance (λ^2)	Error ($1-\lambda^2$)	SCR	AVE
Big Data Analytics Capability (BDAC) (α=0.947)	BDAC1	0.95	0.90	0.10	0.97	0.91
	BDAC2	0.96	0.92	0.08		
	BDAC3	0.94	0.88	0.12		
Green supply chain management (GSCM) (α=0.840)	GSCM1	0.88	0.77	0.23	0.90	0.76
	GSCM2	0.87	0.76	0.24		
	GSCM3	0.86	0.74	0.26		
Economic Performance (ECOP) (α=0.822)	ECOP1	0.83	0.69	0.31	0.88	0.65
	ECOP2	0.77	0.59	0.41		
	ECOP3	0.80	0.64	0.36		
	ECOP4	0.82	0.67	0.33		
Social Performance (SP) (α=0.727)	SP1	0.80	0.64	0.36	0.85	0.65
	SP2	0.83	0.69	0.31		
	SP3	0.78	0.61	0.39		
Environmental Performance (EP) (α=0.735)	EP1	0.82	0.67	0.33	0.85	0.66
	EP2	0.88	0.77	0.23		
	EP3	0.72	0.52	0.48		

Then, we tested the discriminant validity following Fornell and Larcker's (1981) suggestions (Table IV). Fornell and Larcker (1981) stated that a construct shows higher discriminant validity if its square root of AVE is greater than all other constructs' correlation values. The square root of AVEs for each latent variable exceeded its correlations with other constructs, confirming discriminant validity (Fornell and Larcker, 1981; Gold et al., 2001). Cross-loadings further supported this, indicating the constructs are conceptually distinct. Table IV indicates that all the square root values of AVE (highlighted in italics diagonally) meet the required condition, which provides significant evidence of the constructs' discriminant validity.

Table IV. Discriminant Validity Test

	BDAC	GSCM	SP	EP	ECOP
BDAC	*0.95*				
GSCM	0.09	*0.87*			
SP	0.44	0.02	*0.80*		
EP	0.48	0.10	0.56	*0.81*	
ECOP	0.48	0.11	0.55	0.66	*0.81*

Note: Italic represents the root-square of AVE of a construct

5.2 Common Method Bias (CMB)

Survey-based data may be subject to common method biases (CMB) due to consistency in responses and implicit social desirability (Podsakoff et al., 2003). Recognizing potential biases in data obtained from a single source utilizing a survey-based instrument, as Ketokivi and Schroeder (2004) noted, we conducted two tests to assess CMB. Firstly, we performed Harman's single-factor test, following Kock's (2015) guidelines. The analysis revealed that only 37.56% of the total variance could be attributed to a single factor. Kock (2015) suggested that if the explanatory power of the single construct of the total variance is more than 50%, it indicates CMB's presence in the dataset. Thus, CMB is not a major concern in our dataset. Secondly, we conducted the full collinearity test to evaluate vertical and lateral collinearity, generating variance inflation factors (VIFs) for all latent variables using WarpPLS (Kock, 2017). A VIF greater than 3.3 suggests pathological collinearity and potential CMB contamination (Kock, 2017). All VIF values in our analysis were below 3.3, indicating negligible CMB impact.

Furthermore, we checked causality issues before proceeding to the hypothesis testing. We analyzed four indices: Simpson's paradox ratio (SPR), R-squared contribution ratio (RSCR), Statistical suppression ratio (SSR), and Nonlinear bivariate causality direction ratio (NLBCDR) (Table V), following Kock's (2022) suggestions. Our analysis shows the NLBCDR value of 0.833, above its cut-off value of 0.7 (Kock, 2022). The SSR and SPR values were determined to be 1, exceeding the recommended cutoff value of 0.7, indicating a robust value. Additionally, the RSCR value was found to be 1, which is considered acceptable as it surpasses the threshold of 0.9 (Holland, 1986). Table V demonstrates that all indices are in the allowable range, indicating that causality is not a significant concern in our study.

Table V. Causality Assessment Indices

Indices	Values
SPR	1.000, acceptable if >= 0.7
RSCR	1.000, acceptable if >= 0.9
SSR	1.000, acceptable if >= 0.7
NLBCDR	0.833, acceptable if >= 0.7

5.3 Hypothesis Testing

Our study hypotheses have been tested by PLS-SEM (WarpPLS 8.0). The PLS utilizes a bootstrapping technique to determine parameter estimations' standard errors and significance (Chin, 1998). Table VI presents the results of the structural path analysis obtained from the PLS algorithm, showing standardized path coefficients (β) and corresponding p-values. For instance, $\beta = 0.50$, $p < 0.01$, indicates strong support for H1 (BDAC→ECOP), demonstrating that BDAC is a strong predictor of the ECOP. Similarly, H2 (BDAC→SP) ($\beta = 0.45$, $p < 0.01$) and H3 (BDAC→EP) ($\beta = 0.49$, $p < 0.01$) are statistically significant at the 0.01 level. Next, we evaluated the moderation effect of GSCM on the paths joining BDAC and EP (H4a), BDAC and SP (H4b), and BDAC and ECOP (H4c). The results show that all the moderation impacts of GSCM (H4a, H4b, and H4c) are significant at the 0.05 level (Table VI). We also assessed the impact of the control variable, firm size (FS), on our model. However, FS was not found to impact the endogenous variables significantly.

Table VI. Structural Estimates

Hypothesis	Effect of	Effect on	β	p-value	Results
H1	BDAC	ECOP	0.50	<.01	Supported
H2	BDAC	SP	0.45	<.01	Supported
H3	BDAC	EP	0.49	<.01	Supported
H4a	GSCM	BDAC-ECOP	0.15	<.05	Supported
H4b	GSCM	BDAC-SP	0.17	<.05	Supported
H4c	GSCM	BDAC-EP	0.25	<.05	Supported
control variables	FS	ECOP	0.02	0.39	Not significant
	FS	SP	0.03	0.35	Not significant
	FS	EP	0.07	0.18	Not significant

We then assessed the explanatory power of our model by estimating the R^2 values of the endogenous variables. The R^2 values for ECOP, SP, and EP are 0.27, 0.22, and 0.26, respectively (Table VII), indicating moderately strong explanatory power (Chin, 1998). We also determined the f^2 values to analyze the effect size of BDAC on ECOP, SP, and EP (Cohen, 1988). The effect sizes are 0.249, 0.200, and 0.236 (Table VII), respectively, indicating large effect sizes (Cohen, 1988). Furthermore, we calculated Stone-Geisser's Q^2 values to evaluate the predictive capability of our model. We found the Q^2 values for ECOP, SP, and EP are 0.229, 0.261, and 0.276, respectively (Table VII), suggesting the allowable predictive relevance (Peng & Lai, 2012).

Table VII. Coefficient of variation (R^2), predictability (Q^2) and effect size (f^2)

Construct	R^2	Q^2	f^2 in relation to BDAC
ECOP	0.27	0.229	0.249
SP	0.22	0.261	0.200
EP	0.25	0.276	0.236

5.4 Model Fit and Indices

We calculated the average path coefficient (APC), average R-squared (ARS), and Average block VIF (AVIF) to check the fitness and quality of our model (Kock, 2011; Behl et al., 2022). All the values were in the allowable range (Table VIII). The AVIF value below 3.3 indicates the absence of multicollinearity issues in the dataset (Kock, 2011). We also calculated Tenenhaus GoF to measure the goodness of fit, following the suggestions of Tenenhaus et al. (2005). Tenenhaus GoF is found to be 0.449, which is considered medium (Tenenhaus et al., 2005). Based on these findings, we can conclude that our model fits our data well.

Table VIII. Model Fitness and quality indices parameter

Fitness and quality indices	Values
Average path coefficient (APC)	0.226 ($P<0.001$)
Average R-squared (ARS)	0.251 ($P<0.001$)
Average block VIF (AVIF)	1.007 (acceptable if <= 5, ideally <= 3.3)
Tenenhaus GoF	0.449 (small >= 0.1, medium >= 0.25, large >= 0.36)

6.0 Discussion

The results of this study provide significant insights into the relationships among BDAC, GSCM practices, and SC sustainability across economic, social, and environmental dimensions. The findings indicate that BDAC positively influences SC sustainability, addressing our first RQ. Specifically, BDAC was found to be a strong predictor of economic ($\beta = 0.50$, $p < 0.01$), social ($\beta = 0.45$, $p < 0.01$), and environmental performance ($\beta = 0.49$, $p < 0.01$). This outcome aligns with existing literature, consistently highlighting BDA's transformative potential in SC management. For instance, Dubey et al. (2024) and Li et al. (2024) note that BDAC enables firms to process vast amounts of data, leading to improved decision-making, enhanced operational efficiency, and greater agility in responding to market changes. Our study confirms these findings and extends them by empirically validating the positive impact of BDAC on all three dimensions of the TBL. While previous studies have often focused on individual aspects of sustainability, such as economic or environmental performance (Zhu et al., 2022; Morimura & Sakagawa, 2023; Gopal et al., 2024), our research offers a more comprehensive view by examining the combined effects of BDAC across economic, social, and environmental dimensions simultaneously.

Economically, our findings support earlier work by Chong et al. (2023), who highlighted the role of BDAC in optimizing inventory levels, reducing costs, and improving demand forecasting accuracy, which, in turn, enhances financial performance. However, our study contributes to the literature by demonstrating that BDAC's economic benefits also have a cascading effect on social and environmental performance. Socially, our results resonate with the findings of Dubey et al. (2019), who argued that BDAC enhances transparency and traceability in SC, improving labor practices and ensuring compliance with social standards. However, our study shows that these social improvements are also linked to broader supply chain sustainability goals. Environmentally, the positive influence of BDAC on sustainability is consistent with Sahoo et al. (2023), who noted its role in supporting sustainable practices such as monitoring and reducing carbon footprints, managing waste more effectively, and optimizing resource use.

The moderating role of GSCM practices was also confirmed, addressing our second RQ. The moderation effects of GSCM on the relationships between BDAC and ECOP (H4a), SP (H4b), and EP (H4c) were significant at the 0.05 level. Variations in the β values were observed across all dimensions, indicating differing levels of influence. The moderating effect of GSCM on environmental performance is powerful, as it directly and immediately integrates practices such as eco-friendly design, waste reduction, emission minimization, sustainable resource utilization, recycling, and cleaner production (Ihsan & Risonarta, 2023; Shi et al., 2024; Siddiquee et al., 2024; Zi, 2023)These practices significantly improve key environmental metrics, including carbon footprint reductions and enhancements in resource efficiency, thereby emphasizing the most prominent effect. The moderating effect of GSCM on social and economic dimensions is comparatively lower due to high initial costs, delayed economic benefits, limited consumer demand for green products, and competitive pressures. Social impacts are less direct and more challenging to quantify than environmental improvements, relying on factors such as stakeholder engagement, societal awareness, and implementation scale.

This finding is consistent with the DCV, which posits that firms can achieve sustained competitive advantage through the integration and reconfiguration of internal and external competencies (Teece et al., 1997; Ghasemzadeh et al., 2022; Tipu & Fantazy, 2023). While prior studies, such as those by Dzikriansyah et al. (2023) and Huang et al. (2024), have explored the individual impacts of GSCM on sustainability, our research extends this body of work by illustrating how GSCM practices enhance the effectiveness of BDAC in achieving sustainability across multiple dimensions. This integrated approach provides new insights into how firms can leverage dynamic capabilities to navigate complex sustainability challenges.

The DCV emphasizes that it is not just the possession of resources like BDAC that leads to competitive advantage but how firms dynamically integrate, build, and reconfigure these resources in response to changing environments. In this context, GSCM practices serve as complementary capabilities that, when combined with BDAC, enhance a firm's ability to adapt and respond to environmental pressures and opportunities. This synergy between BDAC and GSCM practices highlights a critical extension of the DCV framework. This suggests that dynamic reconfiguring technological and operational capabilities is key to achieving and sustaining competitive advantage in today's rapidly evolving market. For example, Teece (2007) highlights that dynamic capabilities enable firms to create, extend, and modify their resource base to address rapidly changing environments. Our findings suggest that by integrating BDAC with GSCM practices, firms are better positioned to reconfigure their operations to achieve higher levels of sustainability. BDAC provides the technological capabilities to analyze and utilize data for better decision-making, while GSCM practices offer the procedural and operational changes needed to implement sustainable practices. This combination allows firms to continuously adapt their supply chain strategies, processes, and practices to meet sustainability goals, thus achieving a sustained competitive advantage.

6.1 Theoretical Implications

This study makes several theoretical contributions to DCV, BDAC, GSCM, and supply chain sustainability, advancing the understanding of how these constructs interact to shape sustainable SC outcomes. First, this research extends the DCV by demonstrating the synergistic effects of integrating BDAC with GSCM practices to achieve SC sustainability. While the DCV traditionally emphasizes a firm's ability to integrate, build, and reconfigure internal and external competencies in response to environmental changes (Teece, 2007), this study breaks new ground by empirically illustrating how the combination of BDAC and GSCM creates a dynamic interplay that enhances a firm's adaptability and sustainability performance. Previous studies have examined BDAC and GSCM independently (Jeble et al., 2018; Huang et al., 2024), but the interaction between these capabilities within the DCV framework has remained underexplored. By showing how BDAC and GSCM jointly contribute to sustainability across economic, social, and environmental dimensions, this study enriches the DCV by highlighting the importance of integrating complementary capabilities to achieve sustained competitive advantage in an era increasingly defined by sustainability challenges.

Second, the study empirically validates the positive impact of BDAC on the three dimensions of supply chain sustainability—economic, social, and environmental performance—within the context of the TBL framework. This finding not only corroborates existing research that emphasizes the role of BDAC in enhancing operational efficiency and resilience (e.g., Dubey et al., 2020; Liu et al., 2023) but also extends this body of literature by demonstrating the broad applicability of BDAC across multiple dimensions of sustainability. By adopting a comprehensive TBL perspective, this study addresses the call for research that moves beyond the economic benefits of BDAC to explore its role in achieving balanced economic, social, and environmental objectives in SC management.

Third, the study highlights the moderating role of GSCM practices in enhancing the impact of BDAC on SC sustainability. This insight contributes to the literature on SSCM by underscoring the necessity of integrating green practices into data-driven decision-making processes. While prior research has largely focused on the independent effects of GSCM on sustainability (Dzikriansyah et al., 2023; Hejazi et al., 2023), this study reveals that GSCM practices are most effective when combined with advanced technological capabilities like BDAC. This finding advances SSCM theory by illustrating how the alignment of technological and sustainable practices can amplify the positive outcomes of each, thereby offering a more integrated approach to achieving long-term sustainability in SCs.

6.2 Managerial Implications

The findings of this study have several practical implications for SC managers and policymakers. For SC managers, the positive impact of BDAC on SC sustainability underscores the importance of investing in data-driven analytical capabilities. Firms should focus on developing robust data analytics infrastructure, acquiring skilled personnel, and fostering a data-driven culture to harness the full potential of BDAC. By leveraging big data, managers can improve decision-making, enhance operational efficiency, and achieve SSCP.

The significant moderation effects of GSCM practices suggest that firms should integrate green SC management practices with their data analytics initiatives. Managers should adopt practices such as sustainable sourcing, waste reduction, and minimization of carbon footprint to enhance the effectiveness of their BDAC efforts. By aligning GSCM practices with data-driven strategies, firms can achieve a competitive edge while contributing to environmental sustainability.

For policymakers, the study highlights the importance of promoting policies that encourage adopting BDAC and GSCM practices in the supply chain sector. Governments and regulatory bodies should incentivize firms to invest in big data analytics and implement green practices. Policies that support training and development programs in data analytics and sustainability can help build the necessary skills and capabilities within the industry. Additionally, policymakers should encourage collaboration between industry and academia to foster innovation and disseminate best practices in sustainable SC management.

7.0 Conclusion

This study has developed and tested a theoretical framework grounded on DCV theory to explore the role of BDAC in enhancing SC sustainability while examining the moderating effects of GSCM practices. Utilizing data from 159 respondents in the Bangladeshi RMG sector, the findings reveal that BDAC significantly improves economic, social, and environmental performance. Additionally, GSCM practices significantly strengthen the positive impacts of BDAC on these dimensions of sustainability. These results underscore the importance of integrating BDAC with GSCM practices to achieve comprehensive SC sustainability. The study contributes to the DCV by illustrating how the reconfiguration and integration of BDAC and GSCM can lead to sustained competitive advantage and improved sustainable performance in supply chains.

7.1 Limitations and Future Scopes

Despite the valuable insights provided by this study, several limitations should be acknowledged. First, the cross-sectional nature of the data limits the ability to infer causality between BDAC, GSCM practices, and SC sustainability outcomes. Future research could employ longitudinal designs better to capture the dynamic effects of these variables over time.

Second, the study focuses solely on the Bangladeshi RMG sector, As the Bangladeshi RMG sector is the second-largest clothing exporter, holding a 6% share of the global market (Khan & Ullah, 2017), it encompasses a wide range of activities similar to those in other industries. The research findings from this sector provide valuable insights that can be adapted to other industries and regions. However, further studies are necessary to examine these dynamics in different sectors to improve the generalizability of the results. Future research should also explore these relationships across diverse sectors and regions to strengthen external validity.

Third, while this research uses survey data from senior SC executives, incorporating multiple respondents from each firm or triangulating survey data with qualitative interviews could provide a more comprehensive understanding.

The fourth aspect to consider is the influence of various data-driven enabling technologies within the ready-made garment (RMG) sector. Specifically, the application of blockchain technology can enhance transparency and traceability throughout the supply chain, as discussed by Manzoor et al. (2024). Additionally, artificial intelligence (AI) technologies, explored by Fosso Wamba et al. (2024) and Dubey et al. (2024), have the potential to optimize manufacturing processes, improve demand forecasting, and personalize customer experiences. Furthermore, other emerging technologies, such as the Internet of Things (IoT) and data analytics, can also play significant roles in increasing efficiency, reducing waste, and fostering innovation within the RMG industry. Understanding the interplay of these technologies is crucial for driving growth and sustainability in the sector.

Lastly, we applied the DCV perspectives to frame our research; however, future studies may apply other theoretical frameworks to offer a more comprehensive explanation. Researchers could explore additional organizational capabilities or assets that complement BDAC. Moreover, incorporating theoretical perspectives such as the knowledge-based view, contingency theory, information processing theory, organizational learning, and organizational culture might yield valuable extensions to our study.

References

Abuzawida, S. S., Alzubi, A. B., & Iyiola, K. (2023). Sustainable supply chain practices: an empirical investigation from the manufacturing industry. Sustainability, 15(19), 14395.

Akram, H. W., Ahmad, A., Abbas, H., & Akhter, S. (2024). A bibliometric analysis of the genesis, journey, and current status of green supply chain management in the digital economy. Benchmarking: An International Journal.

Al-Khatib, A. W. (2023). The impact of industrial Internet of things on sustainable performance: the indirect effect of supply chain visibility. Business Process Management Journal, 29(5), 1607-1629.

Al-Tarawneh, A., Haddad, E., Al-Dwairi, R., Al-Freijat, S., Mansour, A., & AL-Obaidly, G. (2024). The impact of strategic and innovativeness entrepreneurship and social capital on business overall performance through building a sustainable supply chain management at Jordan Private Universities. Uncertain Supply Chain Management, 12(1), 65-76.

Althaqafi, T. (2023). Cultivating Sustainable Supply Chain Practises in Electric Vehicle Manufacturing: A MCDM Approach to Assessing GSCM Performance. World Electric Vehicle Journal, 14(10), 290.

Ansari, K., & Ghasemaghaei, M. (2023). Big data analytics capability and firm performance: meta-analysis. Journal of Computer Information Systems, 63(6), 1477-1494.

Arias-Pérez, J., Coronado-Medina, A., & Perdomo-Charry, G. (2022). Big data analytics capability as a mediator in the impact of open innovation on firm performance. Journal of Strategy and Management, 15(1), 1-15.

Armstrong, J. S., & Overton, T. S. (1977). Estimating Non-response Bias in Mail Surveys. Journal of Marketing Research, 14(3), 396–402.

Asante-Darko, D., & Osei, V. (2024). Sustainable supply chain management practices and firm performance: the mediating effect of firm capabilities. Management of Environmental Quality: An International Journal, 35(4), 751-779.

Bag, S., Rahman, M. S., Srivastava, G., Shore, A., & Ram, P. (2023). Examining the role of virtue ethics and big data in enhancing viable, sustainable, and digital supply chain performance. Technological Forecasting and Social Change, 186, 122154.

Bagherpasandi, M., Salehi, M., Hajiha, Z., & Hejazi, R. (2024). Presenting a model for enhancing the performance of sustainable supply chain management using a data-driven approach. Benchmarking: An International Journal, (ahead-of-print).

Bahrami, M., & Shokouhyar, S. (2022). The role of big data analytics capabilities in bolstering supply chain resilience and firm performance: a dynamic capability view. Information Technology & People, 35(5), 1621-1651.

Balkumar, K., Gedam, V. V., Himateja, M., Anbuudayasankar, S. P., Narassima, M. S., Ganesh, K., Dwarakanath, M., & Pazhani, S. (2024). Prevalence and future trend in green supply chain management (GSCM): a systematic literature review. Benchmarking: An International Journal, 31(6), 2002-2033.

Behl, A. (2022). Antecedents to firm performance and competitiveness using the lens of big data analytics: a cross-cultural study. Management Decision, 60(2), 368-398.

Behl, A., Gaur, J., Pereira, V., Yadav, R., & Laker, B. (2022). Role of big data analytics capabilities to improve the sustainable competitive advantage of MSME service firms during COVID-19– A multi-theoretical approach. Journal of Business Research, 148, 378-389.

Behl, A., Sampat, B., Gaur, J., Pereira, V., Laker, B., Shankar, A., ... & Roohanifar, M. (2024). Can gamification help green supply chain management firms achieve sustainable results in servitized ecosystem? An empirical investigation. Technovation, 129, 102915.

Belhadi, A., Kamble, S. S., Gunasekaran, A., Zkik, K., & Touriki, F. E. (2023). A Big Data Analytics-driven Lean Six Sigma framework for enhanced green performance: a case study of a chemical company. Production Planning & Control, 34(9), 767-790.

Billah, M. M., Alam, S. S., Masukujjaman, M., Ali, M. H., Makhbul, Z. K. M., & Salleh, M. F. M. (2023). Effects of Internet of Things, supply chain collaboration and ethical sensitivity on sustainable performance: moderating effect of supply chain dynamism. Journal of Enterprise Information Management, 36(5), 1270-1295.

Boreik, D. A. S., Melegy, M. M. A., & Albaz, M. M. A. (2023). The Impact of Big Data Analytics on Investment Efficiency and Financial Performance: Evidence from Saudi Stock Market.

Boyd, B. K., Takacs Haynes, K., Hitt, M. A., Bergh, D. D., & Ketchen Jr, D. J. (2012). Contingency hypotheses in strategic management research: Use, disuse, or misuse? Journal of Management, 38(1), 278-313.

Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: moving toward new theory. International Journal of Physical Distribution & Logistics Management, 38(5), 360-387.

Cetindamar, D., Shdifat, B., & Erfani, E. (2022). Understanding Big Data Analytics Capability and Sustainable Supply Chains. Information Systems Management, 39(1), 19–33.

Cheng, J., Singh, H. S. M., Zhang, Y. C., & Wang, S. Y. (2023). The impact of business intelligence, big data analytics capability, and green knowledge management on sustainability performance. Journal of Cleaner Production, 429, 139410.

Chin, W. W. (1998). Commentary: Issues and Opinion on Structural Equation Modeling. MIS Quarterly, 22(1), 07-16.

Choi, H. Y., & Park, J. (2022). Do data-driven CSR initiatives improve CSR performance? The importance of big data analytics capability. Technological Forecasting and Social Change, 182, 121802.

Chong, C. L., Abdul Rasid, S. Z., Khalid, H., & Ramayah, T. (2023). Big data analytics capability for competitive advantage and firm performance in Malaysian manufacturing firms. International Journal of Productivity and Performance Management.

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences, 2nd Edn. Hillsdale, NJ: Erlbaum.

Conti, R., de Matos, M. G., & Valentini, G. (2023). Big data analytics, firm size, and performance. Strategy Science, 9(2), 135-151.

DeVellis, R.F., 1991. Scale Development: Theory and Applications. Sage Publications, Newbury Park, CA.

Dillman, D. A. (2011). Mail and Internet surveys: The tailored design method--2007 Update with new Internet, visual, and mixed-mode guide. John Wiley & Sons.

Dubey, R., Bryde, D. J., Graham, G., Foropon, C., Kumari, S., & Gupta, O. (2024). The role of alliance management, big data analytics, and information visibility on new-product development capability. Annals of Operations Research, 1-25.

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., ... & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organizations. International Journal of Production Economics, 226, 107599.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Luo, Z., Wamba, S. F., & Roubaud, D. (2019). Can big data and predictive analytics improve social and environmental sustainability? Technological Forecasting and Social Change, 144, 534-545.

Dubey, R., Gunasekaran, A., & Papadopoulos, T. (2024). Benchmarking operations and supply chain management practices using Generative AI: Towards a theoretical framework. *Transportation Research Part E: Logistics and Transportation Review*, *189*, 103689.

Dzikriansyah, M. A., Masudin, I., Zulfikarijah, F., Jihadi, M., & Jatmiko, R. D. (2023). The role of green supply chain management practices on environmental performance: A case of Indonesian small and medium enterprises. Cleaner Logistics and Supply Chain, 6, 100100.

Eisenhardt, K.M. and Martin, J.A. (2000). Dynamic capabilities: what are they? Strategic Management Journal, 21 (10/11), 1105-1121.

Elfeky, A. I. M., Najmi, A. H., & Elbyaly, M. Y. H. (2023). The effect of big data technologies usage on social competence. PeerJ Computer Science, 9, e1691.

Elkington, J. (1998). Partnerships from cannibals with forks: The triple bottom line of 21st-century business. Environmental Quality Management, 8(1), 37-51.

Fantazy, K., & Tipu, S. A. A. (2024). Linking big data analytics capability and sustainable supply chain performance: mediating role of knowledge development. Management Research Review, 47(4), 512-536.

Feng, Y., Lai, K. H., & Zhu, Q. (2022). Green supply chain innovation: Emergence, adoption, and challenges. International Journal of Production Economics, 248, 108497.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39.

Fosso Wamba, S., Guthrie, C., Queiroz, M. M., & Minner, S. (2024). ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*, *62*(16), 5676-5696.

Gallo, H., Khadem, A., & Alzubi, A. (2023). The Relationship between Big Data Analytic-Artificial Intelligence and Environmental Performance: A Moderated Mediated Model of Green Supply Chain Collaboration (GSCC) and Top Management Commitment (TMC). Discrete Dynamics in Nature and Society, 2023(1), 4980895.

Ghasemzadeh, P., Rezayat Sorkhabadi, S. M., Kebriaeezadeh, A., Nazari, J. A., Farzaneh, M., & Mehralian, G. (2022). How does organizational learning contribute to corporate social responsibility and innovation performance? The dynamic capability view. Journal of Knowledge Management, 26(10), 2579-2601.

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. Journal of Management Information Systems, 18(1), 185-214.

Gopal, P. R. C., Rana, N. P., Krishna, T. V., & Ramkumar, M. (2024). Impact of big data analytics on supply chain performance: an analysis of influencing factors. Annals of Operations Research, 333(2), 769-797.

Gupta, Y., Khan, F. M., Kumar, A., Luthra, S., & Queiroz, M. M. (2024). Mobilizing big data analytics capabilities to improve performance of tourism supply chains: the moderating role of dynamic capabilities. The International Journal of Logistics Management, 35(2), 649-679.

Hair, J. F., Sarstedt, M., Matthews, L. M., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: part I – method. European Business Review, 28(1), 63–76.

Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012). The Use of Partial Least Squares Structural Equation Modeling in Strategic Management Research: A Review of Past Practices and Recommendations for Future Applications. Long Range Planning, 45(5), 320–340.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. Industrial Management & Data Systems, 117(3), 442-458.

Hejazi, M. T., Al Batati, B., & Bahurmuz, A. (2023). The influence of green supply chain management practices on corporate sustainability performance. Sustainability, 15(6), 5459.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135.

Holland, P. W. (1986). Statistics and causal inference. Journal of the American statistical Association, 81(396), 945-960.

Holling, H., & Backhaus, L. (2023). A meta-analysis of green supply chain management practices and firm performance. Sustainability, 15(6), 4730.

Huang, X., Ullah, M., Wang, L., Ullah, F., & Khan, R. (2024). Green supply chain management practices and triple bottom line performance: Insights from an emerging economy with a mediating and moderating model. Journal of Environmental Management, 357, 120575.

Ihsan, M. A., & Risonarta, V. Y. (2023). REFERENCE OVERVIEW ON DESIGN AND SIMULATION OF GREEN SUPPLY CHAIN MANAGEMENT. International Journal of Mechanical Engineering Technologies and Applications, 4(2), 177-189.

Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D., & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. International Journal of Logistics Management, 29(2), 513–538.

Jum'a, L., Zimon, D., & Madzik, P. (2024). Impact of big data technological and personal capabilities on sustainable performance on Jordanian manufacturing companies: the mediating role of innovation. Journal of Enterprise Information Management, 37(2), 329–354.

Karmaker, C. L., Al Aziz, R., Ahmed, T., Misbauddin, S. M., & Moktadir, M. A. (2023). Impact of Industry 4.0 technologies on sustainable supply chain performance: The mediating role of green supply chain management practices and circular economy. Journal of Cleaner Production, 419, 138249.

Karunarathna, I., Gunasena, P., Hapuarachchi, T., & Gunathilake, S. (2024). The crucial role of data collection in research: Techniques, challenges, and best practices. Uva Clinical Research, 1-24.

Ketokivi, M.A. and Schroeder, R.G. (2004). Perceptual measures of performance: fact or fiction? Journal of Operations Management, 22 (3), 247-264.

Khan, A. N., & Ullah, M. R. (2017). Export scenario between Bangladesh and China: Opportunities of Bangladesh in RMG sector. Eur Sci J, 13(28), 299-320.

Khan, S. A. R., Yu, Z., & Farooq, K. (2023). Green capabilities, green purchasing, and triple bottom line performance: Leading toward environmental sustainability. Business Strategy and Environment, 32(4), 2022-2034.

Khoa, B. T., Hung, B. P., & Hejsalem-Brahmi, M. (2023). Qualitative research in social sciences: data collection, data analysis and report writing. International Journal of Public Sector Performance Management, 12(1-2), 187-209.

Khokhar, M., Iqbal, W., Hou, Y., Abbas, M., & Fatima, A. (2020). Assessing supply chain performance from the perspective of Pakistan's manufacturing industry through social sustainability. Processes, 8(9), 1064.

Kock, N. (2011). A mathematical analysis of the evolution of human mate choice traits: Implications for evolutionary psychologists. Journal of Evolutionary Psychology, 9(3), 219–247.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1-10.

Kock, N. (2017). Common Method Bias: A Full Collinearity Assessment Method for PLS-SEM. In: Latan, H., Noonan, R. (eds) Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications (pp. 245–257), Springer, Cham.

Kock, N. (2019). From composites to factors: Bridging the gap between PLS and covariance-based structural equation modelling. Information Systems Journal, 29(3), 674–706.

Kock, N. (2022). Using causality assessment indices in PLS-SEM. Data Analysis Perspectives Journal, 3(5), 1-6.

Kumar, A., Shrivastav, S. K., Shrivastava, A. K., Panigrahi, R. R., Mardani, A., & Cavallaro, F. (2023). Sustainable supply chain management, performance measurement, and management: a review. Sustainability, 15(6), 5290.

Kumar, A., Shrivastav, S. K., & Bhattacharyya, S. (2023). Measuring strategic fit using big data analytics in the automotive supply chain: a data source triangulation-based research. *International Journal of Productivity and Performance Management*, *72*(10), 2977-2999.

Le, T. T. (2023). Linking big data, sustainable supply chain management and corporate performance: the moderating role of circular economy thinking. The International Journal of Logistics Management, 34(3), 744-771.

Li, W., Waris, I., & Bhutto, M. Y. (2024). Understanding the nexus among big data analytics capabilities, green dynamic capabilities, supply chain agility, and green competitive advantage: the moderating effect of supply chain innovativeness. Journal of Manufacturing Technology Management, 35(1), 119-140.

Li, Z. (2023). Big Data Management: Empowering Sustainable Logistics with Data-Driven Operation Optimization. Advances in Economics, Management and Political Sciences, 54, 64-68.

Liu, H., Lu, F., Shi, B., Hu, Y., & Li, M. (2023). Big data and supply chain resilience: role of decision-making technology. Management Decision, 61(9), 2792-2808.

Ma, L., & Chang, R. (2024). How big data analytics and artificial intelligence facilitate digital supply chain transformation: the role of integration and agility. Management Decision, (ahead-of-print).

Manzoor, R., Sahay, B. S., Gumte, K., & Singh, S. K. (2024). Blockchain-backed resilient strategies in a stochastic supply chain sourcing and distribution environment under disruption:

implications for B2B sector. *Journal of Business & Industrial Marketing*. DOI: 10.1108/jbim-10-2023-0589.

Moldagulova, A., Satybaldiyeva, R., & Kuandykov, A. (2020, September). Application of big data in logistics. In Proceedings of the 6th International Conference on Engineering & MIS 2020 (pp. 1-6).

Morimura, F., & Sakagawa, Y. (2023). The intermediating role of big data analytics capability between responsive and proactive market orientations and firm performance in the retail industry. Journal of Retailing and Consumer Services, 71, 103193.

Namoun, A., Tufail, A., Khan, M. Y., Alrehaili, A., Syed, T. A., & BenRhouma, O. (2022). Solid waste generation and disposal using machine learning approaches: a survey of solutions and challenges. Sustainability, 14(20), 13578.

Naseer, S., Song, H., Adu-Gyamfi, G., Abbass, K., & Naseer, S. (2023). Impact of green supply chain management and green human resource management practices on the sustainable performance of manufacturing firms in Pakistan. Environmental Science and Pollution Research, 30(16), 48021-48035.

Nisar, Q. A., Haider, S., Ameer, I., Hussain, M. S., Gill, S. S., & Usama, A. (2023). Sustainable supply chain management performance in post COVID-19 era in an emerging economy: a big data perspective. International Journal of Emerging Markets, 18(12), 5900-5920.

Nisar, Q. A., Nasir, N., Jamshed, S., Naz, S., Ali, M., & Ali, S. (2020). Big data management and environmental performance: role of big data decision-making capabilities and decision-making quality. Journal of Enterprise Information Management, 34(4), 1061–1096.

Niska, H., & Serkkola, A. (2018). Data analytics approach to create waste generation profiles for waste management and collection. Waste Management, 77, 477-485.

Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. Journal of Operations Management, 30(6), 467–480.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. Journal of Applied Psychology, 88(5), 879–903.

Pujiarto, B., Hanafi, M., Setyawan, A., Imani, A. N., & Prasetya, E. R. (2021). A data mining practical approach to inventory management and logistics optimization. International Journal of Informatics and Information Systems, 4(2), 112-122.

Raj, R., Kumar, V., & Verma, P. (2023). Big data analytics in mitigating challenges of sustainable manufacturing supply chain. Operations Management Research, 16(4), 1886-1900.

Rashid, A., Baloch, N., Rasheed, R., & Ngah, A. H. (2024). Big data analytics-artificial intelligence and sustainable performance through green supply chain practices in manufacturing firms of a developing country. Journal of Science and Technology Policy Management.

Reddy, S. R. B., & Reddy, S. (2023). Large Scale Data Influences Based on Financial Landscape Using Big Data. Tuijin Jishu/Journal of Propulsion Technology, 44(4), 3862-3870.

Riggs, R., Roldán, J. L., Real, J. C., & Felipe, C. M. (2023). Opening the black box of big data sustainable value creation: the mediating role of supply chain management capabilities and circular economy practices. International Journal of Physical Distribution & Logistics Management, 53(7/8), 762-788.

Saha, P., Belal, H. M., & Talapatra, S. (2024). Driving Towards Sustainable Development Goals (SDGs) in the Ready-Made Garments (RMG) Sector: The Role of Digital Capabilities and Operational Transparency. IEEE Transactions on Engineering Management, (ahead-of-print).

Saha, P., Talapatra, S., Belal, H. M., Jackson, V., Mason, A., & Durowoju, O. (2023). Examining the viability of lean production practices in the Industry 4.0 era: an empirical evidence based on B2B garment manufacturing sector. Journal of Business & Industrial Marketing, 38(12), 2694-2712.

Sahoo, S., Upadhyay, A., & Kumar, A. (2023). Circular economy practices and environmental performance: Analysing the role of big data analytics capability and responsible research and innovation. Business Strategy and the Environment, 32(8), 6029-6046.

Sarkis, J., Zhu, Q., & Lai, K. H. (2011). An organizational theoretic review of green supply chain management literature. International Journal of Production Economics, 130(1), 1-15.

Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. Strategic Management Journal, 35(2), 179–203.

Sfetcu, N. (2024). Impact of Big Data Technology on Contemporary Society.

Shi, H., Feng, T., & Zhu, Z. (2023). The impact of big data analytics capability on green supply chain integration: an organizational information processing theory perspective. Business Process Management Journal, 29(2), 550-577.

Shi, W., Hu, Q., & Zhou, Y. (2024). Evolutionary game analysis of vehicle procurement in the courier industry from the perspective of green supply chain. International Journal of Industrial Engineering Computations, 15(1), 223-234.

Shrivastava, S. (2023). Recent trends in supply chain management of business-to-business firms: a review and future research directions. *Journal of Business & Industrial Marketing*, *38*(12), 2673-2693.

Srivastava, S. K., & Bag, S. (2023). Recent developments on flexible manufacturing in the digital era: A review and future research directions. *Global Journal of Flexible Systems Management*, *24*(4), 483-516.

Siddiquee, M., Shaha, P., & Hasin, A. (2024). Greening the pillars of pharmaceuticals: Sustainable supplier selection in emerging economies. *Journal of Future Sustainability*, 4(3), 159-168.

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and micro foundations of (sustainable) enterprise performance. Strategic Management Journal, 28 (13), 1319-1350.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y. M., & Lauro, C. (2005). PLS path modeling. Computational statistics & data analysis, 48(1), 159-205.

Tiwari, M., Bryde, D. J., Stavropolou, F., Dubey, R., Kumari, S., & Foropon, C. (2024). Modelling supply chain Visibility, digital Technologies, environmental dynamism and healthcare supply chain Resilience: An organisation information processing theory perspective. *Transportation Research Part E: Logistics and Transportation Review*, *188*, 103613.

Tipu, S. A. A., & Fantazy, K. (2023). Examining the relationships between big data analytics capability, entrepreneurial orientation, and sustainable supply chain performance: the moderating role of trust. Benchmarking: An International Journal.

Tsai, J. F., Shen, S. P., & Lin, M. H. (2023). Applying a hybrid MCDM model to evaluate green supply chain management practices. Sustainability, 15(3), 2148.

Wang, C., Tang, F., Zhang, Q., & Zhang, W. (2023). How does corporate social responsibility contribute to innovation performance? The moderating role of social media strategic capability and big data analytics capability. European Journal of Innovation Management.

Wijaya, O., & Said, H. (2024). The mediating role of sustainable supply chain management on entrepreneurship strategy, social capital and SMEs' financial and non-financial performance. Uncertain Supply Chain Management, 12(1), 557-566.

Wiredu, J., Yang, Q., Sampene, A. K., Gyamfi, B. A., & Asongu, S. A. (2023). The effect of green supply chain management practices on corporate environmental performance: Does supply chain competitive advantage matter?. Business Strategy and the Environment, 33(3), 2578-2599.

Xu, J., & Pero, M. E. P. (2023). A resource orchestration perspective of organizational big data analytics adoption: evidence from supply chain planning. International Journal of Physical Distribution & Logistics Management, 53(11), 71-97.

Xu, L., Wei, X., Cao, Y., Peng, X., & Prybutok, V. (2023). Achieving business excellence through sustainable supply chain management. Total Quality Management & Business Excellence, 34(13-14), 1830-1856.

Yadav, I. S., Pahi, D., & Gangakhedkar, R. (2021). The nexus between firm size, growth and profitability: new panel data evidence from Asia–Pacific markets. European Journal of Management and Business Economics, 31(1), 115-140.

Yamin, M. A. Y. (2024). The role of HR practices, big data analytics capabilities, and supply chain resilience in achieving firm disaster immunity: the moderating effect of a data-driven culture. Benchmarking: An International Journal.

Yan, X., Chen, X., Lu, C., Liu, W., Shi, X., & Gong, Y. (2024). Strategy for sustainable supply chain transformation: a resource orchestration perspective. Industrial Management & Data Systems, (ahead-of-print).

Yousefi, S., & Tosarkani, B. M. (2023). Exploring the role of blockchain technology in improving sustainable supply chain performance: a system-analysis-based approach. IEEE Transactions on Engineering Management, 71, 4389-4405.

Zhu, C., Du, J., Shahzad, F., & Wattoo, M. U. (2022). Environment sustainability is a corporate social responsibility: measuring the nexus between sustainable supply chain management, big data analytics capabilities, and organizational performance. Sustainability, 14(6), 3379.

Zi, W. (2023). The Impact of Green Supply Chain Management on Corporate Sustainable Performance: A Review of Research. Financial Engineering and Risk Management, 6(6), 23-27.

Zrigui, I., Khoulji, S., Kerkeb, M. L., Ennassiri, A., & Bourekkadi, S. (2023). Reducing Carbon Footprint with Real-Time Transport Planning and Big Data Analytics. In E3S Web of Conferences (Vol. 412, p. 01082). EDP Sciences.

Big Data Analytics Capability and Supply Chain Sustainability: Analyzing the Moderating Role of Green Supply Chain Management Practices

Abstract

Purpose: This research develops a theoretical framework to understand the role of big data analytics capability (BDAC) in enhancing supply chain sustainability and examines the moderating effect of green supply chain management (GSCM) practices on this relationship.

Design/Methodology: Guided by the dynamic capability view (DCV), we formulated a theoretical model and research hypotheses. We used partial-least-square-based structural equation modeling (PLS-SEM) to analyze data collected from 159 survey responses from Bangladeshi ready-made garments (RMG).

Findings: The statistical analysis revealed that BDAC positively impacts all three dimensions of supply chain sustainability: economic, social, and environmental. Additionally, GSCM practices significantly moderate the relationship between BDAC and supply chain sustainability.

Value/Originality: This study advances the current understanding of supply chain sustainability by integrating BDAC with GSCM practices. It is among the first to empirically investigate the combined effects of BDAC on the three dimensions of sustainability—economic, social, and environmental—while also exploring the moderating role of GSCM practices. By employing the DCV, this research offers a robust theoretical framework highlighting the dynamic interplay between technological and environmental capabilities in achieving sustainable supply chain performance.

Implications: This study makes unique contributions to the operations and supply chain management literature by providing empirical evidence and theoretical insights that extend beyond the focus on single sustainability dimensions. The findings offer valuable guidelines for policymakers and managers to enhance supply chain sustainability through BDAC and GSCM practices.

Keywords: Big data analytics capability (BDAC), dynamic capability view (DCV), sustainable supply chain performance (SSCP), green supply chain management (GSCM).

Type: Research paper

1.0 Introduction

In recent years, the imperative for sustainability within supply chains (SCs) has grown exponentially due to the significant environmental impacts of SC activities, including production, distribution, transportation, and disposal (Bag et al., 2023; Shrivastava, 2023; Yan et al., 2024).

This urgency is driven by increasing global awareness and regulatory pressures, necessitating a shift towards sustainable supply chain management (SSCM) (Le, 2023; Srivastava & Bag, 2023; Jum'a et al., 2024). SSCM seeks to integrate sustainable practices into SC operations to balance economic, social, and environmental performance (Cetindamar et al., 2022). By doing so, SSCM addresses environmental challenges, enhances corporate reputation, reduces costs, and meets regulatory requirements. Pursuing sustainable supply chain performance (SSCP) is now a critical goal for organizations, particularly in emerging economies where the balance between industrial growth and environmental stewardship is precarious (Naseer et al., 2023; Raj et al., 2023).

The triple bottom line (TBL) framework encompasses economic, social, and environmental dimensions, is a cornerstone for understanding sustainability in SCs (Carter & Rogers, 2008). Unlike traditional SC management, which primarily focuses on financial outcomes, SSCM emphasizes the need for a holistic approach that addresses broader sustainability issues (Yousefi & Tosarkani, 2023). This paradigm shift highlights the importance of developing capabilities that enable organizations to adapt and thrive in an increasingly complex and dynamic environment (Huang et al., 2024).

With the advent of advanced technologies, big data analytics (BDA) has become a pivotal factor in optimizing SC performance and achieving competitive advantages (Liu et al., 2023; Kumar et al., 2023; Gopal et al., 2024). Big data (BD), characterized by its volume, variety, velocity, veracity, and value, generates vast amounts of information that can be leveraged through BDA (Rashid et al., 2024). BDA enables firms to process vast amounts of data, uncover hidden patterns, and make data-driven decisions that enhance operational efficiency (Morimura & Sakagawa, 2023). Studies show that BDA positively impacts supply chain performance through enhanced resilience and innovation (Arias-Pérez et al., 2022; Bahrami & Shokouhyar, 2022). Developing BDA capabilities (BDAC) enables firms to execute algorithms faster with larger datasets, improving decision-making and forecasting market preferences (Choi & Park, 2022). BDAC allows organizations to convert data into actionable insights, enhancing SC performance and decision-making (Xu & Pero, 2023). Prominent corporations like Walmart, Uber, Netflix, Google, Amazon, and Facebook have leveraged BDA to benefit their SC functions (Belhadi et al., 2023). Implementing BDA in supply chains improves service supply chain innovation capabilities and overall performance (Sahoo et al., 2023).

Despite the recognized potential of BDAC, there remains a gap in understanding how it influences the three pillars of supply chain sustainability—economic, social, and environmental performance. Though few scholars have looked into the impact of BDAC on a single dimension of SC sustainability, empirical research on their impact across the three dimensions of sustainability is lacking. For instance, some scholars have explored BDAC's impact on environmental sustainability (Dubey et al., 2019; Nisar et al., 2020; Zhu et al., 2022; Belhadi et al., 2023; Sahoo et al., 2023), and others have examined its relationship with economic performance (Dubey et al., 2020; Arias-Pérez et al., 2022; Bahrami, & Shokouhyar, 2022; Behl, 2022; Morimura & Sakagawa, 2023; Gopal et al., 2024), however, comprehensive studies on BDAC's combined

effects on all three dimensions are limited. To address this gap, we pose our first research question (RQ1):

RQ1: What are the impacts of BDAC on the three dimensions of supply chain sustainability?

Boyd et al. (2012) assert that models analyzing direct effects are crucial but insufficient for understanding real-world complexities. Research indicates that BDAC performance depends on various contextual factors (Dubey et al., 2019; Tipu & Fantazy, 2023; Yamin, 2024). Thus, we explore conditions that enhance BDAC effectiveness. Green supply chain management (GSCM) practices have been widely used as a significant influencing element in SC and operations management literature (Sarkis et al., 2011; Khan et al., 2023; Rahman et al., 2023). Sahoo et al. (2023) highlight the importance of selecting appropriate practices for a competitive edge in SCM. Behl et al. (2024) note that GSCM practices can reduce carbon footprints, waste, and hazardous substances in manufacturing, contributing to sustainability. Rashid et al. (2024) suggest that GSCM can enhance technological solutions' effectiveness. Therefore, we propose that GSCM practices may moderate BDAC's impact on SSCP. However, empirical studies on this moderating role are lacking. Thus, we pose our second research question (RQ2):

RQ2: What are the moderating effects of GSCM on the links between BDAC and SSCP?

We develop a theoretical framework based on the dynamic capability view (DCV) to explore BDAC's influence on the three sustainability aspects. The DCV emphasizes firms' adaptation, integration, and reconfiguration of internal and external competencies, such as BDA and GSCM, to achieve sustained competitive advantage and supply chain sustainability (Teece, 2007). We collected 159 responses from the Bangladesh ready-made garments (RMG) industry using a survey-based questionnaire. Our findings enrich the BDAC literature by integrating the DCV to explain how BDAC and GSCM jointly contribute to SC sustainability. Additionally, it provides a nuanced understanding of contextual conditions that enhance BDAC's effectiveness in achieving sustainability goals. Practitioners can leverage these insights to implement BDAC and GSCM practices strategically, improving operational efficiency and environmental performance.

Our document is structured as follows: Section 2 presents the research background and theoretical foundations. Section 3 discusses theoretical model development. Section 4 covers the research methodology, including sample selection, data collection, and non-response bias. Section 5 details the data analysis and results. Section 6 discusses overall findings and future research directions.

2.0 Theoretical background

2.1 DCV

DCV is an extension of the resource-based view (RBV) theory, addressing criticisms that RBV often fails to explain how and under what conditions resources can grant competitive advantages (Eisenhardt & Martin, 2000). DCV provides insights into how organizations can achieve competitive advantages in evolving environments by integrating, reorganizing, and developing internal and external capabilities (Teece et al., 1997; Ghasemzadeh et al., 2022). According to

Teece et al. (1997), dynamic capabilities are defined as a company's ability to adapt to rapidly changing environments by sensing opportunities and threats, seizing opportunities, and transforming resources to maintain a competitive edge.

Dynamic capabilities encompass three primary dimensions: sensing, seizing, and transforming. Sensing involves identifying and assessing opportunities and threats in the market. Seizing refers to mobilizing resources to capture opportunities and mitigate threats. Transforming entails reconfiguring and realigning resources to sustain competitiveness (Teece, 2007).

In this context, BDAC is regarded as a dynamic capability that enables organizations to reconfigure firm-level resources in response to evolving market conditions and technological advancements (Dubey et al., 2019; Bahrami & Shokouhyar, 2022; Sahoo et al., 2023). By effectively processing, analyzing, and visualizing data, BDAC provides valuable insights that enhance decision-making, planning, and execution (Xu & Pero, 2023). Moreover, BDAC fosters innovation and learning by allowing organizations to experiment with various analytical techniques and continuously refine their processes (Belhadi et al., 2023).

Given these arguments, DCV serves as an appropriate theoretical lens for understanding the role of BDAC in achieving business competitiveness in dynamic environments. In this study, we argue that organizations can remain agile, competitive, and resilient by leveraging BDAC as a dynamic capability, ultimately contributing to SSCP.

2.2 BDAC

As businesses have become more technologically advanced, their SCs generate vast amounts of data (Cheng et al., 2023; Riggs et al., 2023). Jum'a et al. (2024) highlight that big data is a novel method for organizing and analyzing this information, providing valuable insights for SC participants. Belhadi et al. (2023) define big data as extensive, diverse observational data that supports various decision-making processes. While almost all firms now have access to big data, traditional methods often fall short of effectively analyzing and deriving meaningful conclusions from large datasets (Bagherpasandi et al., 2024). To address this, organizations require real-time capabilities to handle larger and more complex data sets, leading to commercial benefits. This necessitates the development of new data architectures, analytical techniques, and tools (Bag et al., 2023).

Researchers have acknowledged that the success of big data projects depends not just on data availability, analytical tools, and process utilization but on a broader range of factors (Bahrami & Shokouhyar, 2022; Ma & Chang, 2024). The big BDAC concept was introduced to capture this complexity (Rashid et al., 2024). BDAC is generally defined as an organization's ability to effectively leverage data management, infrastructure, and talent to derive actionable insights, transforming the business into a competitive force (Riggs et al., 2023). With BDAC, organizations can process, analyze, and visualize data, thereby improving planning, decision-making, and mission execution (Shi et al., 2023; Gupta et al., 2024).

Nisar et al. (2023) assert that applying BDAC in supply chains can mitigate various organizational uncertainties related to capacity, supplier availability, and customer demands. Moreover, BDAC can foster process-oriented dynamic capabilities within organizations, enhancing firm performance. By adopting a holistic view of BDAC that encompasses all relevant organizational resources, firms can maximize the strategic value of big data, gaining a sustainable competitive advantage in today's data-driven business environment (Jum'a et al., 2024).

2.3 GSCM

In recent years, there has been a growing emphasis on integrating environmental sustainability into SCM, giving rise to the concept of GSCM. GSCM refers to incorporating eco-friendly practices in supply chain operations, encompassing procurement, production, distribution, and end-of-life management (Feng et al., 2022). This approach aims to minimize SCs' environmental footprint by reducing waste, emissions, and energy consumption while enhancing resource efficiency and sustainability (Sarkis et al., 2011).

GSCM practices include various activities such as green procurement, eco-design, reverse logistics, and sustainable packaging (Behl et al., 2024). Green procurement involves selecting suppliers based on their environmental performance and encouraging them to adopt sustainable practices. Eco-design focuses on creating products with minimal environmental impact throughout their lifecycle, from raw material extraction to disposal. Reverse logistics involves the process of reclaiming products for reuse, recycling, or proper disposal, thereby reducing waste and conserving resources. Sustainable packaging aims to use recyclable or biodegradable materials, reducing the environmental burden of packaging waste (Sarkis et al., 2011; Behl et al., 2024). Proactive GSCM practices ensure regulatory compliance, enhance reputation, and drive economic benefits by improving environmental performance, attracting eco-conscious consumers and investors (Althaqafi, 2023; Tsai et al., 2023; Wiredu et al., 2023).

GSCM practices are adopted by various factors, including regulatory pressures, stakeholder expectations, and the desire for competitive advantage (Karmaker et al., 2023). Governments worldwide have implemented stringent environmental regulations that compel organizations to adopt sustainable practices. Additionally, consumers and other stakeholders increasingly demand environmentally responsible products and practices, prompting companies to integrate sustainability into their SC strategies (Akram et al., 2024). Firms that successfully implement GSCM can achieve significant benefits such as cost savings, improved brand image, and enhanced compliance with environmental standards (Dzikriansyah et al., 2023; Balkumar et al., 2024).

Moreover, GSCM can significantly influence SC sustainability by integrating the TBL principles, which focus on economic, social, and environmental performance (Huang et al., 2024). By reducing environmental impact and promoting social responsibility, GSCM helps organizations achieve a balanced approach to sustainability, which is essential for long-term success and resilience in the competitive market (Khan et al., 2023). In conclusion, GSCM represents a strategic approach to achieving SC sustainability by integrating environmental considerations into SCM. The adoption of green practices not only helps organizations comply with regulatory requirements and meet stakeholder expectations and provides a competitive edge by enhancing operational efficiency and brand reputation (Hunag et al., 2024).

2.4 SSCP

SSCP is an integral concept in contemporary SCM, emphasizing the need for a holistic approach that balances economic, social, and environmental performance. The TBL framework underpins SSCP, advocating that businesses should focus on profitability and consider their social and environmental responsibilities (Elkington, 1998). The pursuit of SSCP is becoming increasingly critical as organizations strive to meet the demands of various stakeholders, including customers, regulators, and the broader community, while ensuring long-term sustainability and competitiveness (Yousefi & Tosarkani, 2023). Moreover, SSCP drive innovation, encouraging the development of new products and processes that are both eco-friendly and cost-effective (Holling & Backhaus, 2023; Kumar et al., 2023).

2.4.1 Economic Performance

The economic dimension of SSCP pertains to the financial health and efficiency of SC operations. This includes cost reduction, improved profitability, and value creation throughout the SC (Cetindamar et al., 2022). Effective SC management practices can lead to significant economic benefits by optimizing resource utilization, enhancing operational efficiency, and reducing waste. Economic sustainability in supply chains ensures long-term financial viability and competitive advantage, crucial for organizational success in a dynamic market environment (Khan et al., 2023; Huang et al., 2024). SSCP boost economic performance by reducing energy and water costs, enhancing efficiency, and leveraging digital technologies for better resource management & driving profitability (Abuzawida et al., 2023; Al-Khatib, 2023; Asante-Darko & Osei, 2023; Billah et al., 2023; Xu et al., 2023).

2.4.2 Social Performance

The social dimension of SSCP focuses on the impact of SC activities on various stakeholders, including employees, communities, and customers. It encompasses labor practices, human rights, community engagement, and customer satisfaction (Karmaker et al., 2023). Ensuring fair labor practices, promoting diversity and inclusion, and engaging in ethical sourcing are key components of social sustainability. By addressing social concerns, organizations can build stronger relationships with stakeholders, enhance brand reputation, and foster customer loyalty, which is essential for sustainable business operations (Dubey et al., 2019; Saha et al., 2023). Ensuring safe working conditions and responsible sourcing are essential for social sustainability. Promoting diversity and societal responsibility strengthens relationships with stakeholders. Prioritizing product safety, social capital comprising networking, trustworthiness, and information exchange plays a significant role in developing sustainable supply chains (Al-Tarawneh et al., 2024; Khokhar et al., 2020; Wijaya & Said, 2024).ss

2.4.3 Environmental Performance

The environmental dimension of SSCP involves minimizing the ecological footprint of SC activities. This includes reducing resource consumption, waste, and emissions throughout the SC (Nisar et al., 2020). Environmental sustainability practices in supply chains often involve adopting green technologies, implementing energy-efficient processes, and promoting the circular economy. By integrating environmental considerations into SCM, organizations can mitigate environmental risks, comply with regulatory requirements, and contribute to global sustainability goals (Zhu et al., 2022; Sahoo et al., 2023). This enhances environmental performance and drives innovation and operational efficiencies (Gallo et al., 2023).

3.0 Theoretical Framework and Hypothesis

The DCV constitutes the basis of our theoretical framework (Figure 1). Drawing on the DCV theory, this study posits that BDAC serves as a critical dynamic capability, enabling firms to reconfigure their resources and processes in response to evolving market conditions and technological advancements (Dubey et al., 2019; Bahrami & Shokouhyar, 2022). BDAC allows organizations to effectively process, analyze, and utilize vast amounts of data, enhancing their economic, social, and environmental performance—key dimensions of SSCP (Dubey et al., 2020; Riggs et al., 2023). Additionally, GSCM practices are hypothesized to play a moderating role in this relationship. By integrating environmental considerations into supply chain operations, we argue that GSCM practices can amplify the positive impact of BDAC on SSCP. This integration is theorized to enhance the firm's ability to achieve sustainability goals, comply with regulatory requirements, and meet stakeholder expectations, ensuring long-term competitiveness and resilience.

3.1 Impact of BDAC on Economic Performance

In the contemporary business environment, maintaining profitability is paramount for firms' long-term survival and competitiveness (Jeble et al., 2018). Economic performance (ECOP) is typically assessed through profitability, competitiveness, cost reduction, and brand equity (Behl, 2022). The existing literature underscores the significant role of BDAC in enhancing ECOP. Bag et al. (2023) state that effective BDAC enables firms to optimize resource allocation, reduce costs, and improve overall profitability through demand forecasting, inventory management, and production planning. Furthermore, Morimura and Sakagawa (2023) argue that BDAC provides real-time insights into market trends and consumer behavior, allowing for more informed and timely decisions that drive economic benefits. Large firms benefit from value-added advantages, while small firms experience increased sales through product innovation. BDA improves investment efficiency, allowing for timely and informed decision-making, and enhances forecasting accuracy by utilizing high-frequency data. In the financial sector, BDA supports risk management and decision-making, promoting strategic agility and sustainable performance in dynamic markets (Ansari & Ghasemaghaei, 2023; Boreik et al., 2023; Conti et al., 2023; Reddy & Reddy, 2023). Additionally, BDAC supports the development of predictive analytics, which can anticipate market fluctuations and optimize pricing strategies (Dubey et al., 2020). From the DCV perspective, BDAC can be seen as a dynamic capability that allows firms to reconfigure their resources and processes to adapt to changing market conditions and achieve superior ECOP (Bahrami & Shokouhyar, 2022; Sahoo et al., 2023). Therefore, we hypothesize:

H1: BDAC has a positive impact on ECOP

3.2 Impact of BDAC on Social Performance

In today's socially conscious business environment, organizations are increasingly expected to go beyond economic success and demonstrate a commitment to social responsibility. Ensuring positive social performance (SP) is crucial for firms to maintain strong stakeholder relationships and foster customer loyalty (Choi & Park, 2022). BDAC can significantly enhance SP by enabling firms to analyze extensive data on employee welfare, working conditions, and community impact (Dubey et al., 2019). Choi and Park (2022) argue that BDAC facilitates better labor practices and more ethical sourcing decisions, ensuring compliance with social standards and regulations. Moreover, BDAC allows organizations to monitor real-time customer feedback and preferences, enhancing customer satisfaction and loyalty through tailored products and services (Jeble et al., 2018). Big Data enables the personalization of services and products, enhancing user satisfaction and engagement while improving social competence in digital learning environments (Sfetcu, 2024). Big data analytics provides insights into human behavior and market trends, benefiting marketing and customer understanding and planning future initiatives. Additionally, it reveals patterns in social interactions that correlate with academic success and foster innovation performance, especially in high-tech firms (Elfeky et al., 2023; Sfetcu, 2024; Wang et al., 2023). Through the DCV lens, BDAC helps firms sense social trends and stakeholder needs, seize opportunities to improve social impact and transform organizational practices to align with social sustainability goals (Dubey et al., 2019; Bahrami & Shokouhyar, 2022). Therefore, we hypothesize:

H2: BDAC has a positive impact on SP

3.3 Impact of BDAC on Environmental Performance

The increasing visibility of global warming effects, driven by carbon emissions, has spurred discussions on environmental concerns from local government bodies to international forums such as the United Nations. As a result, businesses face growing pressure to operate sustainably and comply with regulatory requirements (Rashid et al., 2024). High environmental performance (EP) is essential for firms to reduce their ecological footprint and contribute to global sustainability goals. Scholars widely highlight the critical role of BDAC in achieving EP. Sahoo et al. (2023) argue that BDAC can enhance EP by enabling firms to adopt data-driven approaches for environmental management. BDAC allows for the monitoring and optimizing energy use, waste management, and emission control through advanced analytics and real-time data processing (Nisar et al., 2020; Zrigui et al., 2023) . Real-time waste monitoring with BDA helps companies identify opportunities to reduce waste, minimize landfill use, and promote recycling or reuse(Namoun et al., 2022; Niska & Serkkola, 2018). Big data optimizes routes, schedules, and inventory management, reducing fuel use, emissions, storage needs, and transportation of surplus goods for an environment-friendly logistics process (Li, 2023; Moldagulova et al., 2020; Pujiarto et al., 2021). From the DCV perspective, BDAC provides the dynamic capability to sense environmental challenges, seize opportunities for green innovation, and transform organizational processes to achieve sustainable environmental outcomes (Dubey et al., 2019). By integrating BDAC into their environmental strategies, firms can enhance their ecological performance, comply with environmental standards, and drive innovation for sustainability (Bag et al., 2023; Gallo et al., 2023). Therefore, we hypothesize:

H3: BDAC has a positive impact on EP

3.4 Moderating Effect of GSCM

BDAC provides valuable insights by processing vast amounts of data from various sources, thereby enabling better decision-making and strategic planning (Sahoo et al., 2023; Fantazy & Tipu, 2024). Nisar et al. (2023) note that organizations must implement sustainable practices to leverage BDAC's insights to achieve sustainable advantages effectively. Karmaker et al. (2023) report that integrating GSCM with data-driven technologies can enable organizations to utilize data-driven insights to optimize resource allocation, improve operational efficiency, and reduce costs, thereby enhancing ECOP. Similarly, GSCM practices foster ethical sourcing, fair labor practices, and community engagement, which, when combined with BDAC insights, can significantly enhance SP by building stronger relationships with stakeholders and enhancing brand reputation (Rashid et al., 2024). Furthermore, GSCM practices focus on reducing the environmental impact of SC activities (Feng et al., 2022). By utilizing BDAC, firms can identify inefficiencies and adopt green technologies, energy-efficient processes, and circular economy models, thereby improving EP (Cheng et al., 2023). Thus, we posit that organizations with strong GSCM practices can more effectively utilize the insights provided by BDAC to achieve SSCP. Therefore, we hypothesize:

H4a: GSCM positively moderates the link between BDAC and ECOP

H4b: GSCM positively moderates the link between BDAC and SP

H4c: GSCM positively moderates the link between BDAC and EP.

The theoretical model is presented in Figure 1.

4.0 Research Methodology

This study employs a two-stage mixed methodology, proven effective in previous research (Schilke, 2014; Dubey et al., 2019). The first stage involves developing survey instruments with measurement items extracted from the existing literature, followed by pre-testing with scholars to ensure validity and reliability. In the second stage, a cross-sectional survey was conducted to collect data from diverse sample respondents within the Bangladeshi RMG sector. Analytical methods are selected to systematically and thoroughly collect, analyze, and interpret data, which is essential for obtaining reliable and valid results. These methods help form a holistic picture of the study and understand the correlation of all variables within the research framework (Khoa et al., 2023; Practices, 2024). This systematic approach ensures that the research findings are robust and can be generalized to a broader context.

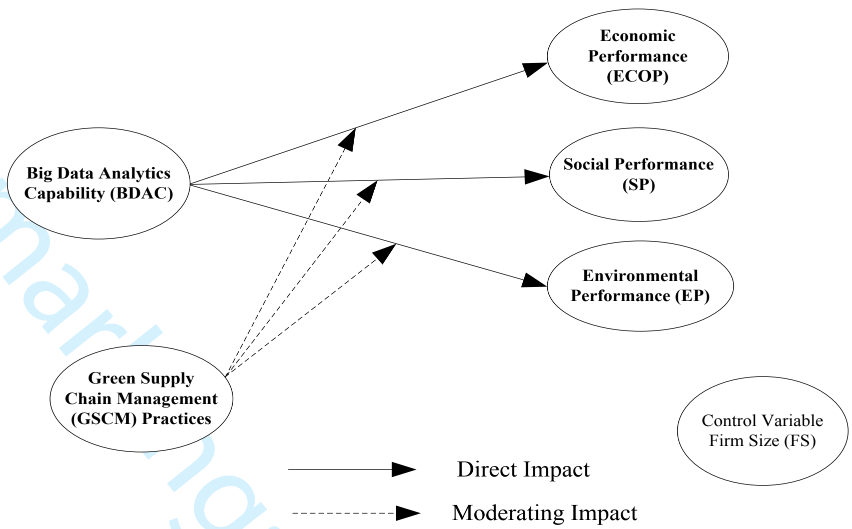

Figure 1. Theoretical Model

4.1 Survey Instrument Development

A survey-based questionnaire was developed to test the proposed model. Measurement items for each construct were sourced from previous relevant literature, with adjustments made to align the items with the context of BDAC. All exogenous and endogenous constructs were operationalized as reflective constructs (see Table I). The survey questionnaire was pre-tested through eight interviews involving five industry experts and three academicians specializing in data analytics and sustainability performance. They evaluated the questionnaire for the suitability of the measurements, clarity of the questions, and potential ambiguities (DeVellis, 1991). Based on their feedback, adjustments were made to enhance the questionnaire's effectiveness and alignment with the model requirements. All measuring scales utilized a seven-point Likert scale, ranging from "1 = strongly disagree" to "7 = strongly agree."

Firm size is a key control variable in corporate finance and governance research due to its substantial influence on financial performance and behavior. Although factors like industry type, firm age, and ownership structure are also relevant, they are often controlled differently or deemed less impactful (Yadav et al., 2021). Prioritizing firm size simplifies analysis and enhances the robustness of findings, especially under data constraints. So to control for potential variations in resources, capabilities, and organizational structures, firm size (FS) was included as a control variable. Larger firms may possess more advanced technological infrastructures and greater financial capacity to implement SC management practices, which could skew results if not controlled (Dubey et al., 2019). Firm size was categorized based on the number of employees: firms with ≤500 employees were classified as small, and firms with >500 employees were classified as large.

4.2 Data Collection

Data were collected using a cross-sectional survey from firms registered with the Bangladesh Garment Manufacturers and Exporters Association (BGMEA). The Bangladeshi RMG sector was selected due to its significant global presence and impact on economic development and sustainability challenges. As one of the largest apparel exporters worldwide, Bangladesh's RMG industry faces pressing issues related to SC sustainability (Saha et al., 2024), making it an ideal context to explore the role of BDAC and the moderating influence of GSCM.

The organizational unit served as our unit of analysis, and the survey was designed for a single respondent. To ensure a representative sample, we employed a simple random sampling technique (Dillman, 2011). The BGMEA database, which includes detailed information on registered RMG firms, served as our sampling frame. 760 firms were selected from this database to participate in the study. The selection process aimed to cover a diverse range of firms in size, market presence, and commitment to integrating technological innovations with sustainable practices. Senior supply chain executives (e.g., purchasing managers, inventory managers, materials managers, procurement managers, sourcing managers, distribution managers, supply chain managers, logistics managers, planning managers, and operations directors) were targeted as respondents. These individuals were chosen due to their comprehensive knowledge and expertise in SC management practices, information flow, and the adoption of data-driven technologies.

Questionnaires were e-mailed to the selected respondents through Google Forms. We followed up with multiple reminders, typically three times to enhance the response rate. In total, we received 159 comprehensive and usable responses, resulting in a response rate of 20.92%.In Bangladeshi corporate offices, employees often face extended working hours, leading to fatigue and a lack of motivation to participate in additional tasks such as surveys. Furthermore, the absence of financial incentives or adequate remuneration for their participation diminishes their interest and willingness to engage, resulting in a notably low response rate for such surveys. However, this response rate is deemed sufficient for PLS-SEM analysis (Dubey et al., 2020; Saha et al., 2023). We ensured the eligibility of respondents by excluding participants who were not from the RMG sector or lacked relevant experience. Additionally, incomplete responses were not included in the analysis.

The demographic profiles of the 159 respondents were analyzed, focusing on key attributes such as firm size, experience, gender distribution, and professional designation. The gender distribution revealed a male-to-female ratio of 125:34. Regarding firm size, most respondents were associated with large firms (135, 84.91%), while a considerably smaller proportion were from small firms (24, 15.09%). All respondents held managerial or higher-level positions. Among these, Supply Chain Managers constituted the largest group (58, 36.48%), followed by Directors of Operations (38, 23.91%), Logistics Managers (18, 11.32%), Procurement Managers (17, 10.69%), Planning Managers (12, 7.54%), Materials Managers (9, 5.66%), and Other Managers (7, 4.40%). In terms of professional experience, the majority of respondents had 6–11 years of experience (91, 57.23%), followed by those with 12–16 years (56, 35.23%) and 17–24 years (12, 7.54%). This analysis highlights significant variation in demographic and professional attributes among the respondents. The sampling and response details are presented in Table II.

Table I. Measures

Construct	Type	Measures	Sources
Big data analytics capability (BDAC)	Reflective	We employ data visualization methods for comprehending intricate information extracted from extensive data sources (BDAC1)	(Dubey et al., 2019; Bahrami & Shokouhyar, 2022; Fantazy & Tipu, 2024)
		We utilize advanced analytical tools (such as optimization, regression, or simulation) to analyze data (BDAC2)	
		We integrate data from multiple sources (including company reports and social media) for comprehensive data analysis (BDAC3)	
Green supply chain management (GSCM)	Reflective	Our firm invests in technologies that enhance energy efficiency across the SC (GSCM1)	(Karmaker et al., 2023; Behl et al., 2024; Huang et al., 2024)
		Our firm implements strategies for recycling, reusing, and safe disposal of products at the end of their lifecycle (GSCM2)	
		Our firm conducts regular audits to ensure compliance with environmental standards and regulations (GSCM3)	
Economic Performance (ECOP)	Reflective	Our firm achieves higher gross profit margins by decreasing materials purchasing costs (ECOP1)	(Jeble et al., 2018; Jum'a et al., 2024)
		Our firm enhances net income margins by reducing energy consumption expenses (ECOP2)	
		Our firm increases operational efficiency by optimizing logistics and transportation costs (ECOP3)	
		Our firm improves cost-efficiency by minimizing fees associated with waste discharge (ECOP4)	
Social Performance (SP)	Reflective	Our firm believes in gender equality (SP1)	(Jeble et al., 2018; Jum'a et al., 2024)
		Our firm places significant emphasis on employee safety and occupational health (SP2)	

		Our firm adheres to international labor standards and conventions (SP3)	
Environmental Performance (EP)	Reflective	Our firm has implemented measures to reduce air emissions (EP1)	(Jeble et al., 2018; Jum'a et al., 2024)
		Our firm has adopted practices for recycling wastewater (EP2)	
		Our firm has taken steps to prevent the discharge of solid waste (EP3)	

4.3 Non-response Bias

Given the survey-based data collection process, we checked for non-response bias following Armstrong and Overton's (1977) guidelines. Collected data were categorized into early and late responses, as early respondents are thought to have greater interest in and understanding of the topic. Then, we conducted a t-test following Armstrong and Overton's (1977) recommendations and found no statistically significant difference between early and late responses. As bias did not influence our research, the two data sets were merged to test our model.

Table II. An overview of the sampling

Criteria	Genre	Number	Responses rate
Gender	Male	125	78.61%
	Female	34	21.39%
Firm size	Small (<500 employees)	24	15.09%
	Large (500-5000 employees)	135	84.91%
Experience	6-11 years	91	57.23%
	12-16 years	56	35.23%
	17-24 years	12	07.54%
Designation	Director of Operations	38	23.91%
	Planning Manager	12	07.54%
	Procurement Manager	17	10.69%
	Materials Manager	9	05.66%
	Supply Chain Manager	58	36.48%
	Logistics Manager	18	11.32%
	Other Manager	7	04.40%

5.0 Data Analysis and Result

To test our theoretical model, we employed WarpPLS 8.0 software, which utilizes the partial least squares-based structural equation modeling (PLS-SEM) technique (Kock, 2019). PLS-SEM is particularly suited for our study due to its predictive orientation (Peng & Lai, 2012) and its ability to effectively handle complex models with smaller sample sizes (Hair et al., 2016). Besides, PLS-SEM is robust to non-normal data distributions and does not require strict assumptions about the underlying data distribution, enhancing its applicability across diverse research domains (Peng &

Lai, 2012; Dubey et al., 2020). Furthermore, PLS-SEM allows for the simultaneous evaluation of measurement and structural models. This dual capability is a powerful tool for theory development and hypothesis testing, enabling us to rigorously assess the predictive accuracy of our independent latent variables (Henseler et al., 2015). Unlike covariance-based SEM (CB-SEM), PLS-SEM considers measurement errors, thus providing more accurate and reliable results (Dubey et al., 2020; Kock, 2019; Tiwari et al., 2024). Therefore, by employing WarpPLS 8.0, we aim to leverage these strengths to comprehensively evaluate the relationships and hypotheses proposed in our study, ensuring robust and reliable results. In addition to reviewing the relevant supporting literature, we undertook a thorough assessment of the minimum sample size required for our study, following the guidelines proposed by Kock and Hadaya (2018). This assessment is particularly important as we plan to perform statistical analyses using Partial Least Squares Structural Equation Modeling (PLS-SEM). Kock and Hadaya (2018) recommend employing two specific tests to determine the necessary sample size: the inverse square root method and the gamma-exponential method. According to their recommendations, for a significance level set at 0.05 and a power level of 0.80, the minimum sample size required should range between 146 and 160 participants. This range is crucial for ensuring that our findings will have adequate statistical power and reliability. In our study, we collected a sample size of 159 participants, which falls comfortably within the recommended range. This indicates that our sample is sufficiently large to support the statistical analyses we intend to conduct, thus enhancing the validity of our research outcomes.

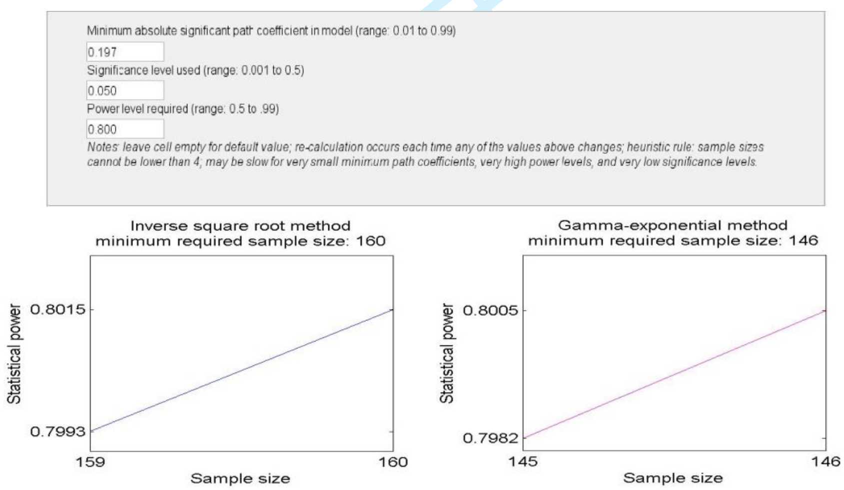

Figure 2: Minimum Sample Size based on Kock & Hadaya (2018) (source: Authors own analysis based on the WarpPLS 8.0)

5.1 Measurement Model

We used confirmatory factor analysis (CFA) to assess our measurement model's convergent and discriminant validity. Following Fornell and Larcker's (1981) recommendations, we reported composite reliability (SCR) values, factor loadings for each measurement item (λ), and the average variance extracted (AVE) values (Table III). As shown in Table III, all factor loadings for the measurement items exceed the threshold limit of 0.5 and the SCR and AVE values also surpass their respective cut-off points (i.e., SCR ≥ 0.7, AVE ≥ 0.5), suggesting high convergent validity of our constructs (Fornell & Larcker, 1981). We further calculated Cronbach's alpha (α) values for each construct to evaluate the reliability of our measurement model (Table III). All α values were above the acceptable threshold of 0.7, confirming the constructs' high internal consistency and reliability (Hair et al., 2017).

Table III. Convergent validity test (SCR, Cronbach's Alpha (α) and AVE)

Construct	Items	Factor loadings (λ)	Variance (λ^2)	Error ($1-\lambda^2$)	SCR	AVE
Big Data Analytics Capability (BDAC) (α=0.947)	BDAC1	0.95	0.90	0.10	0.97	0.91
	BDAC2	0.96	0.92	0.08		
	BDAC3	0.94	0.88	0.12		
Green supply chain management (GSCM) (α=0.840)	GSCM1	0.88	0.77	0.23	0.90	0.76
	GSCM2	0.87	0.76	0.24		
	GSCM3	0.86	0.74	0.26		
Economic Performance (ECOP) (α=0.822)	ECOP1	0.83	0.69	0.31	0.88	0.65
	ECOP2	0.77	0.59	0.41		
	ECOP3	0.80	0.64	0.36		
	ECOP4	0.82	0.67	0.33		
Social Performance (SP) (α=0.727)	SP1	0.80	0.64	0.36	0.85	0.65
	SP2	0.83	0.69	0.31		
	SP3	0.78	0.61	0.39		
Environmental Performance (EP) (α=0.735)	EP1	0.82	0.67	0.33	0.85	0.66
	EP2	0.88	0.77	0.23		
	EP3	0.72	0.52	0.48		

Then, we tested the discriminant validity following Fornell and Larcker's (1981) suggestions (Table IV). Fornell and Larcker (1981) stated that a construct shows higher discriminant validity if its square root of AVE is greater than all other constructs' correlation values. The square root of AVEs for each latent variable exceeded its correlations with other constructs, confirming discriminant validity (Fornell & Larcker, 1981; Gold et al., 2001). Cross-loadings further supported this, indicating that the constructs are conceptually distinct. Table IV indicates that all the square root values of AVE (highlighted in italics diagonally) meet the required condition, which provides significant evidence of the constructs' discriminant validity.

Table IV. Discriminant Validity Test

	BDAC	GSCM	SP	EP	ECOP

BDAC	*0.95*				
GSCM	0.09	*0.87*			
SP	0.44	0.02	*0.80*		
EP	0.48	0.10	0.56	*0.81*	
ECOP	0.48	0.11	0.55	0.66	*0.81*

Note: Italic represents the root-square of AVE of a construct

In our study, we not only applied Fornell and Larcker's (1981) discriminant validity test, but we also implemented an additional validity assessment recommended by Henseler et al. (2015), referred to as the HTMT (Heterotrait-Monotrait Ratio) test. This test is designed to provide a more nuanced evaluation of the discriminant validity of the constructs being analyzed. In our findings, we observed that the HTMT values were consistently below the suggested threshold of 0.9. This outcome is significant as it suggests that the constructs under investigation do indeed satisfy the criteria for discriminant validity, meaning they are distinct and measure different concepts effectively. For further details on our methodology and results, please refer to Appendix 1. In accordance with the criteria established by Fornell & Larcker (1981) and further refined by Henseler et al. (2015), our analysis indicates that the constructs utilized in the study demonstrate both convergent validity and discriminant validity. Convergent validity is confirmed as the constructs show a strong correlation with their respective indicators, indicating they measure the same underlying concept. Meanwhile, discriminant validity ensures that the constructs are distinct from one another, as evidenced by their weak correlations with other constructs. Together, these validations are fundamental to establishing the overall construct validity of our study, ensuring that the measurements accurately reflect the theoretical concepts they aim to capture.

5.2 Common Method Bias (CMB)

Survey-based data may be subject to common method biases (CMB) due to consistency in responses and implicit social desirability (Podsakoff et al., 2003). Recognizing potential biases in data obtained from a single source utilizing a survey-based instrument, as Ketokivi and Schroeder (2004) noted, we conducted two tests to assess CMB. Firstly, we performed Harman's single-factor test, following Kock's (2015) guidelines. The analysis revealed that only 37.56% of the total variance could be attributed to a single factor. Kock (2015) suggested that if the explanatory power of the single construct of the total variance is more than 50%, it indicates CMB's presence in the dataset. Thus, CMB is not a major concern in our dataset. Secondly, we conducted the full collinearity test to evaluate vertical and lateral collinearity, generating variance inflation factors (VIFs) for all latent variables using WarpPLS (Kock, 2017). A VIF greater than 3.3 suggests pathological collinearity and potential CMB contamination (Kock, 2017). All VIF values in our analysis were below 3.3, indicating negligible CMB impact.

Furthermore, we checked causality issues before proceeding to the hypothesis testing. We analyzed four indices: Simpson's paradox ratio (SPR), R-squared contribution ratio (RSCR), Statistical suppression ratio (SSR), and Nonlinear bivariate causality direction ratio (NLBCDR) (Table V), following Kock's (2022) suggestions. Our analysis shows the NLBCDR value of 0.833, above its cut-off value of 0.7 (Kock, 2022). The SSR and SPR values were determined to be 1, exceeding the recommended cutoff value of 0.7, indicating a robust value. Additionally, the RSCR value was found to be 1, which is considered acceptable as it surpasses the threshold of 0.9 (Holland, 1986). Table V demonstrates that all indices are in the allowable range, indicating that causality is not a significant concern in our study.

Table V. Causality Assessment Indices

Indices	Values
SPR	1.000, acceptable if >= 0.7
RSCR	1.000, acceptable if >= 0.9
SSR	1.000, acceptable if >= 0.7
NLBCDR	0.833, acceptable if >= 0.7

5.3 Hypothesis Testing

Our study hypotheses have been tested by PLS-SEM (WarpPLS 8.0). The PLS utilizes a bootstrapping technique to determine parameter estimations' standard errors and significance (Chin, 1998). Table VI presents the results of the structural path analysis obtained from the PLS algorithm, showing standardized path coefficients (β) and corresponding p-values. For instance, $\beta = 0.50$, $p < 0.01$, indicates strong support for H1 (BDAC→ECOP), demonstrating that BDAC is a strong predictor of the ECOP. Similarly, H2 (BDAC→SP) ($\beta = 0.45$, $p < 0.01$) and H3 (BDAC→EP) ($\beta = 0.49$, $p < 0.01$) are statistically significant at the 0.01 level. Next, we evaluated the moderation effect of GSCM on the paths joining BDAC and EP (H4a), BDAC and SP (H4b), and BDAC and ECOP (H4c). The results show that all the moderation impacts of GSCM (H4a, H4b, and H4c) are significant at the 0.05 level (Table VI). We also assessed the impact of the control variable, firm size (FS), on our model. However, FS was not found to impact the endogenous variables significantly.

Table VI. Structural Estimates

Hypothesis	Effect of	Effect on	β	p-value	Results
H1	BDAC	ECOP	0.50	<.01	Supported
H2	BDAC	SP	0.45	<.01	Supported
H3	BDAC	EP	0.49	<.01	Supported
H4a	GSCM	BDAC-ECOP	0.15	<.05	Supported
H4b	GSCM	BDAC-SP	0.17	<.05	Supported
H4c	GSCM	BDAC-EP	0.25	<.05	Supported
control variables	FS	ECOP	0.02	0.39	Not significant
	FS	SP	0.03	0.35	Not significant
	FS	EP	0.07	0.18	Not significant

We then assessed the explanatory power of our model by estimating the R^2 values of the endogenous variables. The R^2 values for ECOP, SP, and EP are 0.27, 0.22, and 0.26, respectively (Table VII), indicating moderately strong explanatory power (Chin, 1998). We also determined the f^2 values to analyze the effect size of BDAC on ECOP, SP, and EP (Cohen, 1988). The effect sizes are 0.249, 0.200, and 0.236 (Table VII), respectively, indicating large effect sizes (Cohen, 1988). Furthermore, we calculated Stone-Geisser's Q^2 values to evaluate the predictive capability of our model. We found the Q^2 values for ECOP, SP, and EP are 0.229, 0.261, and 0.276, respectively (Table VII), suggesting the allowable predictive relevance (Peng & Lai, 2012).

Table VII. Coefficient of variation (R^2), predictability (Q^2) and effect size (f^2)

Construct	R^2	Q^2	f^2 in relation to BDAC
ECOP	0.27	0.229	0.249
SP	0.22	0.261	0.200
EP	0.25	0.276	0.236

5.4 Model Fit and Indices

We calculated the average path coefficient (APC), average R-squared (ARS), and Average block VIF (AVIF) to check the fitness and quality of our model (Kock, 2011; Behl et al., 2022). All the values were in the allowable range (Table VIII). The AVIF value below 3.3 indicates the absence of multicollinearity issues in the dataset (Kock, 2011). We also calculated Tenenhaus GoF to measure the goodness of fit, following the suggestions of Tenenhaus et al. (2005). Tenenhaus GoF is found to be 0.449, which is considered medium (Tenenhaus et al., 2005). Based on these findings, we can conclude that our model fits our data well.

Table VIII. Model Fitness and quality indices parameter

Fitness and quality indices	Values
Average path coefficient (APC)	0.226 (P<0.001)
Average R-squared (ARS)	0.251 (P<0.001)
Average block VIF (AVIF)	1.007 (acceptable if <= 5, ideally <= 3.3)
Tenenhaus GoF	0.449 (small >= 0.1, medium >= 0.25, large >= 0.36)

6.0 Discussion

The results of this study provide significant insights into the relationships among BDAC, GSCM practices, and SC sustainability across economic, social, and environmental dimensions. The findings indicate that BDAC positively influences SC sustainability, addressing our first RQ. Specifically, BDAC was found to be a strong predictor of economic ($\beta = 0.50$, $p < 0.01$), social ($\beta = 0.45$, $p < 0.01$), and environmental performance ($\beta = 0.49$, $p < 0.01$). This outcome aligns with existing literature, consistently highlighting BDA's transformative potential in SC management. For instance, Dubey et al. (2024) and Li et al. (2024) note that BDAC enables firms to process vast amounts of data, leading to improved decision-making, enhanced operational efficiency, and greater agility in responding to market changes. Our study confirms these findings and extends them by empirically validating the positive impact of BDAC on all three dimensions of the TBL. While previous studies have often focused on individual aspects of sustainability, such as economic or environmental performance (Zhu et al., 2022; Morimura & Sakagawa, 2023; Gopal et al., 2024), our research offers a more comprehensive view by examining the combined effects of BDAC across economic, social, and environmental dimensions simultaneously.

Economically, our findings support earlier work by Chong et al. (2023), who highlighted the role of BDAC in optimizing inventory levels, reducing costs, and improving demand forecasting accuracy, which, in turn, enhances financial performance. However, our study contributes to the literature by demonstrating that BDAC's economic benefits also have a cascading effect on social and environmental performance. Socially, our results resonate with the findings of Dubey et al. (2019), who argued that BDAC enhances transparency and traceability in SC, improving labor practices and ensuring compliance with social standards. However, our study shows that these social improvements are also linked to broader supply chain sustainability goals. Environmentally, the positive influence of BDAC on sustainability is consistent with Sahoo et al. (2023), who noted its role in supporting sustainable practices such as monitoring and reducing carbon footprints, managing waste more effectively, and optimizing resource use.

The moderating role of GSCM practices was also confirmed, addressing our second RQ. The moderation effects of GSCM on the relationships between BDAC and ECOP (H4a), SP (H4b), and EP (H4c) were significant at the 0.05 level. Variations in the β values were observed across all dimensions, indicating differing levels of influence. The moderating effect of GSCM on environmental performance is powerful, as it directly and immediately integrates practices such as eco-friendly design, waste reduction, emission minimization, sustainable resource utilization, recycling, and cleaner production (Ihsan & Risonarta, 2023; Shi et al., 2024; Siddiquee et al., 2024; Zi, 2023)These practices significantly improve key environmental metrics, including carbon footprint reductions and enhancements in resource efficiency, thereby emphasizing the most prominent effect. The moderating effect of GSCM on social and economic dimensions is comparatively lower due to high initial costs, delayed economic benefits, limited consumer demand for green products, and competitive pressures. Social impacts are less direct and more challenging to quantify than environmental improvements, relying on factors such as stakeholder engagement, societal awareness, and implementation scale.

This finding is consistent with the DCV, which posits that firms can achieve sustained competitive advantage through the integration and reconfiguration of internal and external competencies (Teece et al., 1997; Ghasemzadeh et al., 2022; Tipu & Fantazy, 2023). While prior studies, such as those by Dzikriansyah et al. (2023) and Huang et al. (2024), have explored the individual impacts of GSCM on sustainability, our research extends this body of work by illustrating how GSCM practices enhance the effectiveness of BDAC in achieving sustainability across multiple dimensions. This integrated approach provides new insights into how firms can leverage dynamic capabilities to navigate complex sustainability challenges.

The DCV emphasizes that it is not just the possession of resources like BDAC that leads to competitive advantage but how firms dynamically integrate, build, and reconfigure these resources in response to changing environments. In this context, GSCM practices serve as complementary capabilities that, when combined with BDAC, enhance a firm's ability to adapt and respond to environmental pressures and opportunities. This synergy between BDAC and GSCM practices highlights a critical extension of the DCV framework. This suggests that dynamic reconfiguring technological and operational capabilities is key to achieving and sustaining competitive advantage in today's rapidly evolving market. For example, Teece (2007) highlights that dynamic capabilities enable firms to create, extend, and modify their resource base to address rapidly changing environments. Our findings suggest that by integrating BDAC with GSCM practices, firms are better positioned to reconfigure their operations to achieve higher levels of sustainability. BDAC provides the technological capabilities to analyze and utilize data for better decision-making, while GSCM practices offer the procedural and operational changes needed to implement sustainable practices. This combination allows firms to continuously adapt their supply chain strategies, processes, and practices to meet sustainability goals, thus achieving a sustained competitive advantage.

6.1 Theoretical Implications

This study makes several theoretical contributions to DCV, BDAC, GSCM, and supply chain sustainability, advancing the understanding of how these constructs interact to shape sustainable SC outcomes. First, this research extends the DCV by demonstrating the synergistic effects of integrating BDAC with GSCM practices to achieve SC sustainability. While the DCV traditionally emphasizes a firm's ability to integrate, build, and reconfigure internal and external competencies in response to environmental changes (Teece, 2007), this study breaks new ground by empirically illustrating how the combination of BDAC and GSCM creates a dynamic interplay that enhances a firm's adaptability and sustainability performance. Previous studies have examined BDAC and GSCM independently (Jeble et al., 2018; Huang et al., 2024), but the interaction between these capabilities within the DCV framework has remained underexplored. By showing how BDAC and GSCM jointly contribute to sustainability across economic, social, and environmental dimensions, this study enriches the DCV by highlighting the importance of integrating complementary capabilities to achieve sustained competitive advantage in an era increasingly defined by sustainability challenges.

Second, the study empirically validates the positive impact of BDAC on the three dimensions of supply chain sustainability—economic, social, and environmental performance—within the context of the TBL framework. This finding not only corroborates existing research that emphasizes the role of BDAC in enhancing operational efficiency and resilience (e.g., Dubey et al., 2020; Liu et al., 2023) but also extends this body of literature by demonstrating the broad applicability of BDAC across multiple dimensions of sustainability. By adopting a comprehensive TBL perspective, this study addresses the call for research that moves beyond the economic benefits of BDAC to explore its role in achieving balanced economic, social, and environmental objectives in SC management.

Third, the study highlights the moderating role of GSCM practices in enhancing the impact of BDAC on SC sustainability. This insight contributes to the literature on SSCM by underscoring the necessity of integrating green practices into data-driven decision-making processes. While prior research has largely focused on the independent effects of GSCM on sustainability (Dzikriansyah et al., 2023; Hejazi et al., 2023), this study reveals that GSCM practices are most effective when combined with advanced technological capabilities like BDAC. This finding advances SSCM theory by illustrating how the alignment of technological and sustainable practices can amplify the positive outcomes of each, thereby offering a more integrated approach to achieving long-term sustainability in SCs.

6.2 Managerial Implications

The findings of this study have several practical implications for SC managers and policymakers. For SC managers, the positive impact of BDAC on SC sustainability underscores the importance of investing in data-driven analytical capabilities. Firms should focus on developing robust data analytics infrastructure, acquiring skilled personnel, and fostering a data-driven culture to harness the full potential of BDAC. By leveraging big data, managers can improve decision-making, enhance operational efficiency, and achieve SSCP.

The significant moderation effects of GSCM practices suggest that firms should integrate green SC management practices with their data analytics initiatives. Managers should adopt practices such as sustainable sourcing, waste reduction, and minimization of carbon footprint to enhance the effectiveness of their BDAC efforts. By aligning GSCM practices with data-driven strategies, firms can achieve a competitive edge while contributing to environmental sustainability.

For policymakers, the study highlights the importance of promoting policies that encourage adopting BDAC and GSCM practices in the supply chain sector. Governments and regulatory bodies should incentivize firms to invest in big data analytics and implement green practices. Policies that support training and development programs in data analytics and sustainability can help build the necessary skills and capabilities within the industry. Additionally, policymakers should encourage collaboration between industry and academia to foster innovation and disseminate best practices in sustainable SC management.

7.0 Conclusion

This study has developed and tested a theoretical framework grounded on DCV theory to explore the role of BDAC in enhancing SC sustainability while examining the moderating effects of GSCM practices. Utilizing data from 159 respondents in the Bangladeshi RMG sector, the findings reveal that BDAC significantly improves economic, social, and environmental performance. Additionally, GSCM practices significantly strengthen the positive impacts of BDAC on these dimensions of sustainability. These results underscore the importance of integrating BDAC with GSCM practices to achieve comprehensive SC sustainability. The study contributes to the DCV by illustrating how the reconfiguration and integration of BDAC and GSCM can lead to sustained competitive advantage and improved sustainable performance in supply chains.

7.1 Limitations and Future Scopes

Despite the valuable insights provided by this study, several limitations should be acknowledged. First, the cross-sectional nature of the data limits the ability to infer causality between BDAC, GSCM practices, and SC sustainability outcomes. Future research could employ longitudinal designs better to capture the dynamic effects of these variables over time.

Second, the study focuses solely on the Bangladeshi RMG sector, As the Bangladeshi RMG sector is the second-largest clothing exporter, holding a 6% share of the global market (Khan & Ullah, 2017), it encompasses a wide range of activities similar to those in other industries. The research findings from this sector provide valuable insights that can be adapted to other industries and regions. However, further studies are necessary to examine these dynamics in different sectors to improve the generalizability of the results. Future research should also explore these relationships across diverse sectors and regions to strengthen external validity.

Third, while this research uses survey data from senior SC executives, incorporating multiple respondents from each firm or triangulating survey data with qualitative interviews could provide a more comprehensive understanding.

The fourth aspect to consider is the influence of various data-driven enabling technologies within the ready-made garment (RMG) sector. Specifically, the application of blockchain technology can enhance transparency and traceability throughout the supply chain, as discussed by Manzoor et al. (2024). Additionally, artificial intelligence (AI) technologies, explored by Fosso Wamba et al. (2024) and Dubey et al. (2024), have the potential to optimize manufacturing processes, improve demand forecasting, and personalize customer experiences. Furthermore, other emerging technologies, such as the Internet of Things (IoT) and data analytics, can also play significant roles in increasing efficiency, reducing waste, and fostering innovation within the RMG industry. Understanding the interplay of these technologies is crucial for driving growth and sustainability in the sector.

Lastly, we applied the DCV perspectives to frame our research; however, future studies may apply other theoretical frameworks to offer a more comprehensive explanation. Researchers could explore additional organizational capabilities or assets that complement BDAC. Moreover, incorporating theoretical perspectives such as the knowledge-based view, contingency theory, information processing theory, organizational learning, and organizational culture might yield valuable extensions to our study.

Appendix 1: HTMT Test (good if <0.90 and best if <0.85)

	BDAC	GSCM	SP	EP	ECOP
BDAC					
GSCM	0.101				
SP	0.528	0.073			
EP	0.566	0.148	0.757		
ECOP	0.543	0.135	0.708	0.842	

Source: The data presented is derived from the authors' own values, based on the output from WarpPLS 8.0.

References

Abuzawida, S. S., Alzubi, A. B., & Iyiola, K. (2023). Sustainable supply chain practices: an empirical investigation from the manufacturing industry. Sustainability, 15(19), 14395.

Akram, H. W., Ahmad, A., Abbas, H., & Akhter, S. (2024). A bibliometric analysis of the genesis, journey, and current status of green supply chain management in the digital economy. Benchmarking: An International Journal.

Al-Khatib, A. W. (2023). The impact of industrial Internet of things on sustainable performance: the indirect effect of supply chain visibility. Business Process Management Journal, 29(5), 1607-1629.

Al-Tarawneh, A., Haddad, E., Al-Dwairi, R., Al-Freijat, S., Mansour, A., & AL-Obaidly, G. (2024). The impact of strategic and innovativeness entrepreneurship and social capital on business overall performance through building a sustainable supply chain management at Jordan Private Universities. Uncertain Supply Chain Management, 12(1), 65-76.

Althaqafi, T. (2023). Cultivating Sustainable Supply Chain Practises in Electric Vehicle Manufacturing: A MCDM Approach to Assessing GSCM Performance. World Electric Vehicle Journal, 14(10), 290.

Ansari, K., & Ghasemaghaei, M. (2023). Big data analytics capability and firm performance: meta-analysis. Journal of Computer Information Systems, 63(6), 1477-1494.

Arias-Pérez, J., Coronado-Medina, A., & Perdomo-Charry, G. (2022). Big data analytics capability as a mediator in the impact of open innovation on firm performance. Journal of Strategy and Management, 15(1), 1-15.

Armstrong, J. S., & Overton, T. S. (1977). Estimating Non-response Bias in Mail Surveys. Journal of Marketing Research, 14(3), 396–402.

Asante-Darko, D., & Osei, V. (2024). Sustainable supply chain management practices and firm performance: the mediating effect of firm capabilities. Management of Environmental Quality: An International Journal, 35(4), 751-779.

Bag, S., Rahman, M. S., Srivastava, G., Shore, A., & Ram, P. (2023). Examining the role of virtue ethics and big data in enhancing viable, sustainable, and digital supply chain performance. Technological Forecasting and Social Change, 186, 122154.

Bagherpasandi, M., Salehi, M., Hajiha, Z., & Hejazi, R. (2024). Presenting a model for enhancing the performance of sustainable supply chain management using a data-driven approach. Benchmarking: An International Journal, (ahead-of-print).

Bahrami, M., & Shokouhyar, S. (2022). The role of big data analytics capabilities in bolstering supply chain resilience and firm performance: a dynamic capability view. Information Technology & People, 35(5), 1621-1651.

Balkumar, K., Gedam, V. V., Himateja, M., Anbuudayasankar, S. P., Narassima, M. S., Ganesh, K., Dwarakanath, M., & Pazhani, S. (2024). Prevalence and future trend in green supply chain management (GSCM): a systematic literature review. Benchmarking: An International Journal, 31(6), 2002-2033.

Behl, A. (2022). Antecedents to firm performance and competitiveness using the lens of big data analytics: a cross-cultural study. Management Decision, 60(2), 368-398.

Behl, A., Gaur, J., Pereira, V., Yadav, R., & Laker, B. (2022). Role of big data analytics capabilities to improve the sustainable competitive advantage of MSME service firms during COVID-19– A multi-theoretical approach. Journal of Business Research, 148, 378-389.

Behl, A., Sampat, B., Gaur, J., Pereira, V., Laker, B., Shankar, A., ... & Roohanifar, M. (2024). Can gamification help green supply chain management firms achieve sustainable results in servitized ecosystem? An empirical investigation. Technovation, 129, 102915.

Belhadi, A., Kamble, S. S., Gunasekaran, A., Zkik, K., & Touriki, F. E. (2023). A Big Data Analytics-driven Lean Six Sigma framework for enhanced green performance: a case study of a chemical company. Production Planning & Control, 34(9), 767-790.

Billah, M. M., Alam, S. S., Masukujjaman, M., Ali, M. H., Makhbul, Z. K. M., & Salleh, M. F. M. (2023). Effects of Internet of Things, supply chain collaboration and ethical sensitivity on sustainable performance: moderating effect of supply chain dynamism. Journal of Enterprise Information Management, 36(5), 1270-1295.

Boreik, D. A. S., Melegy, M. M. A., & Albaz, M. M. A. (2023). The Impact of Big Data Analytics on Investment Efficiency and Financial Performance: Evidence from Saudi Stock Market.

Boyd, B. K., Takacs Haynes, K., Hitt, M. A., Bergh, D. D., & Ketchen Jr, D. J. (2012). Contingency hypotheses in strategic management research: Use, disuse, or misuse? Journal of Management, 38(1), 278-313.

Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: moving toward new theory. International Journal of Physical Distribution & Logistics Management, 38(5), 360-387.

Cetindamar, D., Shdifat, B., & Erfani, E. (2022). Understanding Big Data Analytics Capability and Sustainable Supply Chains. Information Systems Management, 39(1), 19–33.

Cheng, J., Singh, H. S. M., Zhang, Y. C., & Wang, S. Y. (2023). The impact of business intelligence, big data analytics capability, and green knowledge management on sustainability performance. Journal of Cleaner Production, 429, 139410.

Chin, W. W. (1998). Commentary: Issues and Opinion on Structural Equation Modeling. MIS Quarterly, 22(1), 07-16.

Choi, H. Y., & Park, J. (2022). Do data-driven CSR initiatives improve CSR performance? The importance of big data analytics capability. Technological Forecasting and Social Change, 182, 121802.

Chong, C. L., Abdul Rasid, S. Z., Khalid, H., & Ramayah, T. (2023). Big data analytics capability for competitive advantage and firm performance in Malaysian manufacturing firms. International Journal of Productivity and Performance Management.

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences, 2nd Edn. Hillsdale, NJ: Erlbaum.

Conti, R., de Matos, M. G., & Valentini, G. (2023). Big data analytics, firm size, and performance. Strategy Science, 9(2), 135-151.

DeVellis, R.F., 1991. Scale Development: Theory and Applications. Sage Publications, Newbury Park, CA.

Dillman, D. A. (2011). Mail and Internet surveys: The tailored design method--2007 Update with new Internet, visual, and mixed-mode guide. John Wiley & Sons.

Dubey, R., Bryde, D. J., Graham, G., Foropon, C., Kumari, S., & Gupta, O. (2024). The role of alliance management, big data analytics, and information visibility on new-product development capability. Annals of Operations Research, 1-25.

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., ... & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organizations. International Journal of Production Economics, 226, 107599.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Luo, Z., Wamba, S. F., & Roubaud, D. (2019). Can big data and predictive analytics improve social and environmental sustainability? Technological Forecasting and Social Change, 144, 534-545.

Dubey, R., Gunasekaran, A., & Papadopoulos, T. (2024). Benchmarking operations and supply chain management practices using Generative AI: Towards a theoretical framework. *Transportation Research Part E: Logistics and Transportation Review*, *189*, 103689.

Dzikriansyah, M. A., Masudin, I., Zulfikarijah, F., Jihadi, M., & Jatmiko, R. D. (2023). The role of green supply chain management practices on environmental performance: A case of Indonesian small and medium enterprises. Cleaner Logistics and Supply Chain, 6, 100100.

Eisenhardt, K.M. and Martin, J.A. (2000). Dynamic capabilities: what are they? Strategic Management Journal, 21 (10/11), 1105-1121.

Elfeky, A. I. M., Najmi, A. H., & Elbyaly, M. Y. H. (2023). The effect of big data technologies usage on social competence. PeerJ Computer Science, 9, e1691.

Elkington, J. (1998). Partnerships from cannibals with forks: The triple bottom line of 21st-century business. Environmental Quality Management, 8(1), 37-51.

Fantazy, K., & Tipu, S. A. A. (2024). Linking big data analytics capability and sustainable supply chain performance: mediating role of knowledge development. Management Research Review, 47(4), 512-536.

Feng, Y., Lai, K. H., & Zhu, Q. (2022). Green supply chain innovation: Emergence, adoption, and challenges. International Journal of Production Economics, 248, 108497.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39.

Fosso Wamba, S., Guthrie, C., Queiroz, M. M., & Minner, S. (2024). ChatGPT and generative artificial intelligence: an exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*, *62*(16), 5676-5696.

Gallo, H., Khadem, A., & Alzubi, A. (2023). The Relationship between Big Data Analytic-Artificial Intelligence and Environmental Performance: A Moderated Mediated Model of Green Supply Chain Collaboration (GSCC) and Top Management Commitment (TMC). Discrete Dynamics in Nature and Society, 2023(1), 4980895.

Ghasemzadeh, P., Rezayat Sorkhabadi, S. M., Kebriaeezadeh, A., Nazari, J. A., Farzaneh, M., & Mehralian, G. (2022). How does organizational learning contribute to corporate social responsibility and innovation performance? The dynamic capability view. Journal of Knowledge Management, 26(10), 2579-2601.

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. Journal of Management Information Systems, 18(1), 185-214.

Gopal, P. R. C., Rana, N. P., Krishna, T. V., & Ramkumar, M. (2024). Impact of big data analytics on supply chain performance: an analysis of influencing factors. Annals of Operations Research, 333(2), 769-797.

Gupta, Y., Khan, F. M., Kumar, A., Luthra, S., & Queiroz, M. M. (2024). Mobilizing big data analytics capabilities to improve performance of tourism supply chains: the moderating role of dynamic capabilities. The International Journal of Logistics Management, 35(2), 649-679.

Hair, J. F., Sarstedt, M., Matthews, L. M., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: part I – method. European Business Review, 28(1), 63–76.

Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012). The Use of Partial Least Squares Structural Equation Modeling in Strategic Management Research: A Review of Past Practices and Recommendations for Future Applications. Long Range Planning, 45(5), 320–340.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. Industrial Management & Data Systems, 117(3), 442-458.

Hejazi, M. T., Al Batati, B., & Bahurmuz, A. (2023). The influence of green supply chain management practices on corporate sustainability performance. Sustainability, 15(6), 5459.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135.

Holland, P. W. (1986). Statistics and causal inference. Journal of the American statistical Association, 81(396), 945-960.

Holling, H., & Backhaus, L. (2023). A meta-analysis of green supply chain management practices and firm performance. Sustainability, 15(6), 4730.

Huang, X., Ullah, M., Wang, L., Ullah, F., & Khan, R. (2024). Green supply chain management practices and triple bottom line performance: Insights from an emerging economy with a mediating and moderating model. Journal of Environmental Management, 357, 120575.

Ihsan, M. A., & Risonarta, V. Y. (2023). REFERENCE OVERVIEW ON DESIGN AND SIMULATION OF GREEN SUPPLY CHAIN MANAGEMENT. International Journal of Mechanical Engineering Technologies and Applications, 4(2), 177-189.

Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D., & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. International Journal of Logistics Management, 29(2), 513–538.

Jum'a, L., Zimon, D., & Madzik, P. (2024). Impact of big data technological and personal capabilities on sustainable performance on Jordanian manufacturing companies: the mediating role of innovation. Journal of Enterprise Information Management, 37(2), 329–354.

Karmaker, C. L., Al Aziz, R., Ahmed, T., Misbauddin, S. M., & Moktadir, M. A. (2023). Impact of Industry 4.0 technologies on sustainable supply chain performance: The mediating role of green supply chain management practices and circular economy. Journal of Cleaner Production, 419, 138249.

Karunarathna, I., Gunasena, P., Hapuarachchi, T., & Gunathilake, S. (2024). The crucial role of data collection in research: Techniques, challenges, and best practices. Uva Clinical Research, 1-24.

Ketokivi, M.A. and Schroeder, R.G. (2004). Perceptual measures of performance: fact or fiction? Journal of Operations Management, 22 (3), 247-264.

Khan, A. N., & Ullah, M. R. (2017). Export scenario between Bangladesh and China: Opportunities of Bangladesh in RMG sector. Eur Sci J, 13(28), 299-320.

Khan, S. A. R., Yu, Z., & Farooq, K. (2023). Green capabilities, green purchasing, and triple bottom line performance: Leading toward environmental sustainability. Business Strategy and Environment, 32(4), 2022-2034.

Khoa, B. T., Hung, B. P., & Hejsalem-Brahmi, M. (2023). Qualitative research in social sciences: data collection, data analysis and report writing. International Journal of Public Sector Performance Management, 12(1-2), 187-209.

Khokhar, M., Iqbal, W., Hou, Y., Abbas, M., & Fatima, A. (2020). Assessing supply chain performance from the perspective of Pakistan's manufacturing industry through social sustainability. Processes, 8(9), 1064.

Kock, N. (2011). A mathematical analysis of the evolution of human mate choice traits: Implications for evolutionary psychologists. Journal of Evolutionary Psychology, 9(3), 219–247.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1-10.

Kock, N. (2017). Common Method Bias: A Full Collinearity Assessment Method for PLS-SEM. In: Latan, H., Noonan, R. (eds) Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications (pp. 245–257), Springer, Cham.

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. Information Systems Journal, *28*(1), 227-261.

Kock, N. (2019). From composites to factors: Bridging the gap between PLS and covariance-based structural equation modelling. Information Systems Journal, 29(3), 674–706.

Kock, N. (2022). Using causality assessment indices in PLS-SEM. Data Analysis Perspectives Journal, 3(5), 1-6.

Kumar, A., Shrivastav, S. K., Shrivastava, A. K., Panigrahi, R. R., Mardani, A., & Cavallaro, F. (2023). Sustainable supply chain management, performance measurement, and management: a review. Sustainability, 15(6), 5290.

Kumar, A., Shrivastav, S. K., & Bhattacharyya, S. (2023). Measuring strategic fit using big data analytics in the automotive supply chain: a data source triangulation-based research. *International Journal of Productivity and Performance Management*, *72*(10), 2977-2999.

Le, T. T. (2023). Linking big data, sustainable supply chain management and corporate performance: the moderating role of circular economy thinking. The International Journal of Logistics Management, 34(3), 744-771.

Li, W., Waris, I., & Bhutto, M. Y. (2024). Understanding the nexus among big data analytics capabilities, green dynamic capabilities, supply chain agility, and green competitive advantage: the moderating effect of supply chain innovativeness. Journal of Manufacturing Technology Management, 35(1), 119-140.

Li, Z. (2023). Big Data Management: Empowering Sustainable Logistics with Data-Driven Operation Optimization. Advances in Economics, Management and Political Sciences, 54, 64-68.

Liu, H., Lu, F., Shi, B., Hu, Y., & Li, M. (2023). Big data and supply chain resilience: role of decision-making technology. Management Decision, 61(9), 2792-2808.

Ma, L., & Chang, R. (2024). How big data analytics and artificial intelligence facilitate digital supply chain transformation: the role of integration and agility. Management Decision, (ahead-of-print).

Manzoor, R., Sahay, B. S., Gumte, K., & Singh, S. K. (2024). Blockchain-backed resilient strategies in a stochastic supply chain sourcing and distribution environment under disruption: implications for B2B sector. *Journal of Business & Industrial Marketing*. DOI: 10.1108/jbim-10-2023-0589.

Moldagulova, A., Satybaldiyeva, R., & Kuandykov, A. (2020, September). Application of big data in logistics. In Proceedings of the 6th International Conference on Engineering & MIS 2020 (pp. 1-6).

Morimura, F., & Sakagawa, Y. (2023). The intermediating role of big data analytics capability between responsive and proactive market orientations and firm performance in the retail industry. Journal of Retailing and Consumer Services, 71, 103193.

Namoun, A., Tufail, A., Khan, M. Y., Alrehaili, A., Syed, T. A., & BenRhouma, O. (2022). Solid waste generation and disposal using machine learning approaches: a survey of solutions and challenges. Sustainability, 14(20), 13578.

Naseer, S., Song, H., Adu-Gyamfi, G., Abbass, K., & Naseer, S. (2023). Impact of green supply chain management and green human resource management practices on the sustainable performance of manufacturing firms in Pakistan. Environmental Science and Pollution Research, 30(16), 48021-48035.

Nisar, Q. A., Haider, S., Ameer, I., Hussain, M. S., Gill, S. S., & Usama, A. (2023). Sustainable supply chain management performance in post COVID-19 era in an emerging economy: a big data perspective. International Journal of Emerging Markets, 18(12), 5900-5920.

Nisar, Q. A., Nasir, N., Jamshed, S., Naz, S., Ali, M., & Ali, S. (2020). Big data management and environmental performance: role of big data decision-making capabilities and decision-making quality. Journal of Enterprise Information Management, 34(4), 1061–1096.

Niska, H., & Serkkola, A. (2018). Data analytics approach to create waste generation profiles for waste management and collection. Waste Management, 77, 477-485.

Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. Journal of Operations Management, 30(6), 467–480.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. Journal of Applied Psychology, 88(5), 879–903.

Pujiarto, B., Hanafi, M., Setyawan, A., Imani, A. N., & Prasetya, E. R. (2021). A data mining practical approach to inventory management and logistics optimization. International Journal of Informatics and Information Systems, 4(2), 112-122.

Raj, R., Kumar, V., & Verma, P. (2023). Big data analytics in mitigating challenges of sustainable manufacturing supply chain. Operations Management Research, 16(4), 1886-1900.

Rashid, A., Baloch, N., Rasheed, R., & Ngah, A. H. (2024). Big data analytics-artificial intelligence and sustainable performance through green supply chain practices in manufacturing firms of a developing country. Journal of Science and Technology Policy Management.

Reddy, S. R. B., & Reddy, S. (2023). Large Scale Data Influences Based on Financial Landscape Using Big Data. Tuijin Jishu/Journal of Propulsion Technology, 44(4), 3862-3870.

Riggs, R., Roldán, J. L., Real, J. C., & Felipe, C. M. (2023). Opening the black box of big data sustainable value creation: the mediating role of supply chain management capabilities and circular economy practices. International Journal of Physical Distribution & Logistics Management, 53(7/8), 762-788.

Saha, P., Belal, H. M., & Talapatra, S. (2024). Driving Towards Sustainable Development Goals (SDGs) in the Ready-Made Garments (RMG) Sector: The Role of Digital Capabilities and Operational Transparency. IEEE Transactions on Engineering Management, (ahead-of-print).

Saha, P., Talapatra, S., Belal, H. M., Jackson, V., Mason, A., & Durowoju, O. (2023). Examining the viability of lean production practices in the Industry 4.0 era: an empirical evidence based on B2B garment manufacturing sector. Journal of Business & Industrial Marketing, 38(12), 2694-2712.

Sahoo, S., Upadhyay, A., & Kumar, A. (2023). Circular economy practices and environmental performance: Analysing the role of big data analytics capability and responsible research and innovation. Business Strategy and the Environment, 32(8), 6029-6046.

Sarkis, J., Zhu, Q., & Lai, K. H. (2011). An organizational theoretic review of green supply chain management literature. International Journal of Production Economics, 130(1), 1-15.

Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. Strategic Management Journal, 35(2), 179–203.

Sfetcu, N. (2024). Impact of Big Data Technology on Contemporary Society.

Shi, H., Feng, T., & Zhu, Z. (2023). The impact of big data analytics capability on green supply chain integration: an organizational information processing theory perspective. Business Process Management Journal, 29(2), 550-577.

Shi, W., Hu, Q., & Zhou, Y. (2024). Evolutionary game analysis of vehicle procurement in the courier industry from the perspective of green supply chain. International Journal of Industrial Engineering Computations, 15(1), 223-234.

Shrivastava, S. (2023). Recent trends in supply chain management of business-to-business firms: a review and future research directions. *Journal of Business & Industrial Marketing*, *38*(12), 2673-2693.

Srivastava, S. K., & Bag, S. (2023). Recent developments on flexible manufacturing in the digital era: A review and future research directions. *Global Journal of Flexible Systems Management*, *24*(4), 483-516.

Siddiquee, M., Shaha, P., & Hasin, A. (2024). Greening the pillars of pharmaceuticals: Sustainable supplier selection in emerging economies. *Journal of Future Sustainability*, 4(3), 159-168.

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and micro foundations of (sustainable) enterprise performance. Strategic Management Journal, 28 (13), 1319-1350.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y. M., & Lauro, C. (2005). PLS path modeling. Computational statistics & data analysis, 48(1), 159-205.

Tiwari, M., Bryde, D. J., Stavropolou, F., Dubey, R., Kumari, S., & Foropon, C. (2024). Modelling supply chain Visibility, digital Technologies, environmental dynamism and healthcare supply chain Resilience: An organisation information processing theory perspective. *Transportation Research Part E: Logistics and Transportation Review*, *188*, 103613.

Tipu, S. A. A., & Fantazy, K. (2023). Examining the relationships between big data analytics capability, entrepreneurial orientation, and sustainable supply chain performance: the moderating role of trust. Benchmarking: An International Journal.

Tsai, J. F., Shen, S. P., & Lin, M. H. (2023). Applying a hybrid MCDM model to evaluate green supply chain management practices. Sustainability, 15(3), 2148.

Wang, C., Tang, F., Zhang, Q., & Zhang, W. (2023). How does corporate social responsibility contribute to innovation performance? The moderating role of social media strategic capability and big data analytics capability. European Journal of Innovation Management.

Wijaya, O., & Said, H. (2024). The mediating role of sustainable supply chain management on entrepreneurship strategy, social capital and SMEs' financial and non-financial performance. Uncertain Supply Chain Management, 12(1), 557-566.

Wiredu, J., Yang, Q., Sampene, A. K., Gyamfi, B. A., & Asongu, S. A. (2023). The effect of green supply chain management practices on corporate environmental performance: Does supply chain competitive advantage matter?. Business Strategy and the Environment, 33(3), 2578-2599.

Xu, J., & Pero, M. E. P. (2023). A resource orchestration perspective of organizational big data analytics adoption: evidence from supply chain planning. International Journal of Physical Distribution & Logistics Management, 53(11), 71-97.

Xu, L., Wei, X., Cao, Y., Peng, X., & Prybutok, V. (2023). Achieving business excellence through sustainable supply chain management. Total Quality Management & Business Excellence, 34(13-14), 1830-1856.

Yadav, I. S., Pahi, D., & Gangakhedkar, R. (2021). The nexus between firm size, growth and profitability: new panel data evidence from Asia–Pacific markets. European Journal of Management and Business Economics, 31(1), 115-140.

Yamin, M. A. Y. (2024). The role of HR practices, big data analytics capabilities, and supply chain resilience in achieving firm disaster immunity: the moderating effect of a data-driven culture. Benchmarking: An International Journal.

Yan, X., Chen, X., Lu, C., Liu, W., Shi, X., & Gong, Y. (2024). Strategy for sustainable supply chain transformation: a resource orchestration perspective. Industrial Management & Data Systems, (ahead-of-print).

Yousefi, S., & Tosarkani, B. M. (2023). Exploring the role of blockchain technology in improving sustainable supply chain performance: a system-analysis-based approach. IEEE Transactions on Engineering Management, 71, 4389-4405.

Zhu, C., Du, J., Shahzad, F., & Wattoo, M. U. (2022). Environment sustainability is a corporate social responsibility: measuring the nexus between sustainable supply chain management, big data analytics capabilities, and organizational performance. Sustainability, 14(6), 3379.

Zi, W. (2023). The Impact of Green Supply Chain Management on Corporate Sustainable Performance: A Review of Research. Financial Engineering and Risk Management, 6(6), 23-27.

Zrigui, I., Khoulji, S., Kerkeb, M. L., Ennassiri, A., & Bourekkadi, S. (2023). Reducing Carbon Footprint with Real-Time Transport Planning and Big Data Analytics. In E3S Web of Conferences (Vol. 412, p. 01082). EDP Sciences.