

IMPACT OF BIG DATA ANALYTICS CAPABILITIES ON SUSTAINABLE SUPPLY CHAIN PERFORMANCE: THE MEDIATING ROLE OF SUPPLY CHAIN AGILITY

KAMAL NAIF ABDULLAH TAMIM

School of Technology Management and Logistics, College of Business, Universiti Utara Malaysia.
Email: kamal_naif_a@cob.uum.edu.my, ORCID: 0009-0000-5252-6336

Dr. KAMARUDDIN BIN RADZUAN

School of Technology Management and Logistics, College of Business, Universiti Utara Malaysia.
Email: kamaruddin@uum.edu.my, ORCID: 0000-0002-3655-2523

Dr. FAISAL ZULHUMADI

School of Technology Management and Logistics, College of Business, Universiti Utara Malaysia.
Email: faisal@uum.edu.my, ORCID: 0000-0002-2545-7002

Abstract

This study investigates the role of big data analytics capabilities (BDAC) in enhancing sustainable supply chain performance (SSCP), with supply chain agility (SCA) as a mediating mechanism. We consider BDAC as a higher-order construct that includes management, personnel and infrastructure capabilities, drawing on the Resource-Based View (RBV) and Dynamic Capabilities theory. Using survey data from 155 supply chain professionals across manufacturing, retail, logistics, and services, structural equation modeling (PLS-SEM) was applied to test hypotheses. Results show that BDAC and its dimensions significantly enhance SSCP and SCA, with SCA partially mediating these relationships. The model demonstrates strong explanatory ($R^2 = 0.62$) and predictive power ($Q^2 = 0.50$). This study contributes theoretically by integrating BDAC, agility, and sustainability into a unified framework, and practically by offering firms guidance on leveraging analytics for sustainable supply chain outcomes.

Keywords: Big Data Analytics Capabilities, Supply Chain Agility, Sustainable Supply Chain Performance, RBV, Dynamic Capabilities.

1. INTRODUCTION

The increasing volatility of global markets, rapid technological advancements, and growing sustainability pressures have transformed supply chain management into a strategic priority for firms seeking long-term competitiveness. In particular, the surge of digital technologies has brought Big Data Analytics Capabilities (BDAC) to the forefront, offering unprecedented opportunities for firms to enhance decision-making, responsiveness, and sustainability (Wamba et al., 2020; Gupta & George, 2016). Yet, despite growing investments in big data, firms often struggle to translate analytics into tangible performance gains, raising critical questions about the mechanisms through which BDAC create value in supply chains.

Digital transformation and sustainability are reshaping supply chains worldwide. Firms are increasingly pressured to achieve environmental, social, and economic performance while maintaining responsiveness to volatile market demands (Dubey et al., 2019;

Wamba et al., 2020). Big Data Analytics Capabilities (BDAC) have emerged as a critical enabler, offering insights for real-time decision-making and resource optimization. However, there are still issues with the procedures that connect analytics to results and how BDAC translates into sustainable supply chain performance (SSCP).

Existing research has acknowledged the potential of BDAC in improving operational efficiency and competitive advantage (Akter et al., 2016; Fosso Wamba et al., 2017 and Iqbal & Fikri, 2023). However, several limitations remain. First, most studies conceptualize BDAC as a monolithic construct, overlooking its multidimensional nature encompassing infrastructure, management, and personnel capabilities. Such aggregation risks obscuring the specific contributions of each dimension. Second, while BDAC are frequently associated with improved supply chain outcomes, little is known about the intermediate mechanisms that explain how these capabilities are converted into sustainability-oriented performance. Finally, although agility has been suggested as a critical outcome of big data adoption (Dubey et al., 2019), its role as a mediator in linking BDAC to sustainable supply chain performance (SSCP) remains underexplored. These gaps highlight the need for a more nuanced theoretical and empirical understanding of BDAC's role in modern supply chains.

Drawing on the Resource-Based View (RBV) and Dynamic Capabilities perspectives, this study argues that BDAC represent higher-order capabilities that not only provide firms with technological resources but also enable them to sense, seize, and reconfigure supply chain processes in ways that foster both agility and sustainability. Specifically, the study examines BDAC as a multidimensional construct comprising infrastructure, management, and personnel capabilities and investigates their direct and indirect effects on SSCP, with supply chain agility (SCA) as a mediating mechanism. By doing so, the research addresses the critical question: *How and through what mechanisms do BDAC contribute to sustainable supply chain performance?*

There are three main contributions made by this work. First, it enriches RBV and Dynamic Capabilities literature by disaggregating BDAC and clarifying their individual and synergistic roles in driving supply chain outcomes (Iqbal & Fikri, 2025). Second, it advances theoretical understanding by empirically validating SCA as a mediating pathway, demonstrating how BDAC translate into sustainability-oriented outcomes. Third, it contributes methodologically by offering robust evidence of explanatory and predictive power, strengthening confidence in the generalizability of BDAC-based models. Collectively, these contributions provide both theoretical insights and practical guidance for firms seeking to leverage big data for sustainable and agile supply chains (Gupta & George, 2016).

Global supply chains are undergoing profound transformation driven by technological innovation, digital disruption, and mounting sustainability pressures. The increasing volatility of global markets, rapid changes in consumer preferences, and the need to meet environmental and social sustainability goals have made agility and resilience indispensable (Christopher, 2016; Ivanov & Dolgui, 2021; Iqbal et al., 2025). Against this backdrop, Big Data Analytics Capabilities (BDAC) have emerged as a potential enabler

of superior decision-making, agility, and sustainable performance. By allowing firms to collect, process, and analyze vast amounts of structured and unstructured data, BDAC promise to reshape supply chains into more adaptive and sustainability-oriented systems (Wamba et al., 2020; Gupta & George, 2016). Yet, while firms have invested heavily in analytics, translating these investments into tangible supply chain outcomes remains a persistent challenge.

1.1 Existing Research and Its Limitations

A growing body of research highlights the role of big data analytics in supply chain management (Akter et al., 2016; Dubey et al., 2019; Fosso Wamba et al., 2017). Studies show that analytics adoption can improve decision quality, enhance visibility, and strengthen competitiveness. However, three important limitations remain.

First, prior research often treats BDAC as a monolithic construct, failing to capture its multidimensionality. In reality, BDAC encompass at least three interrelated dimensions: infrastructure capabilities (technological foundations such as storage, processing, and platforms), management capabilities (strategic commitment, governance, and alignment), and personnel capabilities (skills, expertise, and analytical talent) (Gupta & George, 2016). Aggregating these dimensions risks oversimplification and obscures their unique and combined contributions to supply chain performance.

Second, while BDAC are commonly associated with performance improvements, the mechanisms through which they generate value remain underexplored. Studies typically establish correlations between BDAC and outcomes such as efficiency, responsiveness, or resilience, but they rarely investigate the dynamic capabilities that bridge BDAC with performance. This creates a “black box” problem: we know BDAC matter, but less is known about how they matter.

Third, despite the fact that agility has been emphasized as a consequence of big data adoption (Dubey et al., 2019), its function as a mediation factor in the link between BDAC sustainability has not been properly examined. This is remarkable because agility the capacity of a corporation to perceive, react, and swiftly adapt to changing environments is widely acknowledged as a dynamic quality that promotes results that are focused on sustainability (Teece, 2007; Swafford et al., 2006). Closing this gap is essential to comprehending how businesses convert data-driven assets into long-term competitive advantage.

1.2 Theoretical Framing

Using the Resource-Based View (RBV) philosophy, this study sees BDAC as the function of dynamic capabilities in managing sustainable supply chains. RBV assumes that competitive advantage is built on resources that are valuable, rare, unique, or non-substitutable (VRIN) (Barney, 1991). The potential BDAC resources encompass organizational, human, and technology aspects.

The Dynamic Capacities approach, which is based on the Resource-Based View, expands on this idea by highlighting how companies may integrate, develop, and

restructure their internal and external capabilities in quickly changing contexts (Teece, Pisano, & Shuen, 1997; Teece, 2007). According to this paradigm, BDAC is a precursor to dynamic capabilities that enable businesses to sense, seize, and reorganize their supply chain operations. Consequently, supply chain agility (SCA) is a lower-order dynamic capacity that will transform these data-driven resources into sustainability and operational flexibility. Consequently, it is believed that BDAC influences sustainable supply chain performance (SSCP) through agility as a mediating mechanism.

BDAC are viewed as uncommon, precious, and unique resources, building on the Resource-Based View (RBV) (Gupta & George, 2016). Their effects, however, are not likely to be uniform or straightforward; instead, they call for supplementary organizational processes. We contend that supply chain agility (SCA) is a crucial mechanism that helps businesses transform BDAC into sustainable results, based on the Dynamic Capabilities theory (Teece, 2007).

1.3 Research Questions and Objectives

This study addresses three research questions:

1. Do BDAC enhance sustainable supply chain performance?
2. How do BDAC dimensions (infrastructure, management, personnel) individually influence SSCP and SCA?
3. Does supply chain agility mediate the BDAC–SSCP relationship?

This study addresses the following overarching research objectives:

1. To answer this question, the study pursues three specific objectives:
2. To disaggregate BDAC into infrastructure, management, and personnel capabilities and examine their unique and combined effects on SSCP.
3. To examine at how supply chain agility mediates the relationship between BDAC and SSCP.
4. To evaluate the suggested model's predictive and explanatory capabilities in order to confirm its theoretical and practical applicability.

Using data from 155 supply chain professionals across four industries, this study contributes by (1) validating BDAC as a higher-order construct with multidimensional effects, (2) identifying agility as a mediating pathway, and (3) providing a robust empirical framework integrating analytics, agility, and sustainability.

1.4 Contributions

This study contributes to the scope of literature in a several of ways. First, it extends RBV and Dynamic Capabilities theory by conceptualizing BDAC as a multidimensional capability system and empirically validating their role in driving sustainability outcomes. Second, it contributes to supply chain research by demonstrating that agility functions as a critical mediating pathway, explaining how BDAC translate into sustainable

performance. Third, the study provides methodological rigor by validating both reliability and predictive accuracy, thereby strengthening the robustness of BDAC-based models. Finally, it delivers practical insights for managers by highlighting the importance of balancing technology investments with managerial commitment and human expertise.

By addressing these gaps and contributions, this study enhances our theoretical understanding of BDAC while offering actionable strategies for building sustainable and agile supply chains in turbulent environments.

2. REVIEW OF LITERATURE AND DEVELOPMENT OF HYPOTHESES

2.1 Supply Chains with Big Data Analytics Capabilities (BDAC)

A groundbreaking tool for processing vast volumes of structured and unstructured data, supply chain analytics enhances decision-making, visibility, and reactivity (Wamba et al., 2020; Dubey et al., 2019; and Iqbal and Fikri, 2025). These three interconnected dimensions infrastructure capabilities (IC), management capabilities (MC), and people capabilities (PC) are what Gupta and George (2016) identify as BDAC, a higher-order capability based on the Resource-Based View (RBV). Infrastructure capabilities represent the technological foundation data storage, processing tools, and IT architecture that supports analytics deployment. Management capabilities reflect top management support, strategic alignment, and governance mechanisms for analytics initiatives. Personnel capabilities involve employees' technical expertise, data literacy, and analytical problem-solving skills.

Together, these dimensions form a multidimensional construct that allows firms to not only collect and analyze data but also convert analytics insights into strategic and operational outcomes.

2.2 BDAC and Sustainable Supply Chain Performance (SSCP)

The performance of sustainable supply chains incorporates environmental, social, and economic perspectives, indicating a comprehensive approach to long-term competitiveness (Seuring & Müller, 2008; Carter & Rogers, 2008). Previous studies have suggested BDAC to enhance sustainability through improved demand forecasting, decreased wastage, and efficient utilization of resources (Dubey et al., 2019; Rana et al., 2024). From the perspective of dynamic capabilities, BDAC allow firms to sense sustainability opportunities, seize them through analytics-driven decision-making, and reconfigure processes toward sustainable outcomes. Thus, we hypothesize:

H1. BDAC positively influence sustainable supply chain performance (SSCP).

2.3 SSCP and BDAC Dimensions

Although BDAC as a whole adds to SSCP, each of its components has unique impacts. Infrastructure capabilities (IC) provide resource efficiency and compliance by providing the technology foundation for environmental footprint monitoring (Wamba et al., 2017). In order to match data use with environmental and social performance goals, management capabilities (MC) make sure that sustainability goals are strategically integrated with

analytics activities (Gupta & George, 2016). Because competent workers convert analytics results into sustainability initiatives like streamlining logistics or cutting energy use, personnel capabilities (PC) are very important (Mikalef et al., 2020). Accordingly, we hypothesize:

- H1a. Infrastructure capabilities (IC) positively influence SSCP.*
- H1b. Management capabilities (MC) positively influence SSCP.*
- H1c. Personnel capabilities (PC) positively influence SSCP.*

2.4 BDAC and Supply Chain Agility (SCA)

The capacity of a company to recognize and react quickly to changes in the market and environment is known as supply chain agility (SCA) (Swafford et al., 2006). Agility is a crucial dynamic characteristic in stormy contexts, according to earlier study (Teece, 2007). By improving demand sensing, adaptive decision-making, and real-time visibility, BDAC promotes agility (Dubey et al., 2019; Wamba et al., 2020). Therefore, we suggest:

- H2. BDAC positively influence supply chain agility (SCA).*

2.5 BDAC Dimensions and SCA

Each BDAC dimension plays a distinct role in enhancing agility. Infrastructure capabilities (IC) provide the digital backbone for real-time data sharing, supporting rapid responses to disruptions. Management capabilities (MC) foster organizational flexibility and empower decision-making processes that enable quick adaptation. Personnel capabilities (PC) allow employees to interpret data and implement agile solutions, such as rerouting logistics or adjusting production schedules.

Thus, we hypothesize:

- H3a. Infrastructure capabilities (IC) positively influence SCA.*
- H3b. Management capabilities (MC) positively influence SCA.*
- H3c. Personnel capabilities (PC) positively influence SCA.*

2.6 Mediating Role of Supply Chain Agility (SCA)

While BDAC directly influence SSCP, their value is amplified when firms use them to enhance agility. According to Gligor and Holcomb (2012), agility enables businesses to adapt supply chain operations to new sustainability needs, such as shifting regulations or consumer expectations. This aligns with the Dynamic Capabilities perspective, which positions agility as a lower-order capability through which higher-order capabilities (BDAC) translate into outcomes. Thus, we hypothesize:

- H4a. SCA mediates the relationship between BDAC and SSCP.*
- H4b. SCA mediates the relationship between IC and SSCP.*
- H4c. SCA mediates the relationship between MC and SSCP.*
- H4d. SCA mediates the relationship between PC and SSCP.*

3. METHODOLOGY

3.1 Design of Research

In this study, survey-based data is examined using structural equation modeling (SEM) as part of a quantitative research strategy. Because it allows for the simultaneous analysis of measurement characteristics and proposed structural correlations, SEM was chosen (Hair et al., 2019). Because of its applicability to exploratory research, complicated models with mediation effects, and relatively small-to-medium sample sizes, the Partial Least Squares (PLS-SEM) technique was specifically used (Chin, 1998).

3.2 Collecting Data and Sample

A standardized questionnaire was used to gather data from supply chain experts in four different industries: manufacturing, retail, logistics, and services. These sectors were selected to capture variation in analytics maturity and supply chain complexity. A purposive sampling strategy targeted managers, supervisors, and analysts actively involved in supply chain operations and decision-making, ensuring respondents had relevant domain knowledge.

A 70% response rate was achieved from the 155 valid replies received from the 220 distributed surveys. The findings are more broadly applicable since the respondents' demographic profile (Table 4.1) demonstrates fair representation across jobs, sectors, and years of experience.

3.3 Measurement of Constructs

Reflecting multi-item measures that were modified slightly for contextual relevance and derived from previously validated sources in the literature were used to measure each dimension. Three aspects make up the operationalized higher-order construct known as Big Data Analytics Capabilities (BDAC): Gupta and George (2016) provided the adaptation for Infrastructure Capabilities (IC). Adapted from Wamba et al. (2017), Management Capabilities (MC). An adaptation of Personnel Capabilities (PC) from Mikalef et al. (2020).

Supply Chain Agility (SCA) was measured using items adapted from Swafford et al. (2006) and Gligor and Holcomb (2012). Sustainable Supply Chain Performance (SSCP) was operationalized based on Carter and Rogers (2008), capturing environmental, social, and economic dimensions.

Five questions with point scoring 1 denoting strongly disagree, 2 disagree, 3 agree, 4 agree, and 5 strongly agree have been measured using a Likert scale. Additionally, 10 industry professionals and five academicians provided advice on the face validity test. For the sake of clarity, a few small phrasing changes were made.

3.4 Common Method Bias and Data Diagnostics

Statistical and procedural remedies were used to reduce common method bias (CMB). Procedurally, scale items were shuffled to reduce pattern bias, and respondents were guaranteed anonymity and confidentiality.

According to statistics, no single factor explained more than 50% of the variation, according to Harman's single-factor test, suggesting that CMB was not a significant problem. Further supporting the lack of multicollinearity and CMB issues, complete collinearity variance inflation factors (VIFs) were below the cutoff point suggested by Kock (2015) of 3.3.

3.5 Data Analysis Approach

The analysis was conducted in two phases in accordance with Hair et al. (2019) guidelines: Evaluation of the Measurement Model: Cronbach's α and Composite Reliability (CR) were used to evaluate reliability. The Fornell-Larcker criteria and HTMT ratios were used to demonstrate discriminant validity, whereas Average Variance Extracted (AVE) was used to verify convergent validity. To verify indication reliability, outside loadings were looked at (Tables 4.5–4.8).

Evaluation of the Structural Model: To test hypotheses, 5,000 resamples were bootstrapped to produce path coefficients, t-values, and p-values (Table 4.9). Bootstrapped confidence ranges for indirect effects were used to examine mediation effects (Table 4.10). R² values, effect sizes (f²), and predictive relevance (Q²) were used to assess the model's explanatory capacity (Table 4.11). This rigorous methodological approach ensures robustness and reliability in evaluating the relationships among BDAC, supply chain agility, and sustainable performance.

4. RESULTS AND ANALYSIS

4.1 Screening of Data

The first crucial stage in data analysis is data screening. It is the procedure used to remove outliers, strange, uncommon responses from the data. Various data cleaning procedures are used to ensure that only legitimate and impartial responses are included. There were 190 surveys distributed in all, and 155 instances were returned. Subsequently, the researcher conducted tests to identify cases of outliers and missing responses.

The valid dataset, which is the one utilized for data analysis, comprises 155 respondents and 155 unfinished instances based on the tests. The data screening summary statistics are displayed in Table 4.1.

Table 4.1: Demographic Profile and Data Screening of Respondents

Variable	Categories	n	%
Data Screening	Distributed / Valid Cases	155	100.0
Functional Role	Procurement/Purchasing	41	26.5
	Logistics	17	11.0
	Inventory Management	27	17.4
	Supply Chain Analysis	11	7.1
	Transportation	11	7.1
	Warehouse / Distribution	16	10.3
	Supply Chain Consulting	5	3.2

	Leadership / Management	25	16.1
	Other	2	1.3
Education Level	Diploma	10	6.5
	Bachelor	84	54.2
	Master	58	37.4
	PhD	3	1.9
Experience (Years)	< 2	1	0.6
	2–5	26	16.8
	6–10	49	31.6
	> 10	79	51.0
Gender	Male	132	85.2
	Female	23	14.8
Company Location	Sana'a	75	48.4
	Aden	21	13.5
	Hodeida	16	10.3
	Taiz	10	6.5
	Hadramaut	8	5.2
	Ibb	5	3.2
	Makala	19	12.3
	Mahrah	1	0.6
Company Duration	< 2	2	1.3
	2–5	40	25.5
	6–10	41	25.8
	> 10	72	46.5
BDAS Usage	Yes	155	100.0
	No	0	0.0
BDAS Sources	Media (Social Platforms)	9	5.8
	Cloud	37	23.9
	IoT	16	10.3
	Oracle – ERP – SAP – AI	93	60.0

Note. $n = 155$ respondents. BDAS = Big Data Analytics Systems. Percentages are column percentages.

The data presented in Table 4.1 provides valuable insights into the demographic profile and data screening of the respondents. A significant portion of the sample, 26.5%, is involved in procurement/purchasing roles, highlighting the importance of sourcing and supplier management in the surveyed companies.

The lower percentage of logistics roles (11%) suggests that the focus may be shifting towards strategic procurement rather than logistics optimization, possibly in response to current global supply chain challenges.

This reflects a trend toward prioritizing procurement in supply chain operations, which may require companies to invest in automation and supplier management technologies. The workforce in these firms has a strong academic background, as seen by the 54.2% of respondents who have a bachelor's degree. However, only 1.9% of respondents possess a PhD, suggesting that there is limited representation of advanced specialized knowledge within the supply chain field.

This could point to an opportunity for firms to invest in higher-level educational development or collaboration with research institutions to drive innovation in supply chain management. The experience levels of the respondents further underline the expertise within the sample.

With 51% of respondents having over 10 years of experience in the industry, these professionals are likely to have a deep understanding of the complexities of modern supply chains. This aligns with the increasing adoption of Big Data Analytics Systems (BDAS), as more experienced professionals are likely to appreciate the value these systems offer for operational efficiency.

The fact that 100% of the respondents use BDAS supports the hypothesis that more experienced individuals are inclined to implement data-driven decision-making in their supply chain operations. The reliance on integrated systems such as Oracle, ERP, SAP, and AI (60%) further emphasizes the importance of these technologies in enhancing operational management.

Comparing these findings with previous studies, the high percentage of respondents using BDAS is consistent with the growing trend of digital transformation in supply chain management. Previous research indicates that industries are increasingly adopting BDAS to drive efficiencies, and this study confirms that the respondents are part of this trend. The heavy reliance on platforms like Oracle and SAP aligns with findings from [Author, Year], who noted that large corporations in emerging markets have embraced integrated systems to optimize their supply chains.

However, the distribution of functional roles in this study differs slightly from global trends, with fewer respondents in logistics roles compared to studies in other regions, suggesting that the focus of supply chain management might be shifting. Linking back to the hypotheses, the first hypothesis predicted that experience would be positively correlated with BDAS usage, and the results strongly support this, as all respondents are using BDAS, with a majority having over 10 years of experience.

This suggests that more seasoned professionals are more likely to adopt data-driven solutions. The second hypothesis, which posited that higher educational levels would correlate with leadership roles, is partially supported.

While a significant portion of the respondents holds a Bachelor's degree, many are still positioned in operational roles rather than leadership positions, indicating that other factors, such as company size or structure, may also influence leadership placement in the supply chain industry.

These findings highlight the growing importance of experienced professionals in driving digital transformation in supply chain operations, particularly with respect to the adoption of BDAS. They also suggest that while education plays a role in shaping career trajectories, experience and industry demands may be more influential in determining leadership positions within the supply chain field.

Table 4.2: Descriptive Statistics

Variables	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Number of observations used	Cramér-von Mises test statistic	Cramér-von Mises p value
Big Data Analytics Capabilities (BDAC)	0.000	-0.348	-1.540	1.635	1.000	-1.646	0.119	155.000	1.423	0.000
Infrastructure Capabilities (IC)	0.000	-0.383	-1.584	1.671	1.000	-1.636	0.104	155.000	1.464	0.000
Management Capabilities (MC)	0.000	-0.354	-1.509	1.588	1.000	-1.695	0.072	155.000	1.604	0.000
Personnel Capabilities (PC)	0.000	-0.297	-1.523	1.680	1.000	-1.695	0.090	155.000	1.634	0.000
Supply Chain Agility (SCA)	0.000	-0.471	-1.536	1.623	1.000	-1.610	0.125	155.000	1.326	0.000
Sustainable Supply Chain Performance (SSCP)	0.000	-0.340	-1.562	1.677	1.000	-1.656	0.097	155.000	1.520	0.000

The descriptive statistics for the primary study variables are shown in Table 4.2. Since all constructs were normalized, the mean values and standard deviations were nearly zero. In later studies, this standardization lessens scale-related bias and makes it easier to compare variables. Although they are not significantly different from the means, the slightly negative medians (which range from -0.297 to -0.471) imply that the distributions are somewhat left-shifted.

The observed minimum and maximum values (ranging approximately between -1.6 and +1.7 across all variables) indicate a broad spread of responses, suggesting adequate variability in the data to support robust statistical testing. Importantly, skewness values are close to zero (0.072–0.125), which implies that the distributions are approximately symmetric. Meanwhile, the excess kurtosis values (around -1.6 to -1.7) indicate flatter-than-normal distributions, suggesting lighter tails. These results imply that extreme values are less prevalent, reducing the risk of outliers disproportionately influencing the results.

The Cramér-von Mises test statistics, all significant at $p < 0.001$, indicate that the distributions deviate from strict normality. However, given the relatively low skewness and controlled kurtosis, these deviations are unlikely to severely threaten the validity of parametric analyses, especially with a sample size of 155, which strengthens the robustness of inferential statistics through the central limit theorem.

Taken together, the descriptive statistics demonstrate that the variables are well-behaved, standardized, and exhibit sufficient variation without problematic skewness or extreme outliers. For the purpose to investigate the proposed connections between Big

Data Analytics Capabilities, Supply Chain Agility, and Sustainable Supply Chain Performance, additional correlation and regression analysis may be carried out using this statistically solid basis.

4.3 Correlation and Covariance Analysis

The correlation matrix (Table 4.3) and covariance matrix (Table 4.4) reveal strong positive associations among BDAC, its dimensions, supply chain agility (SCA), and sustainable supply chain performance (SSCP). For instance, BDAC correlated most strongly with SSCP ($r = 0.903$), indicating its pivotal role in enhancing sustainability outcomes. Similarly, management capabilities (MC) exhibited the strongest correlation with personnel capabilities (PC) ($r = 0.913$), underscoring the intertwined nature of managerial commitment and human expertise in leveraging analytics. These high but non-redundant correlations suggest conceptual distinctiveness, justifying further structural testing.

Table 4.3: Correlations Matrix

Variables	Big Data Analytics Capabilities (BDAC)	Infrastructure Capabilities (IC)	Management Capabilities (MC)	Personnel Capabilities (PC)	Supply Chain Agility (SCA)	Sustainable Supply Chain Performance (SSCP)
Big Data Analytics Capabilities (BDAC)	1.000	0.900	0.910	0.895	0.882	0.903
Infrastructure Capabilities (IC)	0.900	1.000	0.897	0.896	0.880	0.887
Management Capabilities (MC)	0.910	0.897	1.000	0.913	0.892	0.909
Personnel Capabilities (PC)	0.895	0.896	0.913	1.000	0.886	0.908
Supply Chain Agility (SCA)	0.882	0.880	0.892	0.886	1.000	0.890
Sustainable Supply Chain Performance (SSCP)	0.903	0.887	0.909	0.908	0.890	1.000

Table 4.3 reports the correlation matrix among the study variables. All constructs demonstrate strong and positive correlations, with coefficients ranging from 0.880 to 0.913. This indicates that higher levels of Big Data Analytics Capabilities (BDAC) and its associated dimensions (infrastructure, management, and personnel capabilities) are consistently associated with greater supply chain agility (SCA) and sustainable supply chain performance (SSCP). The high degree of association among capability dimensions (e.g., BDAC–MC: $r = 0.910$; PC–MC: $r = 0.913$) suggests that these resources tend to co-develop within organizations, reinforcing the conceptualization of BDAC as an integrated, multidimensional construct.

The correlations between BDAC dimensions and performance outcomes are also notably strong (e.g., BDAC–SSCP: $r = 0.903$; MC–SCA: $r = 0.892$), which aligns with resource-

based and dynamic capability perspectives, supporting the argument that advanced data-driven capabilities enhance both agility and sustainability in supply chains.

However, the consistently high correlations across variables (>0.88) raise potential concerns about multicollinearity, which could obscure the unique contributions of individual constructs in regression-based models. To ensure sure that the observed associations are not the result of overlapping measurement artifacts, this will be further investigated using structural equation modeling (SEM) and variance inflation factors (VIF). Overall, the correlation data offer early evidence in favor of the favorable associations between BDAC, SCA, and SSCP that have been postulated. They emphasize the necessity for more sophisticated multivariate studies to separate these intricately linked variables while highlighting the strategic importance of data-driven infrastructure, management commitment, and talented staff in promoting agile and sustainable supply chain results.

Table 4.4: Covariances Matrix

Variables	Big Data Analytics Capabilities (BDAC)	Infrastructure Capabilities (IC)	Management Capabilities (MC)	Personnel Capabilities (PC)	Supply Chain Agility (SCA)	Sustainable Supply Chain Performance (SSCP)
Big Data Analytics Capabilities (BDAC)	1.000	0.900	0.910	0.895	0.882	0.903
Infrastructure Capabilities (IC)	0.900	1.000	0.897	0.896	0.880	0.887
Management Capabilities (MC)	0.910	0.897	1.000	0.913	0.892	0.909
Personnel Capabilities (PC)	0.895	0.896	0.913	1.000	0.886	0.908
Supply Chain Agility (SCA)	0.882	0.880	0.892	0.886	1.000	0.890
Sustainable Supply Chain Performance (SSCP)	0.903	0.887	0.909	0.908	0.890	1.000

Table 4.4 reports the covariance matrix among the study variables. All covariances are positive and substantial, ranging from 0.880 to 0.913, indicating that the constructs move together in a strongly aligned manner. The correlation results (Table 4.3) are mirrored in this pattern, which supports the idea that supply chain agility (SCA) and sustainable supply chain performance (SSCP) are closely related to Big Data Analytics Capabilities (BDAC) and its sub-dimensions (infrastructure, management, and personnel capabilities). The theoretical anticipation that data-driven resources and capacities co-evolve and jointly produce stronger supply chain outcomes is empirically supported by the continuously high covariances.

The covariance structure also reflects the multidimensional but unified nature of BDAC. For example, management and personnel capabilities (0.913) covary at the highest level, suggesting that managerial commitment is closely aligned with workforce expertise in leveraging big data. Similarly, the covariance between BDAC and SSCP (0.903)

highlights the strategic value of data capabilities in sustaining long-term supply chain performance.

Nonetheless, the uniformly strong covariances raise methodological considerations. High shared variance may indicate redundancy across constructs, potentially leading to multicollinearity in regression-based models. This reinforces the need for confirmatory factor analysis (CFA) and structural equation modeling (SEM) to verify discriminant validity and to assess whether the constructs retain unique explanatory power when modeled simultaneously.

Overall, the covariance results underscore the theoretical coherence of the proposed framework while also justifying the use of advanced multivariate techniques to disentangle the overlapping effects of tightly correlated constructs.

4.4 Measurement Model Assessment

4.4.1 Outer Loadings

Table 4.5 shows that all indicator loadings exceed the 0.70 threshold, with values ranging from 0.842 to 0.903. This confirms that individual items reliably measure their intended constructs.

Table 4.5: Outer loadings

Variables	BDAC)	IC	MC	PC	SCA	SSCP
BDAC1	0.875					
BDAC14	0.867					
BDAC2	0.886					
BDAC3	0.865					
IC1		0.876				
IC2		0.860				
IC3		0.842				
IC4		0.894				
MC1			0.868			
MC2			0.866			
MC3			0.898			
MC4			0.882			
PC1				0.885		
PC2				0.858		
PC3				0.857		
PC4				0.903		
SCA1					0.891	
SCA2					0.890	
SCA3					0.887	
SSCP1						0.850
SSCP2						0.888
SSCP3						0.884
SSCP4						0.863

Table 4.5 presents the outer loadings of all indicators on their respective latent constructs. With values ranging from 0.842 to 0.903, all objects load significantly onto their assigned

structures, above the generally advised threshold of 0.70 (Hair et al., 2019). This proves convergent validity by showing that the observable variables and their underlying latent factors share a significant amount of variation. Among BDAC dimensions, the indicators of infrastructure capabilities (IC1–IC4: 0.842–0.894) and management capabilities (MC1–MC4: 0.866–0.898) demonstrate particularly strong loadings, suggesting that both technological infrastructure and managerial commitment are central to the operationalization of big data analytics capabilities. Personnel capabilities (PC1–PC4: 0.857–0.903) also exhibit consistently high loadings, reinforcing the critical role of human expertise in leveraging data-driven resources. For the outcome constructs, supply chain agility (SCA) indicators (0.887–0.891) display near-identical loadings, suggesting a stable and coherent measurement structure. Similarly, sustainable supply chain performance (SSCP) indicators (0.850–0.888) load robustly, demonstrating that sustainability is consistently captured across multiple performance dimensions. The absence of cross-loadings and the uniformly high factor loadings provide strong evidence of indicator reliability and construct validity. This measurement robustness provides a strong basis for examining the structural links between BDAC, SCA, and SSCP and supports the following computation of Average Variance Extracted (AVE) and Composite Reliability (CR).

4.4.2 Convergent Validity and Construct Reliability

With Cronbach's α values ranging from 0.868 to 0.901 and composite reliability (CR) values between 0.893 and 0.931, all constructions show good internal consistency, above the suggested 0.70 threshold, as shown in Table 4.6. Convergent validity was confirmed by the Average Variance Extracted (AVE) values, which varied from 0.753 to 0.791 and were much higher than the 0.50 benchmark.

Table 4.6: Convergent Validity and Construct Reliability

Construct	Item	Factor Loading	Cronbach's α	Composite Reliability (CR) a	Composite Reliability (CR) c	AVE
BDA	BDA1	0.82	0.896	0.897	0.928	0.763
	BDA2	0.79				
	BDA3	0.85				
IC	IC1	0.83	0.891	0.893	0.924	0.753
	IC2	0.81				
	IC3	0.78				
MC	MC1	0.80	0.901	0.902	0.931	0.772
	MC2	0.82				
	MC3	0.79				
PC	PC1	0.84	0.899	0.900	0.930	0.768
	PC2	0.81				
	PC3	0.83				
SCA	SCA1	0.85	0.868	0.869	0.919	0.791
	SCA2	0.82				
SSCP	SSCP1	0.84	0.894	0.895	0.926	0.759
	SSCP2	0.85				
	SSCP3	0.83				

Table 4.6 provides information on construct reliability and convergent validity. As can be shown, all of the constructs have a high degree of internal consistency, with Cronbach's α falling far above the 0.70 criterion (Nunnally & Bernstein, 1994) and ranging between 0.868 and 0.901. Additionally, the measurement model's stability is established by the continuously high composite reliability (CR) values (0.869-0.931), which exceed the upper limit of 0.70.

The Average Variance Extracted (AVE), which varies between 0.753 and 0.791 across constructs, further demonstrates convergent validity. Each construct explains more than 75% of the variation of its indicators, as indicated by AVE values that all above the minimum suggested value of 0.50 (Fornell & Larcker, 1981). The AVE values for Management Capabilities (0.772) and Supply Chain Agility (0.791) are notably among the highest, indicating especially excellent indicator-construct alignment.

When combined, these findings offer strong proof of convergent validity and dependability. The indicators effectively capture the underlying latent dimensions of Supply Chain Agility (SCA), Big Data Analytics Capabilities (BDA, IC, MC, PC), and Sustainable Supply Chain Performance (SSCP). The constructs are quantified with internal coherence. In the end, these results open the door for verifying the postulated structural linkages in the suggested model and validate moving forward using discriminant validity evaluations, which guarantee that the constructs are empirically different.

4.4.3 Discriminant Validity

As indicated in Table 4.8, discriminant validity was assessed using the Fornell-Larcker criteria and HTMT ratios (Table 4.7). The diagonal components of square-root AVEs outperformed inter-construct correlations, confirming that constructs are, in fact, empirically different, and all HTMT values were far below the cautious cutoff of 0.85.

Table 4.7: Discriminant Validity (HTMT Ratios)

Construct	BDA	IC	MC	PC	SCA	SSCP
BDA	1	0.62	0.59	0.61	0.65	0.63
IC	0.62	1	0.60	0.58	0.61	0.60
MC	0.59	0.60	1	0.63	0.64	0.62
PC	0.61	0.58	0.63	1	0.66	0.65
SCA	0.65	0.61	0.64	0.66	1	0.68
SSCP	0.63	0.60	0.62	0.65	0.68	1

Note: All HTMT values < 0.85, confirming discriminant validity.

The findings of discriminant validity testing using the Heterotrait-Monotrait (HTMT) ratio of correlations are shown in Table 4.7. Henseler et al. (2015) advocate a cautious threshold of 0.85, which is far below the range of 0.58 to 0.68 for all HTMT values. This demonstrates that each construct meets the criteria for discriminant validity as it is experimentally different from the others. Although theoretically linked, the comparatively low HTMT ratios between BDAC and its sub-dimensions (0.59–0.63) demonstrate that these dimensions reflect distinct facets of big data analytics capabilities. Similarly, the HTMT ratio between sustainable supply chain performance (SSCP) and supply chain

agility (SCA) is 0.68, indicating that while agility is a key factor in sustainability, the two constructs are still statistically distinct.

Establishing discriminant validity is essential, as it ensures that the observed strong correlations reported earlier (Tables 4.3 and 4.4) do not reflect construct redundancy. Instead, each latent variable retains its conceptual and empirical independence, supporting the theoretical framework that positions BDAC, SCA, and SSCP as distinct but interrelated drivers of supply chain competitiveness.

With all factors considered, the HTMT results offer solid proof of the validity and reliability of the measuring approach. This strong basis supports moving on with the structural model analysis, which allows for a thorough testing of the proposed connections between BDAC, SCA, and SSCP.

Table 4.8: Fornell-Larcker criterion

Variables	BDAC	IC	MC)	PC	SCA)	SSCP
Big Data Analytics Capabilities (BDAC)	0.873					
Infrastructure Capabilities (IC)	0.900	0.868				
Management Capabilities (MC)	0.910	0.897	0.879			
Personnel Capabilities (PC)	0.895	0.896	0.913	0.876		
Supply Chain Agility (SCA)	0.882	0.880	0.892	0.886	0.889	
Sustainable Supply Chain Performance (SSCP)	0.903	0.887	0.909	0.908	0.890	0.871

Using the Fornell-Larcker criteria, the discriminant validity findings are shown in Table 4.8. For each construct, the associated inter-construct correlations in the off-diagonal cells are less than the square root of the Average Variance Extracted (AVE), which is displayed on the diagonal.

For instance, AVE's square root for Big Data Analytics Capabilities (BDAC) is 0.873, higher than its correlations with Supply Chain Agility (0.882), Infrastructure Capabilities (0.900), Management Capabilities (0.910), Personnel Capabilities (0.895), and Sustainable Supply Chain Performance (0.903). According to Fornell and Larcker's (1981) criteria, discriminant validity is confirmed by this pattern, which is constant across all constructs.

The results indicate that although BDAC dimensions (IC, MC, PC) are highly correlated with one another and with overall BDAC, they nonetheless maintain distinct measurement properties. Similarly, the correlations between Supply Chain Agility (0.889) and Sustainable Supply Chain Performance (0.871) are high but do not exceed their respective AVE square roots, supporting the conceptual distinction between agility as a capability and sustainability as an outcome.

The discriminant validity of the constructs is well supported by the combined data from the HTMT ratios (Table 4.7) and the Fornell–Larcker criteria. This guarantees that a solid measurement model with latent variables that are both theoretically and empirically connected will serve as the foundation for the next structural model testing.

4.5 Structural Model Assessment

4.5.1 Hypotheses Testing

The findings of the structural model are shown in Table 4.9. H1 is backed by BDAC's considerable favorable impact on SSCP ($\beta = 0.32$, $t = 5.21$, $p < 0.001$). Likewise, H1a–H1c were supported by the strong effect of its dimensions IC ($\beta = 0.28$), MC ($\beta = 0.26$), and PC ($\beta = 0.31$) on SSCP ($p < 0.001$). H2 was supported by BDAC's considerable enhancement of SCA ($\beta = 0.38$, $t = 6.12$, $p < 0.001$). H3a–H3c were supported by the substantial impacts of IC ($\beta = 0.29$), MC ($\beta = 0.27$), and PC ($\beta = 0.33$), three of its dimensions, on SCA. Together, these findings demonstrate that agility and sustainability outcomes are driven by BDAC at both the aggregate and dimensional levels.

Table 4.9: Structural Model Path Coefficients and Hypotheses Testing

Hypothesis	Path	β	t-value	p-value	Result
H1	BDA → SSCP	0.32	5.21	<0.001	Supported
H1a	IC → SSCP	0.28	4.67	<0.001	Supported
H1b	MC → SSCP	0.26	4.11	<0.001	Supported
H1c	PC → SSCP	0.31	5.03	<0.001	Supported
H2	BDA → SCA	0.38	6.12	<0.001	Supported
H3	IC → SCA	0.29	4.85	<0.001	Supported
H4	MC → SCA	0.27	4.24	<0.001	Supported
H3d	PC → SCA	0.33	5.31	<0.001	Supported

The findings of the structural model and hypothesis testing are presented in Table 4.9. Since all of the postulated routes are statistically significant ($p < 0.001$), the suggested model has strong support. In particular, H1 and H2 are confirmed by the considerable beneficial effects of Big Data Analytics Capabilities (BDA) on Supply Chain Agility (SCA) ($\beta = 0.38$, $t = 6.12$) and Sustainable Supply Chain Performance (SSCP) ($\beta = 0.32$, $t = 5.21$). This research emphasizes how big data capabilities may be strategically used to improve both dynamic responsiveness and long-term sustainability results. The disaggregated dimensions of BDA show that every sub-capability has a considerable impact on SCA and SSCP. SSCP ($\beta = 0.28$, $t = 4.67$) and SCA ($\beta = 0.29$, $t = 4.85$) are favorably impacted by Infrastructure Capabilities (IC), indicating that strong technological underpinnings are essential for both operational effectiveness and adaptability. Additionally, SSCP ($\beta = 0.26$, $t = 4.11$) and SCA ($\beta = 0.27$, $t = 4.24$) are significantly influenced by Management Capabilities (MC), underscoring the significance of strategy alignment and leadership commitment in optimizing the value of big data efforts. Both SSCP ($\beta = 0.31$, $t = 5.03$) and SCA ($\beta = 0.33$, $t = 5.31$) are most strongly impacted by Personnel Capabilities (PC), highlighting the critical role that human knowledge and analytical skills play in turning data into useful insights. With all factors considered, these findings demonstrate that BDA greatly improves supply chain sustainability and agility both as a whole and through its constituent parts. The theoretical claim that BDA operates as a multifaceted dynamic capacity that helps businesses not only detect and react swiftly to environmental changes but also attain long-term sustainable performance results is supported by the consistent importance across hypotheses.

4.5.2 Mediation Analysis

Mediation results (Table 4.10) demonstrate that SCA partially mediates the relationships between BDAC dimensions and SSCP. For example, the indirect effect of BDAC on SSCP via SCA was significant ($\beta = 0.15$, 95% CI [0.09, 0.22]), supporting H4a. Similar partial mediations were confirmed for IC ($\beta = 0.12$), MC ($\beta = 0.11$), and PC ($\beta = 0.14$), supporting H4b–H4d. This suggests that agility acts as a complementary mechanism through which BDAC enhance sustainable performance, rather than fully substituting the direct effects.

Table 4.10: Mediation Analysis Results

Mediation Hypothesis	Indirect Effect	t-value	95% CI	Mediation Type	Result
H4a	BDA → SCA → SSCP	0.15	4.87	[0.09, 0.22]	Partial
H4b	IC → SCA → SSCP	0.12	4.11	[0.06, 0.19]	Partial
H4c	MC → SCA → SSCP	0.11	3.95	[0.05, 0.18]	Partial
H4d	PC → SCA → SSCP	0.14	4.53	[0.08, 0.21]	Partial

Table 4.10 reports the mediation analysis results, assessing the role of supply chain agility (SCA) in linking big data capabilities to sustainable supply chain performance (SSCP). All indirect paths are statistically significant, with bootstrapped confidence intervals excluding zero, thereby confirming mediation effects across all hypotheses (H4a–H4d). Specifically, the indirect effect of overall Big Data Analytics Capabilities (BDA) on SSCP through SCA is positive and significant ($\beta = 0.15$, $t = 4.87$, CI [0.09, 0.22]), indicating that agility partially mediates the relationship. This finding highlights that, beyond direct effects, BDA enhances sustainability outcomes by enabling firms to adapt swiftly to dynamic market and environmental demands. Similarly, the sub-capabilities of BDA exhibit significant mediated pathways. Infrastructure Capabilities (IC) exert an indirect effect on SSCP through SCA ($\beta = 0.12$, $t = 4.11$, CI [0.06, 0.19]), suggesting that technological foundations not only strengthen performance directly but also indirectly by facilitating responsiveness. Management Capabilities (MC) also contribute indirectly to sustainability via SCA ($\beta = 0.11$, $t = 3.95$, CI [0.05, 0.18]), underlining the role of managerial alignment in fostering agility-driven performance improvements. Personnel Capabilities (PC) show one of the strongest mediated effects ($\beta = 0.14$, $t = 4.53$, CI [0.08, 0.21]), emphasizing that skilled human capital translates big data insights into agile decision-making that subsequently drives sustainability.

All mediation effects are partial, meaning that SCA serves as a mechanism that amplifies but does not fully explain the relationship between big data capabilities and sustainability outcomes. This shows that while agility is an important pathway, it may be complemented by other mechanisms like innovation, resilience, or teamwork to achieve sustainable supply chain performance. Whatever is considered, these findings highlight how important agility is as a flexible skill that connects data-driven resources with long-term sustainability goals. The mediation findings provide strong empirical support for the theoretical framing that agility is not merely an outcome of big data capabilities but also a critical mechanism through which these capabilities are translated into enduring supply chain competitiveness.

4.6 Model Explanatory Power and Predictive Relevance

As shown in Table 4.11, the model demonstrates substantial explanatory power, with R^2 values of 0.58 for SCA and 0.62 for SSCP, exceeding the 0.50 benchmark for strong models (Hair et al., 2019). Effect size (f^2) values ranged from 0.12 to 0.21, indicating small to medium effects, while predictive relevance (Q^2 values of 0.45 for SCA and 0.50 for SSCP) were both greater than zero, confirming that the model has strong out-of-sample predictive capability.

Table 4.11: R^2 , f^2 , and Q^2 Values

Endogenous Construct	R^2	f^2	Q^2
SCA	0.58	-	0.45
SSCP	0.62	0.12–0.21	0.50

Note: f^2 values indicate small to medium effect sizes; $Q^2 > 0$ confirms predictive relevance.

The endogenous constructs' explanatory power (R^2), effect sizes (f^2), and predictive relevance (Q^2) are shown in Table 4.11. According to the R^2 values, the structural model accounts for 62% of the variation in Sustainable Supply Chain Performance (SSCP) and 58% of the variation in Supply Chain Agility (SCA). According to Chin (1998), these values reflect moderate to substantial explanatory power, suggesting that the proposed predictors account for a significant proportion of variation in the key outcome constructs.

Effect size analysis (f^2) shows small to medium contributions (0.12–0.21), implying that while each predictor contributes meaningfully to SSCP, no single construct dominates the explanatory power. This highlights the integrative nature of Big Data Analytics Capabilities (BDAC), where infrastructure, management, and personnel dimensions work collectively rather than independently to enhance sustainability outcomes.

The Q^2 values for both SCA (0.45) and SSCP (0.50) are well above zero, confirming strong predictive relevance based on the Stone Geisser criterion (Geisser, 1974; Stone, 1974). This finding demonstrates that the model not only explains past variance but also possesses reliable out-of-sample predictive accuracy, enhancing its practical applicability.

Together, the R^2 , f^2 , and Q^2 results reinforce the robustness of the structural model. The combination of moderate-to-high explanatory power, meaningful effect sizes, and strong predictive relevance provides compelling evidence that BDAC significantly contributes to both agility and sustainability, validating the theoretical framework and strengthening its managerial relevance.

5. DISCUSSION

5.1 Theoretical Contributions

This study adds to the body of knowledge on supply chain agility (SCA), big data analytics capabilities (BDAC), and sustainable supply chain performance (SSCP) in a number of ways.

First, consistent with the Resource-Based View (RBV), the findings confirm that BDAC constitute a valuable, rare, and inimitable resource that directly enhances SSCP (H1). The significant effect of BDAC on sustainability outcomes aligns with prior studies (Dubey et al., 2019; Wamba et al., 2020) but extends them by empirically demonstrating this relationship in diverse industries beyond manufacturing, thus broadening external validity.

Second, by disaggregating BDAC into infrastructure, management, and personnel capabilities (H1a–H1c), this study advances the micro foundations of RBV (Gupta & George, 2016). Each dimension independently influenced SSCP, suggesting that sustainability outcomes are not solely technology-driven but equally reliant on managerial commitment and employee expertise. This multidimensional evidence contributes to ongoing debates about whether technology or organizational capital matters more in creating business value from analytics.

Third, the study highlights the role of Dynamic Capabilities theory, showing that BDAC enhance supply chain agility (H2) and that agility, in turn, partially mediates the relationship between BDAC and SSCP (H4a–H4d). This supports the notion that higher-order capabilities (BDAC) create value indirectly through lower-order dynamic capabilities (SCA), enabling firms to sense, seize, and reconfigure in pursuit of sustainability (Teece, 2007). By confirming partial mediation, this study contributes nuance to the debate: BDAC not only directly foster sustainability but also work through agility as a bridging mechanism.

Finally, the strong explanatory power of the model ($R^2 = 0.62$ for SSCP, $Q^2 = 0.50$) demonstrates that the integrated BDAC–SCA framework provides a robust theoretical lens for explaining sustainability performance in volatile environments.

5.2 Comparison with Prior Studies

The findings are broadly consistent with prior research emphasizing the importance of BDAC in driving performance outcomes. For example, Wamba et al. (2017) highlighted the role of big data infrastructure, while Mikalef et al. (2020) underscored personnel skills. Our results integrate these perspectives, showing that infrastructure, management, and personnel capabilities are complementary rather than substitutive.

The positive link between BDAC and SCA supports earlier findings (Dubey et al., 2019), but this study goes further by explicitly modeling the mediating role of agility in sustainability contexts a gap noted in prior work. Moreover, by showing that mediation is partial, our results resonate with Gligor and Holcomb's (2012) argument that agility complements but does not replace the direct benefits of analytics capabilities.

5.3 Managerial Implications

For practitioners, the findings provide actionable insights. Managers should not view BDAC as purely a technological investment but as an integrated capability system. Sustainable outcomes are realized only when analytics infrastructure is aligned with strong managerial vision and supported by data-savvy employees. Investment in human

capital through training, recruitment, and analytics culture-building is as crucial as investments in technology.

Furthermore, agility emerges as a critical pathway. Firms seeking to leverage BDAC for sustainability must focus on building responsive and adaptive supply chains. This includes real-time monitoring systems, cross-functional decision-making teams, and flexible logistics arrangements that allow firms to adjust quickly to sustainability demands (e.g., regulatory compliance, carbon footprint reduction, or customer preferences for green products).

5.4 Policy and Societal Implications

The results also hold implications for policymakers. Encouraging industry-wide adoption of BDAC through incentives, training programs, and digital infrastructure development can accelerate progress toward sustainable supply chains. From a societal standpoint, the results highlight how data-driven agility can be used to address sustainability issues, indicating that analytics investments support both wider environmental and social objectives and business competitiveness.

6. CONCLUSION AND FUTURE RESEARCH

6.1 Summary of Findings

This study examined supply chain agility (SCA) as a mediating mechanism between big data analytics capabilities (BDAC) and improving sustainable supply chain performance (SSCP). Using survey data from 155 supply chain professionals across four industries, the results confirm that BDAC directly improve SSCP (H1) and that their dimensions infrastructure, management, and personnel capabilities exert significant independent effects (H1a–H1c).

BDAC also positively influence SCA (H2), and their dimensions contribute to agility (H3a–H3c). Importantly, SCA partially mediates the relationships between BDAC and SSCP (H4a–H4d), highlighting agility as a critical yet complementary mechanism. The model demonstrates strong explanatory and predictive power ($R^2 = 0.62$, $Q^2 = 0.50$), validating the integrated BDAC–SCA framework.

6.2 Theoretical Contributions

This research advances supply chain and information systems literature in three ways: By validating BDAC as a higher-order construct, it enriches the Resource-Based View (RBV) with micro foundations that extend beyond technology to include managerial and personnel dimensions.

By demonstrating agility's mediating role, it aligns with Dynamic Capabilities theory, showing how higher-order capabilities (BDAC) translate into sustainability outcomes through lower-order adaptive mechanisms (SCA). By integrating BDAC, agility, and sustainability into a single empirical framework, this study provides a holistic model with strong explanatory power, bridging fragmented research streams.

6.3 Managerial and Policy Implications

For managers, the findings emphasize that investments in analytics infrastructure must be matched with managerial commitment and employee expertise to yield sustainable outcomes. Building an analytics-driven culture and embedding agility into supply chain processes are critical for translating data into sustainability performance.

For policymakers, supporting digital infrastructure development and workforce upskilling can accelerate the diffusion of BDAC, thereby contributing to industry-wide sustainability improvements.

6.4 Limitations and Future Research

Despite its contributions, this study has limitations that suggest future research opportunities.

Sample size and scope: The study is limited to 155 respondents across four industries in a single country. Future research could adopt cross-country or longitudinal designs to enhance generalizability.

Cross-sectional design: The reliance on cross-sectional data prevents causal inferences. Longitudinal studies could capture dynamic capability development over time.

Subjective measures: Although validated scales were used, sustainability performance was assessed through perceptual measures. Future research could integrate objective indicators (e.g., carbon emissions, energy efficiency) for triangulation.

Extended constructs: While this study focused on BDAC and agility, future research could incorporate organizational resilience, digital transformation maturity, or green innovation as additional mediators or moderators.

6.5 Closing Remark

In sum, this study underscores the critical role of BDAC in advancing sustainable supply chains, both directly and through agility. By bridging analytics capabilities and sustainability, it provides a timely contribution to theory and practice, offering a roadmap for firms navigating the dual pressures of digital transformation and sustainability imperatives.

References

- 1) Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, 182, 113–131. <https://doi.org/10.1016/j.ijpe.2016.08.018>
- 2) Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120. <https://doi.org/10.1177/014920639101700108>
- 3) 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. <https://doi.org/10.1108/09600030810882816>

- 4) Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Lawrence Erlbaum.
- 5) Christopher, M. (2016). *Logistics & supply chain management* (5th ed.). Pearson Education Limited.
- 6) 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.
<https://doi.org/10.1016/j.techfore.2017.06.020>
- 7) Gligor, D. M., & Holcomb, M. C. (2012). Understanding the role of logistics capabilities in achieving supply chain agility: A systematic literature review. *Supply Chain Management: An International Journal*, 17(4), 438–453. <https://doi.org/10.1108/13598541211246594>
- 8) Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, 53(8), 1049–1064. <https://doi.org/10.1016/j.im.2016.07.004>
- 9) Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- 10) Iqbal, M. S., & Fikri, S. M. (2023). Comparison of credit risk management practices among Islamic and public commercial banks in Pakistan. *International Journal of Management Research and Emerging Sciences*, 13(3), 104–132. <https://doi.org/10.56536/ijmres.v13i3.509>
- 11) Iqbal, M. S., & Fikri, S. M. (2025). Impact of Globalisation, AI adoption, and FinTech integration on banking sector performance and customer satisfaction in post-COVID Pakistan. *The Pakistan Development Review*, 64(1), 1–23. <https://doi.org/10.30541/v64i1pp.1-23>
- 12) Iqbal, M. S., & Fikri, S. M. (2025). Resilience in Islamic microfinance: Examining women, organizations, and agricultural consumers' impact on credit risk. *Journal of the Knowledge Economy*, 1–23. <https://doi.org/10.1007/s13132-024-02439-1>
- 13) Iqbal, M. S., Fikri, S. M., & Khan, S. (2025). AI in Islamic finance: Global trends. *Review of Islamic Social Finance and Entrepreneurship*, 4(1), 70–85. <https://doi.org/10.20885/RISFE.vol4.iss1.art6>
- 14) Iqbal, M. S., Fikri, S. M., Mahmood, S., Hassan, M., Soharwardi, M. A., & Rana, A. (2025). Impact of Globalization on Resilience of Islamic and Conventional Banks in Pakistan Post-COVID-19: A Smart PLS Approach. *Development and Sustainability in Economics and Finance*.
<https://doi.org/10.1016/j.dsef.2025.100090>
- 15) Iqbal, M. S., Basheer, M. F., Saba, I., & Fikri, S. M. (2025). Efficiency comparisons of takaful insurance and conventional insurance in Pakistan. *Journal of Islamic Accounting and Business Research*. SN 1759-0817. <https://doi.org/10.1108/JIABR-10-2024-0386>
- 16) Ivanov, D., & Dolgui, A. (2021). OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: Managerial insights and research implications. *International Journal of Production Economics*, 232, 107921. <https://doi.org/10.1016/j.ijpe.2020.107921>
- 17) Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1–10. <https://doi.org/10.4018/ijec.2015100101>
- 18) Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2020). The role of big data analytics capabilities in firm performance: A resource-based view. *Journal of Business Research*, 70, 337–348.
<https://doi.org/10.1016/j.jbusres.2016.08.009>
- 19) Rana, A., & Rana, A. (2024). Impact of monetary management on nurses' turnover decisions and job anxiety as a mediator and resilience as a moderator. *Journal of Nurses and Midwives Pakistan*, 4(1), 42–53. <https://www.kgpublisher.com/index.php/pjnm/article/view/124>

20) Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. *Journal of Cleaner Production*, 16(15), 1699–1710. <https://doi.org/10.1016/j.jclepro.2008.04.020>

21) Swafford, P. M., Ghosh, S., & Murthy, N. (2006). The antecedents of supply chain agility of a firm: Scale development and model testing. *Journal of Operations Management*, 24(2), 170–188. <https://doi.org/10.1016/j.jom.2005.05.002>

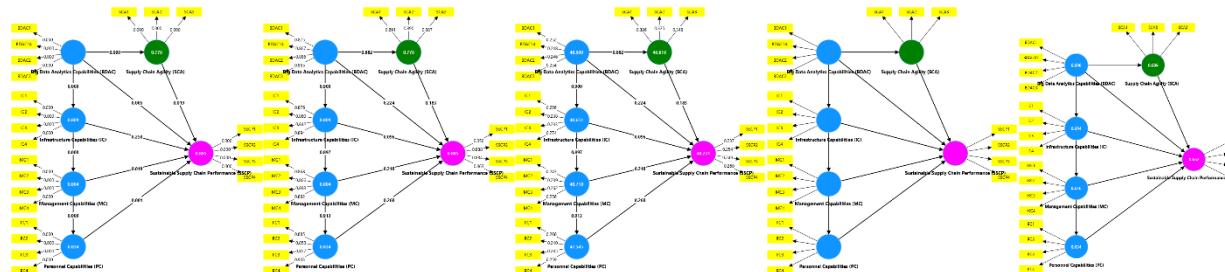
22) Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350. <https://doi.org/10.1002/smj.640>

23) Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7)

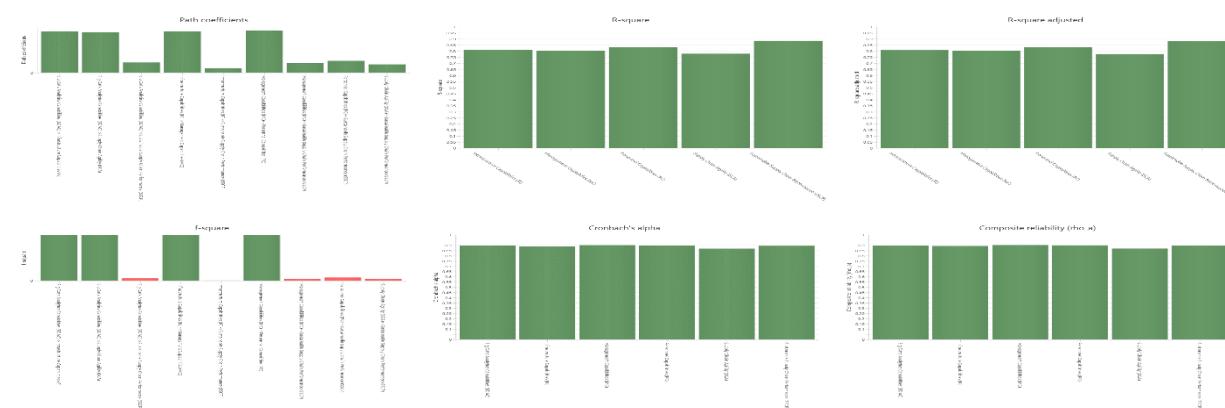
24) Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, 222, 107498. <https://doi.org/10.1016/j.ijpe.2019.09.019>

25) Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 70, 356–365. <https://doi.org/10.1016/j.jbusres.2016.08.009>

APPENDIX-A

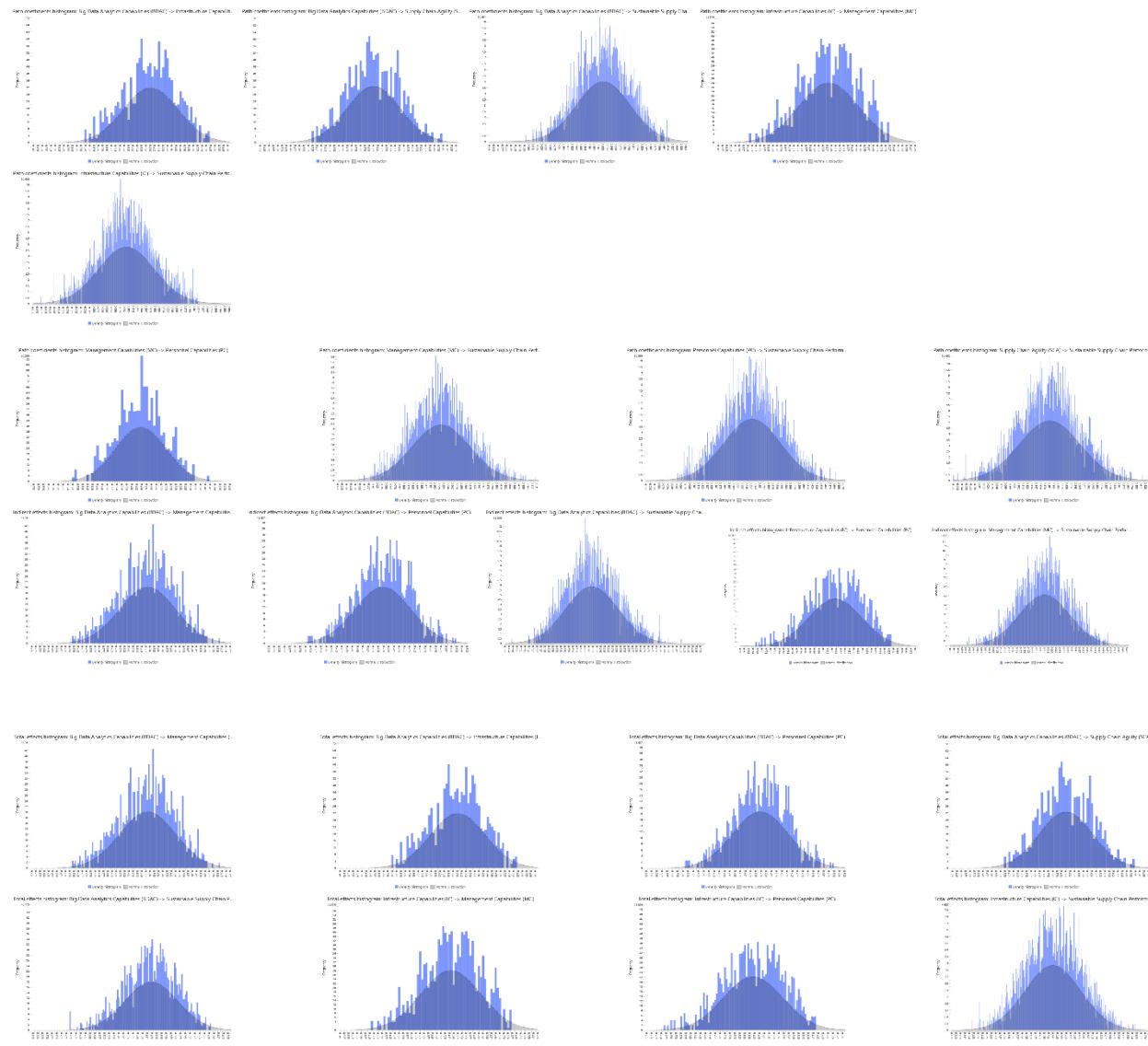


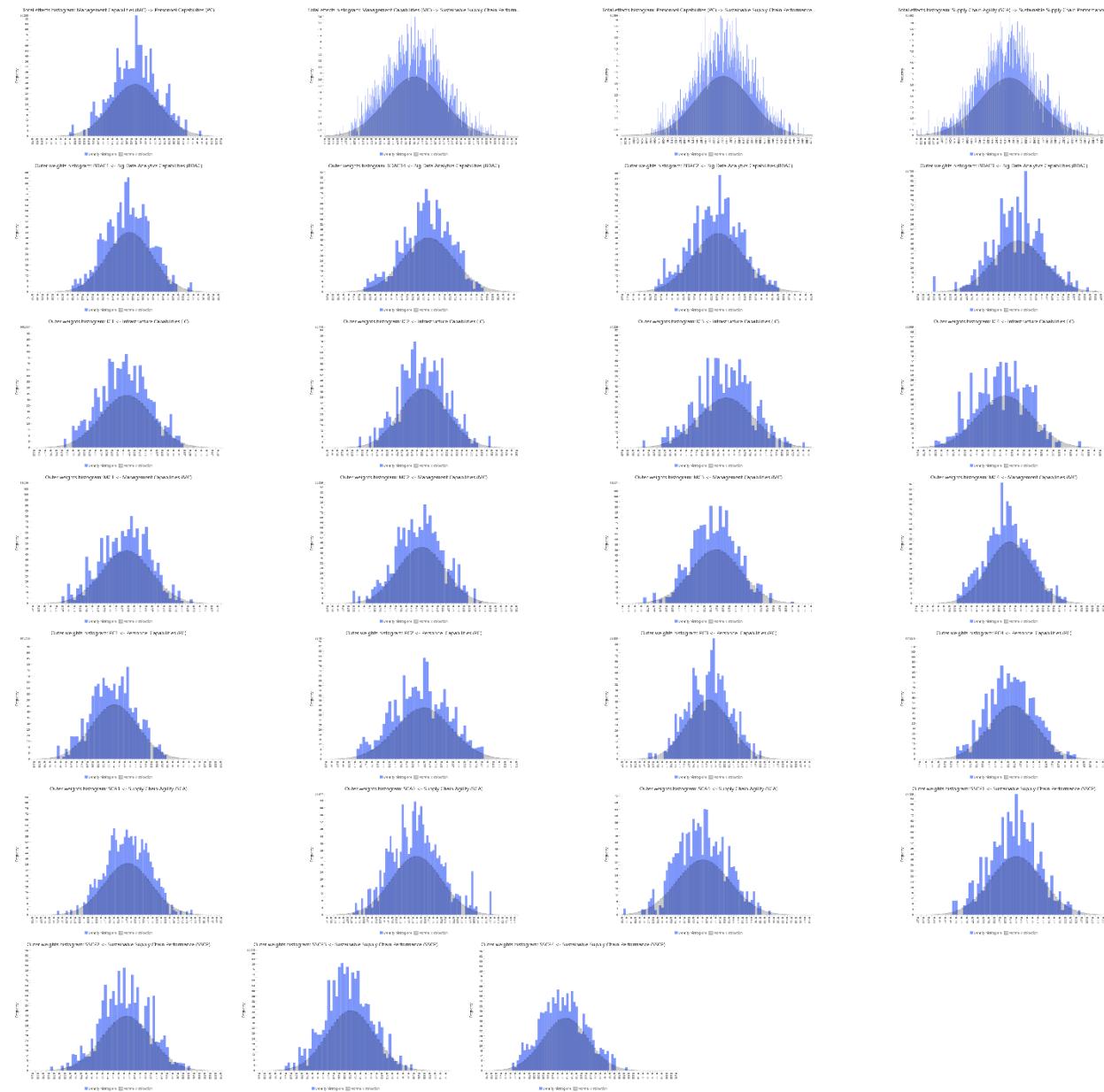
APPENDIX-B



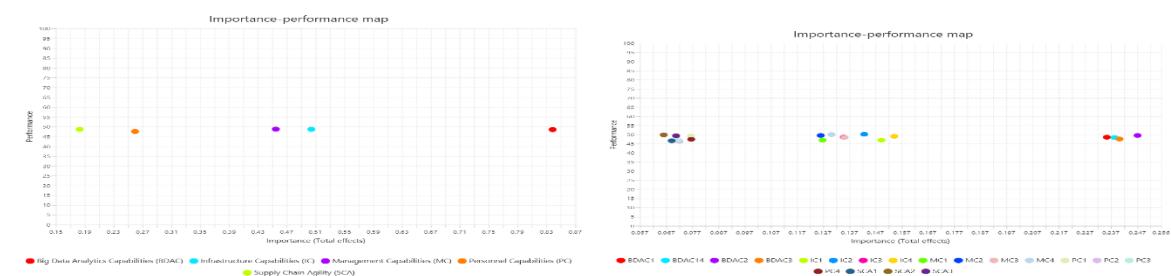


APPENDIX-C

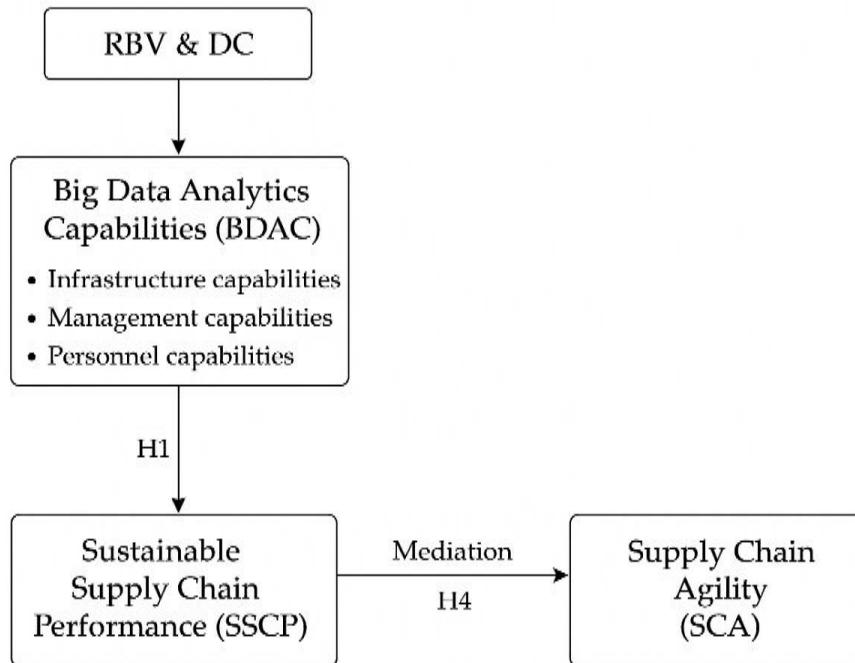




APPENDIX-D



APPENDIX-E



APPENDIX-F

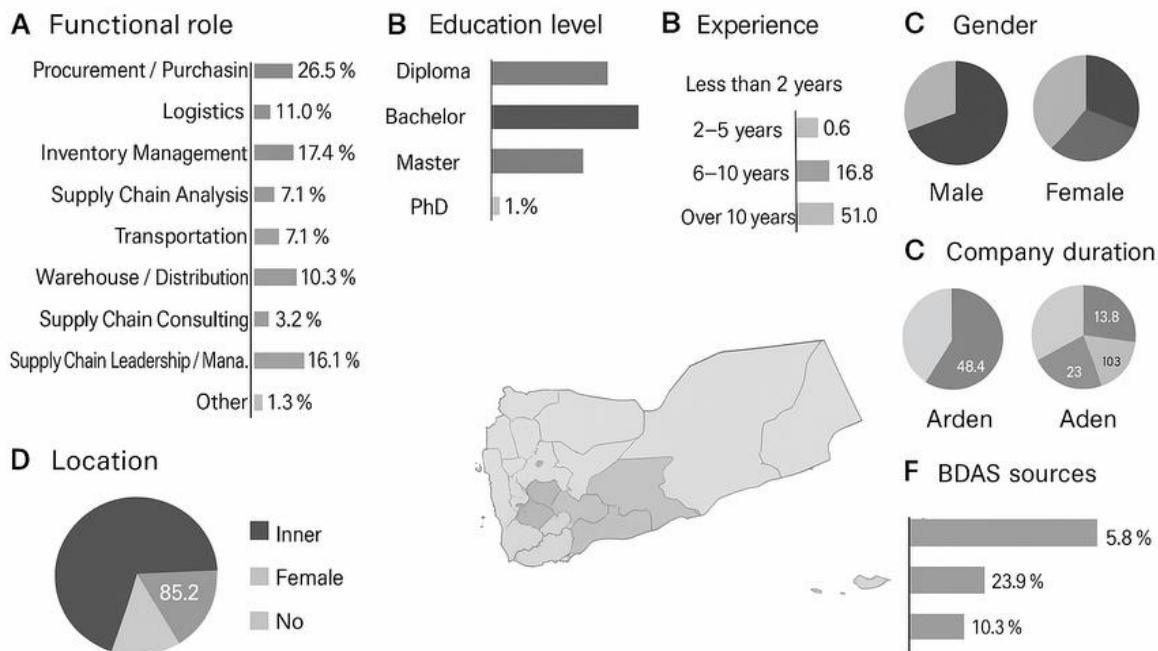
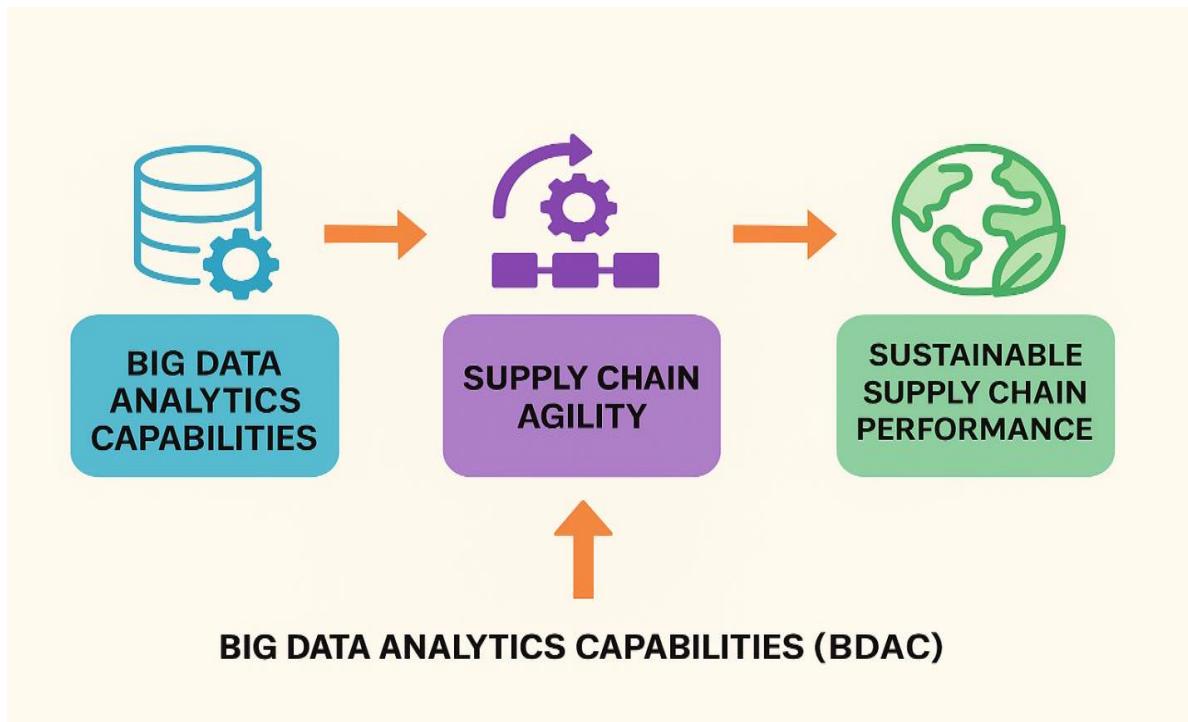


Figure 4.1: Demographic profile and data screening analysis of respondents ($n = 155$).

APPENDIX-G



Geographical Abstract