THE ASIAN BULLETIN OF BIG DATA MANAGMENT
Vol. 5. Issue 4 (2025)
https://doi.org/10.62019/1y0ef318

ASIAN BULLETIN OF BIG DATA MANAGEMENT
ISSN (Print): 2959-0795
http://abbdm.com/
ISSN (online): 2959-0809

Role of Big Data Analytics Capabilities on Green Supply Chain Performance in Pakistan

Minhaj Ikram*, Ali Ismail

Chronicle

Article history
Received: July 29, 2025
Received in the revised format: Aug 22, 2025
Accepted: Sept 126, 2025
Available online: Oct 19, 2025

Minhaj Ikram is currently affiliated with the IU Business School (IUBS), Iqra University, Pakistan.
Email: minhajikram@gmail.com

Ali Ismail is currently affiliated with the Pakistan International Airline, Pakistan.
Email: engr.alihussain02@gmail.com

Corresponding Author*

Abstract

This research delves into the impact of Big Data Analytics Capabilities (BDAC) on the performance of green supply chains in Pakistan. The investigation relies on primary data obtained from the manufacturing sectors, utilizing a sample size of 129 for the final analysis. Structural equation modeling (SEM) through SmartPLS 4 was employed for data analysis. The findings reveal a statistically significant and positive correlation between BDAC and Green Innovation (GI), Green Supply Chain Integration (GSCI), and Green Supply Chain Performance (GSCP). Notably, the study underscores the more pronounced impact of BDAC on Green Innovation compared to its effects on Green Supply Chain Integration and Performance. Several limitations were encountered during the study, including reliance on a questionnaire for primary data collection, the utilization of cross-sectional data, and the focus on a singular context within one country. Despite these constraints, the results offer valuable insights for stakeholders and policymakers in Pakistan's manufacturing sector, supporting effective management of organizational competencies related to big data analytics to enhance both green innovation and green supply chain performance.

Keywords: Big Data Analytics Capabilities (BDAC); Green Innovation (GI); Green Supply Chain Integration (GSCI); Green Supply Chain Performance (GSCP) and Green Supply Chain (GSC).

INTRODUCTION

Over the past two decades, the global business landscape has undergone profound transformation. Rapid globalization, digitalization, and sustainability imperatives have compelled organizations to strategically utilize their resources to improve performance in increasingly volatile and dynamic markets (Cao & Zhang, 2011). Today's firms operate within environments characterized by high uncertainty, technological disruption, and environmental consciousness. As a result, the traditional focus on profitability and operational efficiency has evolved toward incorporating ecological and social sustainability. Increasing stakeholder pressure—emanating from governments, customers, competitors, and activist groups—has forced companies to adopt environmentally responsible practices and reconfigure their supply chain structures to meet sustainability demands (Chang, 2011; Yang & Lin, 2020). Consequently, environmental sustainability has emerged as a decisive factor influencing corporate competitiveness and long-term viability. This shift in corporate strategy has given rise to Green Supply Chain (GSC) practices and Green Innovation (GI), which emphasize balancing economic performance with ecological responsibility (Sun & Sun, 2021). Green Supply Chain Integration (GSCI) and GI have become essential mechanisms through which firms mitigate environmental impacts while maintaining operational efficiency and profitability. Supply chain sustainability has further demonstrated its potential to generate customer value by strengthening inter-firm linkages among suppliers, distributors, and consumers. These linkages facilitate resource sharing, enhance responsiveness, and promote financial benefits through coordinated sustainability initiatives (Aviles-Gonzalez et al., 2017). Moreover, such strategic alignment fosters the creation of novel competitive advantages by embedding environmental responsibility into the core business model (Jajja et al., 2018). Organizations increasingly recognize the green supply chain as a source of competitive advantage. Achieving this advantage requires strategic commitment, collaboration with supply chain partners, and continuous innovation. Research highlights that Big Data Analytics Capabilities (BDAC) have emerged as a critical enabler of these goals (Mani et al., 2017; Lamba et al., 2019; Al-Khatib et al., 2022). The ability to collect, process, and interpret large volumes of data empowers organizations to make informed decisions, optimize resource use, and identify areas for environmental improvement. BDAC thus represent a transformative tool for achieving both operational excellence and ecological sustainability.

However, the globalized supply chain landscape has also become increasingly complex. Factors such as shortened product lifecycles, heightened customer expectations, rapid technological changes, and dynamic market conditions have introduced significant challenges to maintaining supply chain efficiency (Fazlollahi & Franke, 2018). In this context, innovation and adaptability have become indispensable capabilities. Green Innovation (GI), defined as the development and implementation of environmentally friendly products, services, and processes, is now considered a strategic pathway to achieving sustainable competitiveness (Lisi et al., 2020). BDAC play a vital role in enabling GI by providing insights into supplier selection (Lamba et al., 2019), designing optimal sales networks (Al-Khatib & Ahmed, 2022), and enhancing innovation processes (Yildizbasi & Arioz, 2022; Bhatti et al., 2022; Centobelli et al., 2022). These capabilities allow firms to derive actionable intelligence, minimize waste, and create value-driven innovations that improve overall GSC effectiveness.

Despite these benefits, integrating GI within the structure of GSCs remains a complex endeavor. Managerial, organizational, and technical challenges often hinder the seamless implementation of green initiatives (Burki, 2018; Song et al., 2019). Achieving effective green innovation requires alignment across departments, technological readiness, and cultural adaptation—factors that are not always present in developing economies. Understanding the antecedents that foster GI and GSCI is therefore essential for both theoretical advancement and practical implementation.

GSC Integration (GSCI) has attracted considerable attention from scholars and practitioners as a key determinant of environmental collaboration and operational synergy (Lo et al., 2018; Benzidia et al., 2021; Kong et al., 2021; Xi et al., 2022). GSCI reflects the extent to which firms incorporate environmental objectives within their supply chain relationships, fostering alignment among partners to jointly address ecological challenges (Yang et al., 2020). Previous research has largely examined the organizational and inter-firm characteristics influencing GSCI (Afum et al., 2020; Cai et al., 2020; Wang et al., 2018; Wang & Feng, 2022). However, limited empirical studies have explored BDAC as a critical antecedent of GSCI (Benzidia et al., 2021; Shafique et al., 2018). Given that BDAC enhance visibility, coordination, and decision-making, it is plausible that they play an essential role in deepening GSCI and fostering overall supply chain sustainability (Brinch, 2018; Gang et al., 2016). Recent studies underscore BDAC as a foundation for intelligent decision-making and innovation in sustainable operations. By uncovering hidden patterns and trends, BDAC improve operational efficiency, reduce waste, and enhance environmental performance (Pawar & Paluri, 2022; Al-Khatib & Shuhaiber, 2022). These analytical capabilities facilitate real-time monitoring of emissions, resource utilization, and logistics, leading to smarter and greener supply chain practices (Sarkis et al., 2017; Zhang et al., 2018; Govindan et al., 2015). BDAC not only improve operational performance but also foster innovation, compliance with environmental regulations, and transitions toward circular economy models (Davenport & Harris, 2007; Chae & Olson, 2015; Peng et al., 2019; Preston et al., 2019; Zhou et al., 2019).

In the context of Pakistan, sustainability has gained increasing attention due to industrial growth, resource constraints, and rising environmental concerns. Manufacturers and corporations are increasingly acknowledging the importance of adopting green practices to reduce ecological footprints and ensure long-term viability (Awan et al., 2022). BDAC offer Pakistani firms an opportunity to harness data for improved decision-making, foster innovation, and strengthen environmental performance (Waqas & Tan, 2023). Despite this potential, challenges remain regarding data infrastructure, standardization, and analytics competencies. The integration of BDAC into GSC frameworks is often hindered by inadequate infrastructure, lack of standardized sustainability metrics, and limited human expertise (Iqbal et al., 2018; Ahmad et al., 2019; Mishra et al., 2018; Gligor et al., 2019).

Scholars have identified several gaps in the literature that warrant deeper exploration. These include the absence of comprehensive predictive models to assess environmental impacts (Ivanov, 2018), limited cost-benefit analyses of BDAC for sustainable operations (Kusi-Sarpong et al., 2016), and insufficient research on real-time decision support systems (Ivanov, 2020). Additionally, there is a need to examine BDAC's role in enhancing supply chain resilience amid environmental disruptions (Ivanov & Dolgui, 2020) and ensuring compliance with evolving regulatory standards (Gungor & Gupta, 2019). While technologies such as IoT and blockchain offer new opportunities for integration with BDAC, research on their combined implications for GSC performance remains scarce (Min et al., 2020; Chae & Olson, 2017). Issues of data quality, reliability, and visibility within green supply chains also remain unresolved (Kannan et al., 2016; Jayaraman & Luo, 2019; Govindan et al., 2020). Furthermore, the adoption of BDAC among small and medium enterprises (SMEs) presents unique challenges due to limited financial and technical resources (Dubey et al., 2019).

In light of these limitations, there exists a pressing need to examine how BDAC influence GI, GSCI, and overall GSC performance, particularly in developing economies like Pakistan. The current body of research provides insufficient insight into the interconnections among these variables and their combined implications for sustainability. This study addresses this critical gap by investigating the impact of BDAC on GI and GSCI, and their subsequent effects on GSC performance.

Grounded in the Resource-Based View (RBV) and Dynamic Capability Theory (DCT), this research posits that BDAC act as valuable, rare, and inimitable resources that enhance organizational adaptability and innovation (Barney, 1991; Teece, 2007). These capabilities enable firms to integrate sustainability within strategic decision-making, thereby fostering long-term competitive advantage. The study aims to contribute theoretically by expanding understanding of BDAC's role in sustainable supply chain management, and practically by providing empirical evidence to guide managers and policymakers in Pakistan. The findings are expected to offer insights into how firms can strategically invest in data analytics to drive green innovation, strengthen supply chain integration, and improve environmental performance. By bridging the existing knowledge gap, this research aspires to support both academic scholarship and industrial transformation toward sustainable business practices. For policymakers and practitioners in Pakistan, the study provides actionable directions for leveraging BDAC to achieve environmental stewardship, enhance competitiveness, and contribute to sustainable economic growth (Awan et al., 2022).

LITERATURE REVIEW

Theoretical Background

The Resource-Based Theory (RBT) and the Dynamic Capability Theory (DCT) together provide the theoretical foundation for this study. According to RBT, a firm's ability to achieve superior performance depends on how effectively it acquires, develops, and utilizes valuable, rare, inimitable, and non-substitutable (VRIN) resources (Barney, 1991). The theory emphasizes that organizations possess heterogeneous resources—tangible and intangible—that determine their competitiveness and long-term sustainability. In the context of Industry 4.0, firms combine organizational, human, and technological competencies to enhance productivity, reduce costs, and drive innovation (Al-Khatib, 2022a, b). These competencies illustrate RBT's central premise that effective resource orchestration enables firms to transform capabilities into strategic advantages.

RBT highlights the importance of identifying and leveraging core competencies that provide a unique edge (Lee et al., 2017; Al-Rakhami et al., 2021). Resources can be categorized as tangible assets (e.g., data systems, infrastructure, and analytical technologies), intangible assets (e.g., organizational learning and data-driven culture), human skills (technical and managerial), and organizational capabilities (e.g., innovation and supply chain management). When integrated effectively, these resources foster sustainable competitive advantage by enabling innovation and operational excellence (Amaya et al., 2022). However, RBT's limitation lies in its relatively static view of resources, as it does not fully address how firms adapt and reconfigure them in dynamic environments.

The Dynamic Capability Theory (DCT) extends RBT by emphasizing a firm's ability to integrate, build, and reconfigure competencies to address rapidly changing environments (Teece et al., 1997; Eisenhardt & Martin, 2000). It focuses on sensing opportunities, seizing them through innovation, and transforming existing resources to maintain competitiveness. DCT is particularly relevant in contexts characterized by technological disruption, globalization, and environmental uncertainty, where adaptability becomes a critical success factor (Shan et al., 2019). Firms with strong dynamic capabilities can better identify emerging risks and opportunities, innovate proactively, and sustain performance advantages (Ambrosini & Bowman, 2009; Helfat & Peteraf, 2009; Zhou et al., 2016).

Innovation and learning form the core of dynamic capabilities. Organizations that continuously acquire and apply new knowledge are better positioned to refine processes, develop new products, and respond to environmental challenges (Babu et al., 2021). DCT also provides strategic guidance for resource allocation, ensuring investments are directed toward activities that align with changing market and sustainability demands. In contrast to RBT's focus on resource possession, DCT emphasizes renewal and transformation—making it essential for firms operating in fast-changing and sustainability-driven industries.

Together, RBT and DCT offer a comprehensive framework for understanding how Big Data Analytics Capabilities (BDAC) can drive Green Innovation (GI), Green Supply Chain Integration (GSCI), and performance. RBT explains how BDAC act as strategic resources, while DCT elucidates how firms can dynamically leverage and reconfigure these capabilities to foster innovation, adaptability, and sustainable competitive advantage.

HYPOTHESIS DEVELOPMENT

Big Data Analytics Capabilities Positively Affect Green Innovation

Green Innovation (GI) includes all environmentally oriented advancements in products, services, or processes that mitigate ecological harm and optimize resource use (Elias, 2020). Rooted in the Natural Resource-Based View (NRBV), GI enhances strategic competence and fosters sustainable value creation (Hart, 1995; Hart & Dowell, 2011; Arranz et al., 2020). Recent studies affirm that Big Data Analytics Capabilities (BDAC) enhance GI by providing real-time insights, enabling data-driven innovation, and supporting ecological initiatives (Mani et al., 2017; Imran et al., 2021; Waqas et al., 2021; Dong et al., 2022; Mavi & Mavi, 2021). BDAC empower firms to identify patterns, improve forecasting, and translate environmental data into actionable innovation strategies (Bag et al., 2020; Arici et al., 2022).
H1: Big Data Analytics Capabilities positively affect Green Innovation.

Big Data Analytics Capabilities Positively Relate to Green Supply Chain Integration

BDAC facilitate environmentally sustainable operations by enabling data-driven integration across the supply chain (Benzidia et al., 2021; Song et al., 2017). Grounded in the Overarching Integrated Process Team (OIPT) framework, BDAC enhance green supplier, internal, and customer integration by improving data quality, communication, and responsiveness (Ashaari et al., 2021; Chen et al., 2015; Galbraith, 1974; Bahrami & Shokouhyar, 2021; Brinch, 2018). Prior studies highlight BDAC's role in reducing uncertainty and strengthening collaboration (Cai et al., 2020; Razaghi & Shokouhyar, 2021; Wong et al., 2020; Wu, 2013; Baah et al., 2021; Kong et al., 2021; Yang et al., 2021).
H2: Big Data Analytics Capabilities positively relate to Green Supply Chain Integration.

Big Data Analytics Capabilities Positively Affect Green Supply Chain Performance

Green Supply Chain (GSC) performance integrates economic, environmental, and operational efficiency (Peng et al., 2020). BDAC enhance GSC performance by improving forecasting, optimizing logistics, and minimizing ecological impact (Wamba et al., 2017; Dubey et al., 2020; Sharma et al., 2022). By leveraging technological, human, and organizational resources, BDAC refine decision-making and strengthen collaboration (Gunasekaran et al., 2017; Lee & Mangalaraj, 2022; Nguyen et al., 2018). They also reduce material waste, improve supply-demand alignment, and predict environmental risks (Lee, 2017; Seyedan & Mafakheri, 2020; Wang et al., 2016; Papadopoulos et al., 2017; Belhadi et al., 2021).
H3: Big Data Analytics Capabilities positively affect Green Supply Chain Performance.

Green Innovation Positively Affects Green Supply Chain Performance

Green Innovation (GI) enhances sustainable supply chain practices by improving production, purchasing, and distribution efficiency (Junaid et al., 2022). Studies show

GI strengthens GSC performance through eco-innovation, R&D, and collaboration (Bag et al., 2022; Fernando et al., 2019; Rodríguez-González et al., 2022). GI enables knowledge sharing, trust, and learning among supply chain partners, reducing waste and enhancing adaptability (Lisi et al., 2020; Kong et al., 2020; Seman et al., 2012). Consistent with NRBV, GI drives superior outcomes and long-term competitiveness (Wong et al., 2020; Wu, 2013).

H4: Green Innovation positively affects Green Supply Chain Performance.

Green Supply Chain Integration Positively Relates to Green Innovation

Knowledge sharing and collaboration with suppliers and customers accelerate Green Innovation (Wong et al., 2011; Zhao et al., 2018). Green Supply Chain Integration (GSCI) improves knowledge flow, resolves conflicts, and supports eco-friendly design (Koufteros et al., 2005; Lau et al., 2010; Wong et al., 2020; Song et al., 2018). Supplier collaboration fosters environmental learning, data processing, and co-creation, driving Green Product Development Innovation (Qu & Liu, 2022; Pham & Pham, 2021; Freije et al., 2021; Junaid et al., 2022).

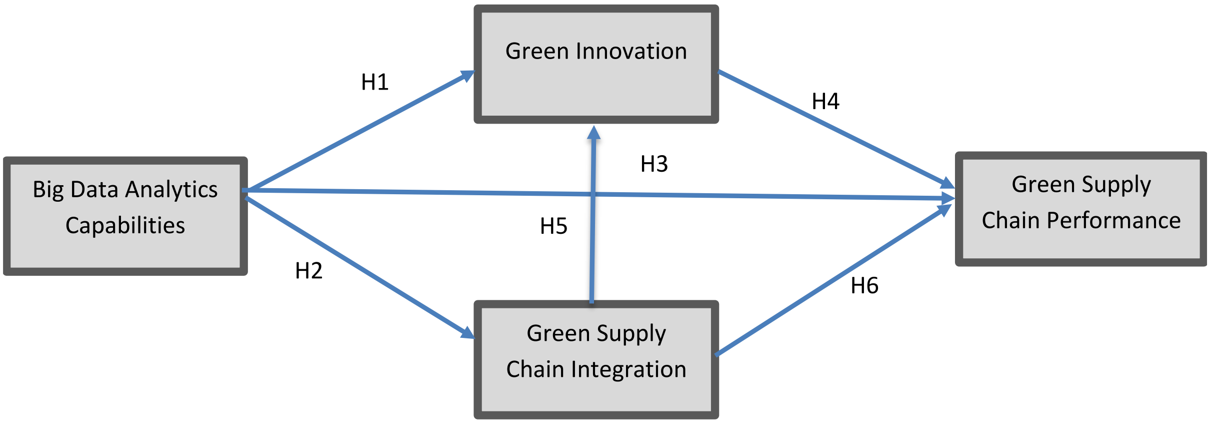
H5: Green Supply Chain Integration positively relates to Green Innovation.

Green Supply Chain Integration Positively Relates to Green Supply Chain Performance

Grounded in the relational view, Supply Chain Integration (SCI) enhances collaboration and competitive advantage (Jajja et al., 2018). Internal, supplier, and customer integration improve coordination, forecasting, and product quality (Flynn et al., 2010; Qi et al., 2017; Huo et al., 2016; Ni & Sun, 2019; Wang & Zhang, 2019). Supplier integration strengthens productivity, reduces costs, and supports innovation (Khanuja & Jain, 2019; Shou et al., 2018; Kim & Chai, 2016; Seo et al., 2014). Collectively, these integrations improve GSC efficiency and responsiveness.

H6: Green Supply Chain Integration positively relates to Green Supply Chain Performance

CONCEPTUAL FRAMEWORK



RESEARCH METHODOLOGY

This study adopts a quantitative approach aligned with prior comparative research to examine relationships among Big Data Analytics Capabilities (BDAC), Green Innovation (GI), Green Supply Chain (GSC) Integration, and GSC Performance. Statistical and mathematical analyses, including regression and measures of central tendency, were used to validate relationships and ensure reliability (Creswell & Creswell, 2018; Hair et al., 2021). An explanatory research design was employed to identify causal connections between BDAC, GI, GSC Integration, and GSC Performance. Grounded in the Resource-Based View (RBV) and Dynamic Capability Theory (DCT), the study investigates how data-driven capabilities foster innovation and sustainability performance (Barney, 1991; Teece, 2007).

Primary data were collected through self-administered online questionnaires, while secondary data were sourced from published studies and reports (Saunders et al., 2019). The survey consisted of two sections: demographic information and construct-related items measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The target population included industrial professionals utilizing BDAC in manufacturing firms across Pakistan. A total of 129 valid responses were obtained from participants of varied managerial levels, firm sizes (SECP, 2022), educational backgrounds, and experience. SPSS (version 22) confirmed the adequacy of this sample size for hypothesis testing (Hair et al., 2021).

A purposive sampling method was adopted for its cost-effectiveness and accessibility (Etikan et al., 2016). Questionnaire items were adapted from validated literature to ensure construct reliability (Podsakoff et al., 2003).

Data analysis was conducted using SPSS and SmartPLS. SPSS was used for descriptive and demographic analysis, while SmartPLS facilitated validity, reliability, and structural assessments through Partial Least Squares Structural Equation Modeling (PLS-SEM). This integrated approach ensures methodological rigor and empirical precision in evaluating how BDAC influences green innovation and supply chain performance.

DATA ANALYSIS

Initially, researchers conducted data screening to ensure accuracy and reliability before analysis. The process involved cleaning and validating the dataset using SPSS. Out-of-range values were checked and corrected, with none found beyond acceptable limits. Since the data were collected through an online survey that required all fields to be completed before submission, missing values were minimal. Researchers then examined univariate and multivariate outliers using Z-scores (±3.29) and Mahalanobis distance with chi-square criteria (Tabachnick & Fidell, 2007). Six univariate and three multivariate outliers were identified and removed, resulting in a clean and reliable dataset for further analysis.

DEMOGRAPHIC ANALYSIS

Table 1.
Demographic Analysis

Demographics Items	Frequency	Percentage
Education		
Undergraduate	33	**25.6%**
Graduate	30	**23.3%**
Masters	58	**45.0%**
Others	8	**6.2%**
Management Levels		
First-Line Supervisor	14	**10.9%**
Middle Management	79	**61.2%**

Top Level Management	36	**27.9%**
Experience		
Less than 5 years	44	**34.1%**
Between 5 – 10 years	53	**41.1%**
More than 10 years	32	**24.8%**
Industry Type		
Textile	20	**16.8%**
Energy & Power	12	**10.1%**
Petroleum / Chemical	11	**9.2%**
Steel Making	7	**5.9%**
Pharmaceutical	18	**15.1%**
Automotive	13	**10.9%**
Food and/ or Beverages	4	**3.4%**
Electronics Manufacturing	7	**5.9%**
Beauty & Well Being	5	**4.2%**
Home Care / Personal Care	8	**6.7%**
Others	24	**18.6%**
Firm Size (As per SECP 2022)		
Small (Turnover not exceeding Rs.150 million)	27	**20.9%**
Medium (Turnover greater than Rs.150 million but not exceeding Rs.800 million)	68	**52.7%**
Large (Turnover above Rs.800 million)	34	**26.4%**

The table summarizes key quantitative attributes of the study's variables: Education, Management Level, Experience, Industry Type, and Firm Size. A total of 129 valid responses were collected, slightly below the recommended sample size of 137 (Daniel Sooper's calculator). Most respondents held a Master's degree (45%), followed by undergraduate (23.3%) and graduate degrees (25.6%), while 6.2% had other qualifications. Regarding experience, 41.1% had 5–10 years, 34.1% had less than 5 years, and 24.8% had over 10 years. Industry-wise, textiles (20.9%), pharmaceuticals (15.1%), and energy & power (10.1%) were the top sectors. Most respondents (62.7%) represented medium-sized firms, followed by large (26.4%) and small (20.9%) firms.

DATA ANALYSIS

Data analysis was performed using responses from 129 fully completed online questionnaires, with no missing or excluded data, ensuring a complete and reliable dataset. Exploratory analysis was conducted using SmartPLS 3.0, based on a research model comprising four constructs and 27 items. Data reliability was tested through Cronbach's Alpha, with acceptable values ranging between 0.6 and 0.9, confirming internal consistency. Discriminant validity was then assessed to ensure that the constructs measured were conceptually distinct, following the framework introduced by Campbell (1959). This evaluation involved three key methods: Cross Loadings, Fornell–Larcker Criterion, and Heterotrait–Monotrait (HTMT) Ratio.

Construct Validity

Table 2.
Result of reliability analysis

Variables	Items	Cronbach's Alpha	Composite Reliability (Rho_c)	Average Variance Extracted
Big Data Analytics Capabilities (BDAC)	6	0.820	0.881	**0.649**
Green Innovation (GI)	5	0.870	0.907	**0.661**
Green Supply Chain Integration (GSCI)	11	0.916	0.931	**0.629**
Green Supply Chain Performance (GSCP)	5	0.878	0.911	**0.673**

The reliability test aims to assess the internal consistency of the research data. To determine reliability, we employed Cronbach's alpha as a measure of data reliability. Reliability analysis is commonly used to rigorously evaluate data consistency and the test's capability to measure consistently. In this study, we utilized Cronbach's alpha extensively to assess the reliability of the research variables.

Hence, Cronbach's alpha serves as a vital indicator of reliability, and the assessment of its value is of paramount significance (Tavakol and Dennick, 2011). Cronbach's alpha ranges between 0 and 1, and there is no strict lower threshold for the coefficient. The closest value to 1.0 indicates the highest level of reliability, while values below 0.5 are considered unacceptable (Gliem and Gliem, 2003). In our research study, the Cronbach's alpha values range from 0.779 to 0.897, all of which meet the established reliability criteria, allowing the data to be utilized for further analyses.

Outer Loading

Convergent validity, within the context of factor analysis, pertains to the statistical validity of the relationship or coherence among items, indicating the extent to which they collectively represent the underlying construct. Convergent validity is typically assessed through the average variance extracted (AVE), as advocated by Fornell and Larcker in 1981. According to established criteria, the AVE should surpass 0.5, and the composite reliability should exceed 0.7 (Hamid, Sami, and Sidek, 2017). The outcomes of the convergent validity analysis are presented below :

Table 3.
Outer loading

	BDAC	GI	GSCI	GSCP
BDAC3	0.795			
BDAC4	0.827			
BDAC5	0.840			
BDAC6	0.758			
GI1		0.782		
GI2		0.841		
GI3		0.858		
GI4		0.873		
GI5		0.700		
GSCI10			0.783	
GSCI11			0.761	
GSCI4			0.799	
GSCI5			0.774	
GSCI6			0.831	
GSCI7			0.802	
GSCI8			0.800	
GSCI9			0.792	
GSCP1				0.755
GSCP2				0.820
GSCP3				0.848
GSCP4				0.856
GSCP5				0.819

Discriminant Validity

Discriminant validity is the process by which the items or variables are assessed based on their ability to differentiate one construct from another, especially when those constructs are closely related within the research model (Michalos, 2014). Discriminant validity comprises three components, with the first part being referred to as cross-loading, the second part as Fornell-Larcker, and the final part involving the Heterotrait and Monotrait (HTMT) ratio. In our research study, we exclusively applied the last two components.

Discriminant Validity Using Fornell-Larcker:

In the Fornell-Larcker table, the diagonal values should be greater than the corresponding values in their respective columns, and the main diagonal values should be greater than 0.7. In the presented table, the first stage of discriminant validity has been successfully achieved, as evident from the provided values.

Table 4.
Discriminant Validity (Fornell-Larcker Criterion)

	BDAC	GI	GSCI	GSCP
BDAC	**0.806**			
GI	0.636	**0.813**		
GSCI	0.406	0.444	**0.793**	
GSCP	0.584	0.685	0.508	**0.820**

HeterotraitMonotrait (HTMT) Ratio:

Previous studies have demonstrated discriminant validity with Heterotrait-Monotrait (HTMT) ratios of 0.85 and 0.90 in their models. However, standards have been adjusted, and the threshold is now set at or below 0.85. To measure discriminant validity, the Heterotrait-Monotrait (HTMT) method, a factor correlation technique (Henseler, Hubona, & Ray, 2016), is used, and it should be significantly less than 1. In our research, the discriminant validity meets the HTMT criteria. The outcomes of discriminant validity are mentioned below.

Table 5.
HeterotraitMonotrait (HTMT) Ratio

	BDAC	GI	GSCI	GSCP
BDAC				
GI	0.750			
GSCI	0.455	0.493		
GSCP	0.681	0.781	0.554	

R Square and Q Square

After model validation, predictive relevance was assessed using R^2 and Q^2 values as suggested by Henseler et al. (2009). Using the blindfolding procedure in SmartPLS, Q^2 values above 0.00 confirmed model predictability. The results showed R^2 values of 0.446 for Green Innovation (GI), 0.165 for Green Supply Chain (GSC) Integration, and 0.545 for GSC Performance (GSCP). Corresponding Q^2 values were 0.385, 0.129, and 0.325, respectively, indicating that all dependent constructs demonstrate satisfactory predictive relevance.

Table 6.
Predictive Relevance of the Model

Dependent Variables	R-Square	Q-Square
Green Innovation (GI)	0.446	0.385
Green Supply Chain Integration (GSCI)	0.165	0.129
Green Supply Chain Performance (GSCP)	0.545	0.325

Hypotheses testing using SEM

Hypotheses were tested using SEM with the bootstrapping method of 5,000 samples (Hair Jr et al., 2016). BDAC was the exogenous variable, while GI, GSC Integration, and GSC Performance were endogenous variables. Relationships were assessed through path coefficients (β), p-values, and t-statistics, with significance at $p \leq 0.05$ and $t \geq 2$ (Ifinedo, 2011; Eckblad, 1991). As shown in Table 4.7, all hypothesized relationships were significant, supporting the proposed model.

Table 7.
Path coefficients

Number	Hypothesis	Estimation β	T Statistics	P Values	Decision
H1	BDAC → GI	0.546	7.248	0.000	Accepted
H2	BDAC → GSCI	0.406	3.957	0.000	Accepted
H3	BDAC → GSCP	0.203	2.212	0.027	Accepted
H4	GI → GSCP	0.457	4.985	0.000	Accepted
H5	GSCI → GI	0.222	2.323	0.020	Accepted
H6	GSCI → GSCP	0.222	2.557	0.011	Accepted

A path coefficient (β) indicates the strength and direction of the relationship among variables. A positive β signifies a direct relationship, whereas a negative β denotes an inverse association. The findings reveal that Big Data Analytics Capabilities (BDAC) exert a significant positive influence on Green Innovation (GI) ($\beta = 0.546$, $t = 7.248$, $p = 0.000$), supporting H1. This implies that a one-unit increase in BDAC enhances GI by 0.546 units, underscoring the critical role of data-driven decision-making in promoting green innovation within Pakistan's industrial sector. Similarly, BDAC positively impacts Green Supply Chain Integration (GSCI) ($\beta = 0.406$, $t = 3.957$, $p = 0.000$), supporting H2. This relationship highlights BDAC's role in fostering coordination and collaboration among stakeholders to strengthen GSC integration.

For H3, BDAC also shows a positive and significant effect on Green Supply Chain Performance (GSCP) ($\beta = 0.203$, $t = 2.212$, $p = 0.027$), suggesting that data analytics capabilities contribute to improving organizational and supply chain performance. Green Innovation (GI) likewise demonstrates a strong positive effect on GSCP ($\beta = 0.457$, $t = 4.985$, $p = 0.000$), supporting H4 and indicating that innovative environmental practices enhance efficiency, profitability, and competitive advantage across supply chains. Moreover, GSCI significantly influences GI ($\beta = 0.222$, $t = 2.323$, $p = 0.020$), supporting H5 and emphasizing that effective integration with suppliers and customers facilitates innovation by reducing process uncertainty. Finally, GSCI has a significant positive impact on GSCP ($\beta = 0.222$, $t = 2.557$, $p = 0.011$), supporting H6, and demonstrating that integration across the supply chain enhances sustainability performance and operational outcomes in the Pakistani manufacturing context.

In terms of analytical procedures, SmartPLS and SPSS were employed for hypothesis testing and data validation. Tests such as bootstrapping, blindfolding, and the PLS algorithm confirmed model reliability and validity. The Fornell–Larcker criterion verified discriminant validity, and all constructs met established benchmarks. Since the questionnaire was based on previously validated instruments, a pilot study was deemed unnecessary. The instrument was reviewed by both academic and industry experts before final deployment. With 129 valid responses, the data provided strong empirical support for the proposed model, confirming the significant role of Big Data Analytics Capabilities in advancing Green Innovation, Supply Chain Integration, and Sustainable Performance in Pakistan's industrial sector.

CONCLUSION AND RECOMMENDATIONS

Research Contributions

This research made a contribution to the effects of GI, GSC Integration and GSC performance. Results shows that BDAC has significance and positive impact on GI, GSC Integration and GSC Performance in Pakistan. GI and GSC Integration also have significance and positive impact on GSC Performance in Pakistan. GSC integration also has significance and positive impact of GI which means there is a strong relationship exist between the GI and GSC integration. As the level of BDAC increases, the application of green innovation is correspondingly enhanced, leading to improved SC performance and overall sustainability performance

RECOMMENDATIONS

It is recommended based on research's findings that BDACs have significant effect on GI, GSC integration and GSC performance. Conduct further empirical research to investigate the specific mechanisms through which BDACs influence GI, GSC integration, and GSC performance. This could include case studies, longitudinal studies, and cross-national comparisons. Investigate the impact of BDACs on various aspects of sustainable performance, such as resource efficiency, environmental impact, and social responsibility. Examine the potential of BDACs to support the development of circular economy models in manufacturing sectors. Identify key performance indicators (KPIs) for measuring the success of BDAC implementation in manufacturing firms. Conduct research to identify the factors that influence the adoption of BDACs by different types of manufacturing firms, such as size, industry, and location. Investigate the potential of emerging technologies, such as artificial intelligence (AI) and the Internet of Things (IoT), to enhance the capabilities of BDACs. Conduct research to identify the impact of BDACs on job creation and economic growth in manufacturing sectors. Considering the dynamic nature of technology, the thesis recommends ongoing investments in research and development to stay abreast of emerging trends and advancements in big data analytics technologies applicable to green supply chain practices. In line with the global nature of supply chains, further research is recommended to explore the applicability of the study's findings in diverse international contexts, contributing to the generalizability and transferability of knowledge beyond the confines of Pakistan's manufacturing sector.

RESEARCH LIMITATION

The research's findings were based on Pakistan only so the information collection was limited to Pakistani sectors. The findings cannot be applied outside of Pakistan.

The research's findings were limited to the variable i.e., Big Data Analytics Capabilities (BDAC). Various contingent factors might be present that can influence these effects, including firms learning capabilities, firms' flexibility, external pressures, and firms' ambidexterity. Investigating the possible roles of these moderators in the relationship between BDAC and supply chain visibility (SCV) could be a worthwhile avenue of exploration.

FUTURE RECOMMENDATION

The research's findings might be helpful in Green Supply Chain Performance (GSCP) in future research. Research limitation was mentioned in section 5.3 can be explored in upcoming study. This research work proposes that future studies consider the examination of additional constructs, such as risk management within green SC, the cultivation of green firms culture, and the dissemination of green knowledge etc. Further factors that impact on can be studied later. Increase sample size and different respondent to assess model hypothesis in forthcoming research. Qualitative study can be used to perform research. Others model can be used to conduct research in future.

DECLARATIONS

Acknowledgement: We appreciate the generous support from all the contributor to the research and their different affiliations.
Funding: No funding body in the public, private, or nonprofit sectors provided a particular grant for this research.
Availability of data and material: In the approach, the data sources for the variables are stated.
Authors' contributions: Each author participated equally in the creation of this work.
Conflicts of Interest: The authors declare no conflict of interest.

Consent to Participate: Yes

Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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