

BIG DATA ANALYTICS AND INNOVATION IN THE SUSTAINABLE PERFORMANCE OF ELECTRONIC WASTE REVERSE LOGISTICS: AN EMPIRICAL STUDY IN INDIA

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Abstract

Electronic waste (e-waste), encompassing discarded electrical and electronic devices, demands effective reverse logistics management to ensure optimal resource use and environmental preservation. Despite growing interest in Big Data Analytics within the scientific community, its slow practical implementation in e-waste management and the absence of validated measurement models hinder both industry adoption and empirical studies. To address these challenges and drawing upon the Resource-Capability-Advantage (RCA) theory, this study aims to investigate the interplay between Big Data Analytics (BDA) management capabilities, BDA talent capabilities, Reverse Logistics (RL) innovation, and sustainable RL performance. A conceptual model was tested using primary data from practitioners and managers in India's e-waste reverse logistics network, with Structural Equation Modeling (SEM) as the primary analytical method. The results highlight the multifaceted contributions of Big Data Analytics Management and Talent Capabilities to Reverse Logistics Innovation and Sustainable Reverse Logistics Performance.

Keywords: Big Data Analytics (BDA), e-Waste, Reverse Logistics Innovation, Sustainable Reverse Logistics Performance

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Introduction

E-waste, an abbreviation for electronic waste, encompasses discarded electrical or electronic devices. This category covers a broad spectrum of products, including computers, televisions, mobile phones, and household appliances, which are no longer in use due to malfunction, obsolescence, or other factors (Baldé et al., 2017). The production and utilization of electronic devices are experiencing exponential growth. The growing accumulation of e-waste is an increasing environmental concern, as it contains hazardous substances such as lead, mercury, and cadmium, which can pose significant risks if not properly handled (Forti et al., 2020). With their limited lifespan, the quantity of discarded electronic devices is also escalating proportionally, contributing to a significant global pollution issue. Simultaneously, the rise in industrialization and urbanization has led to a surge in concrete production and consumption, causing environmental issues through resource depletion (Kang et al., 2023). Effectively managing electronic waste becomes a significant concern, given the specific challenges and complexities arising from technological innovations and a diverse range of products (Yla-Mella et al., 2004). The rapid evolution of consumer lifestyles and shifts in the acquisition and usage patterns of electrical and electronic devices (EEDs) has led to shorter replacement cycles and an increased demand for more advanced equipment (Kang et al., 2020). Globally recognized as a crucial aspect of waste management (Musson et al., 2000; Leclerc & Badami, 2020; Zeng et al., 2017; Kahhat et al., 2008; Ilankoon et al., 2018; Ikhlayel, 2018), electronic waste (e-waste) contains hazardous components that pose environmental threats.

Managing e-waste becomes particularly challenging in developing countries due to the inadequacy of proper infrastructural facilities (Garlapati, 2016; Baidya et al., 2020). Effectively handling the reverse supply chain of e-waste is crucial for sustainable development and societal well-being. Numerous reverse logistics designs have been proposed in the literature to address this issue (Ayvaz et al., 2015; John et al.,

2018; Islam & Huda, 2018; Lara et al., 2019; Safdar et al., 2020). However, studies indicate that these designs face their own set of challenges (Khatriwal et al., 2009; Kinobe et al., 2012; Demajorovic et al., 2016; Garlapati, 2016). Technological advancements, particularly those driven by the internet, have facilitated the collection, management, and analysis of data, ushering in significant changes in logistics processes (Manyika et al., 2013). The revolutionary change in data and information is commonly known as big data (Davenport et al., 2012). Various terms, including SCM data science (Waller & Fawcett, 2013), predictive analytics (Schoenherr & Speier-Peró, 2015), business analytics, big data analytics, and supply chain analytics (Wang et al., 2016), have been used to describe the integration of big data into SCM and logistics. Essentially, these terms encompass similar technologies that employ advanced quantitative and qualitative analytical techniques, leveraging vast and diverse datasets in SCM and logistics. The ability to harness billions of gigabytes of real-time data represents a potentially game-changing scenario. Despite the unstructured nature of most real-time data, advanced technologies and tools exist for analyzing such data descriptively, predictively, and prescriptively, supporting both operational and strategic decision-making processes. A burgeoning aspect of e-waste management involves employing data analytics to oversee e-waste handling and disposal, thereby mitigating environmental impacts (Mahdi, 2017).

Big data is recognized as an optimal technology in this context (Lu, 2018). Additionally, the potential of big data extends to improving logistics performance, measurable in terms of market, operational, and financial metrics (Golobic & Smith, 2013; Gunasekaran & Kobu, 2007; Hult et al., 2008). As the technology revolution unfolds, an escalating number of electronic devices infiltrate our surroundings. The disposal of these items through traditional means poses a significant environmental threat due to the presence of built-in hazardous components once they become obsolete. In recent years, Big Data Analytics (BDA) applications have gained increasing attention within the scientific community. However, there exist gaps in the utilization of BDA, particularly in the realm of e-waste management, resulting in its industry adoption remaining in its early stages. Furthermore, empirical contributions in this specific domain have been hampered by the lack of properly validated measurement models.

Given these challenges, this study utilizes a cross-sectional research design based on the Resource-Capability-Advantage (RCA) theory to investigate the interplay between Big Data Analytics (BDA) management capabilities, BDA talent capabilities, Reverse Logistics (RL) innovation, and sustainable RL performance within the e-waste management sector. Data was gathered from practitioners and managers in India's e-waste reverse logistics network at a single point in time, capturing a comprehensive snapshot for analysis. Structural Equation Modeling (SEM) served as the primary analytical method, allowing for the simultaneous exploration of these complex relationships and providing insights into how BDA capabilities can foster innovation and improve sustainability in RL systems. To empirically assess the impact of Big Data Analytics (BDA) capabilities on sustainable reverse logistics performance, a conceptual model has been developed. This model also examines how Reverse Logistics (RL) Innovation influences the relationships between BDA capabilities and the sustainable reverse logistics performance of e-waste. A comprehensive understanding of how BDA management capabilities, along with talent capabilities, contribute to the improvement of sustainable reverse logistics performance in e-waste will provide practitioners with valuable insights for more informed decision-making.

In light of this, the research work aims to achieve the following objectives:

To analyze the degree of impact of BDA Capabilities on both RL Innovation and the Sustainable Reverse Logistics Performance of e-waste.

To analyze the impact of Reverse Logistics Innovation on the relationships between BDA Capabilities and Sustainable Reverse Logistics Performance of e-waste.

Conceptual Framework and methodology

Sustainable supply chain performance can be achieved through effective BDA management capability, particularly under conditions of high environmental uncertainty, a critical factor for organizations (Janssen et al., 2017). The application of BDA in strategic sourcing and procurement holds particular significance, especially in areas such as demand planning and logistics activities (Tiwari et al., 2018), necessitating specialized staff skills (Wood et al., 2017). Enhancing employee competencies based on BDA capabilities can, in turn, positively influence the operational styles of companies (Dries et al., 2012; Malik & Singh, 2014). Both BDA management capabilities and talent capabilities exert a significant impact on sustainable supply chain outcomes, as demonstrated by Bag et al. (2020). Findings from Bag and team

(2020) underscore the significant influence of management capabilities in big data analytics on both the development of innovative green products and the outcomes of sustainable supply chains. Additionally, the capabilities of big data analytics talent demonstrate a somewhat less prominent yet still meaningful impact on employee development and the outcomes of sustainable supply chains. Braganza and colleagues (2017) highlighted the importance of strategic capabilities within Big Data (BD) initiatives. The study underscores the substantial potential for comprehensive employee development through Big Data Analytics (BDA) capabilities, as emphasized in opportunities identified by Dries et al. (2012). As a result, the capabilities of BDA talent play a critical role in fostering effective employee development, shaping companies' working styles, and cultivating new employee competencies (Malik & Singh, 2014). The increasing prevalence of vast data in various facets of contemporary organizations adds complexity to employee development (Shah et al., 2017). In terms of information support, Daugherty et al. (2001) found that dedicating management resources significantly influences the achievement of Reverse Logistics (RL) program goals. Their later work in 2005 emphasized the essential role of utilizing information technology (IT) capabilities in RL management, showing positive impacts on economic and service quality performance through information support for returns authorization, tracking, and handling. A comprehensive six-year review by Tiwari et al. (2018) delves into the application of Big Data Analytics (BDA) in supply chain management, covering strategic sourcing, procurement, demand planning, and logistics. Evolving processing technologies are expected to support collaborative and simultaneous smart services, incorporating intelligent processors for various processing modes to meet diverse requirements (Zhong et al., 2016). Additionally, Jack et al. (2010) demonstrated that RL capabilities contribute to cost savings. Despite the acknowledged adaptability of BDA in planning, its effective use often necessitates specialized staff skills (Wood et al., 2017). In terms of innovation, Richey et al. (2005) argued that resources can be strategically directed toward cultivating innovative RL capabilities to enhance performance and achieve competitive differentiation. The research utilizes the resource-capability-advantage (RCA) theory, as outlined by Hunt and Morgan (1996), as the conceptual framework to explore the influence of developing RL-related capabilities and outcomes. Rekha and Resmi (2021) underscored the influence of technology on innovation, which subsequently affects service quality and firm performance. Olorunniwo and Li's (2010) further emphasized the positive influence of IT operational characteristics, information sharing, and association on RL performance. The findings indicate a positive relationship between RL innovation and both environmental and economic performance, as reported by Huang and Yang in 2014. In order to empirically assess the influence of Big Data Analytics (BDA) Capabilities on sustainable reverse logistics performance within the realm of e-waste, and to analyze the impact of RL Innovation, we have devised a conceptual model. Grounded in both existing literature and the study's objectives, this conceptual model clarifies the relationships among critical constructs: BDA Management Capabilities, BDA Talent Capabilities, RL Innovation, and Sustainable Reverse Logistics Performance.

Figure 1 illustrates the conceptual model for this study.

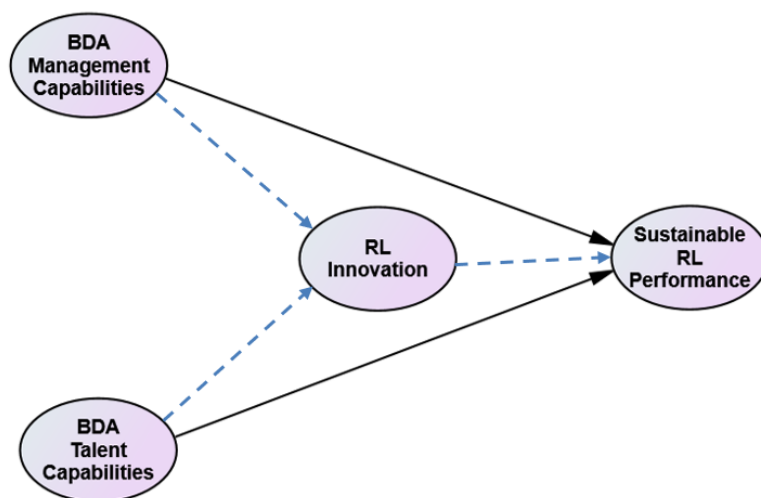


Figure 2 Conceptual Model

Three statistical hypotheses have been formulated, and they are outlined as follows:

H1: BDA Management Capabilities (a) and BDA Talent Capabilities (b) are positively related to the RL Innovation of e-waste.

H2: BDA Management Capabilities (a) and BDA Talent Capabilities (b) are positively related to Sustainable Reverse Logistics Performance of e-waste.

H3: In the relationships between BDA Management Capabilities (a) and BDA Talent Capabilities (b), with the Sustainable Reverse Logistics Operational Performance of e-waste, RL Innovation acts as a mediator.

The proposed study aligns with Positivism, employing a Deductive approach as the statistical hypothesis seeks to test a theory. This study aims to conduct a causal analysis to examine the impact of BDA capabilities on Sustainable Reverse Logistics Operational Performance, considering the influence of RL Innovation. Therefore, the proposed research adopts a Quantitative, Descriptive, Analytical approach, emphasizing model building. To address our research inquiries, we adopted a methodological approach involving structural equation modeling, utilizing primary data gathered through a structured questionnaire distributed to practitioners and managers at various stages of the e-waste reverse logistics network (Cross-sectional Design) in India. This approach enables us to simultaneously examine hypothesized relationships and mediation effects. The scales, sourced from established studies, were carefully chosen to confirm both reliability and validity in our study. These include BDA Management Capability (6 items) and BDA Talent Capability (9 items), measured using a 5-point Likert scale (from 1 for 'strongly disagree' to 5 for 'strongly agree'), which was used and adapted from Akter et al. (2016) and Bag et al. (2020). RL Innovation (5 items) was measured using a 7-point scale (from 1 for 'strongly disagree' to 7 for 'strongly agree') and adapted from Huang & Yang (2014). Finally, Sustainable RL Performance (6 items) was measured using a 5-point Likert scale (from 1 for 'very low' to 5 for 'very high') and adapted from Khalili-Damghani et al. (2015). To investigate the research inquiries, we selected participants from practitioners and managers engaged in different phases of the e-waste reverse logistics network within the Indian electronic industry. Our survey's random sample was drawn from a list obtained from the open Government Data Portal. We gathered 241 complete and valid responses through the administration of a structured questionnaire in digital format, free from any missing values or outliers.

Table 1 summarizes the respondents' work experience in supply chain and logistics, along with their proficiency in IT and Big Data Technologies. The findings indicate that the majority of respondents possess over a decade of work experience and demonstrate proficiency levels above intermediate in both IT and Big Data Technologies. This suggests a considerable depth of knowledge, which should adequately address the survey's inquiries.

Table 1 Respondents' work experience and proficiency in IT and Big Data Technologies

	Novice	Beginner	Intermediate	Advanced	Expert
Proficiency in overall IT knowledge	8.71%	12.45%	28.63%	29.46%	20.75%
Proficiency in Big Data Technologies	9.54%	20.75%	23.65%	24.07%	21.99%
	Less than 5 years	5 - 10 years	11 - 15 years	Above 15 years	
Work Experience	13.29%	20.75%	35.68%	30.29%	

*Source: Constructed by the authors based on primary data
n=241*

Data Analysis

In this study, the Zskewness and multivariate Zkurtosis values are found to be within the specified critical range of ± 2.58 (at a 0.01 significance level). This confirmation indicates that the data associated with each construct display characteristics consistent with a normal distribution. Additionally, both Levene's test and Box's M test yield non-significant results, surpassing the 0.05 threshold (Hair et al., 2006), signifying the fulfillment of the assumption of homoscedasticity. Moreover, the results of the curvilinear regression for both datasets reveal the highest and statistically significant values in the linear regression equation model, providing affirmation that both datasets adhere to the assumption of linearity. Lastly, all independent variables exhibit VIF values below 5, along with tolerances above 0.2, indicating the absence of multicollinearity concerns. Detailed summary statistics for the latent constructs are presented in Table 2.

Table 2 Summary Statistics for Latent Constructs

Construct	Measurement Items	Item Code	Mean	Std. Deviation
BDA Management Capabilities (Aker et al., 2016) (Bag et al., 2020)	We continuously examine the innovative green opportunities for the strategic use of BDA	BMC1	3.02	1.072
	We enforce adequate plans for the introduction and utilization of BDA	BMC2	2.95	1.198
	We perform BDA planning processes in systematic and formalized ways	BMC3	3.00	1.082
	We frequently adjust BDA plans to better adapt to changing environmental conditions	BMC4	2.94	1.142
	In our organization, business analysts and design people meet frequently to discuss important issues both formally and informally	BMC5	2.90	1.178
	In our organization, information is widely shared between business analysts and line people so that those who make decisions or perform jobs have access to all available know-how	BMC6	2.94	1.213
BDA Talent Capabilities (Aker et al., 2016) (Bag et al., 2020)	Our analytics personnel are very capable in terms of programming skills	BTC1	3.24	1.321
	Our analytics personnel are very capable in terms of managing project lifecycles	BTC2	3.21	1.282
	Our analytics personnel are very capable in the areas of data and network management and maintenance	BTC3	3.15	1.251
	Our analytics personnel show superior understanding of technological trends	BTC4	3.17	1.327
	Our analytics personnel are very knowledgeable about the critical factors for the success of our organization	BTC5	3.25	1.270
	Our analytics personnel understand our organization's policies and plans at a very high level	BTC6	3.22	1.302
	Our analytics personnel are very knowledgeable about the business environment	BTC7	3.32	1.348
	Our analytics personnel work closely with suppliers for providing key inputs useful for developing innovative green products	BTC8	3.16	1.212
	Our analytics personnel work closely with customers and maintain productive user/client relationships	BTC9	3.18	1.300
RL Innovation (Huang and Yang, 2014)	Firm address RL activities mainly with technology firms that have development (customization)	RLI1	4.11	1.641
	To better handle returns, firm created own systems and procedures (formalization)	RLI2	4.09	1.637
	When products are returned, firm is good at finding own ways of handling them (flexibility)	RLI3	4.01	1.666
	To better manage RL activities, firm's information system is available (information-related ability)	RLI4	4.09	1.673
	To better handle RL, firm has well connectivity at marketing – operations interface (functional integration)	RLI5	4.19	1.706
Sustainable RL Performance (Khalili-Damghani et al., 2015)	Percentage of reduction of consumption of rare material/ non-renewable energy/hazardous materials/ products / process (Green image)	SRP1	3.25	1.168
	Feasibility in recycling/ repair options (Flexibility)	SRP2	3.37	1.208
	Number of faulty/ badly damaged returns (Quality)	SRP3	3.24	1.239
	Return rates by returns' reason (Responsiveness)	SRP4	3.19	1.237
	Total cost for testing/ sorting/ repair/ refurbishment/ remarketing/ redistribution inventory/ Reverse distribution / land filling/ scrapping/ information and communication technology (ICT) support installed for RL (Expenses)	SRP5	3.29	1.221
	Cost avoidance by reusing refurbished parts/products in the forward supply chain/ recycling materials (Value recovered)	SRP6	3.35	1.243

Source: Constructed by the authors based on primary data
n=241

The results of individual Confirmatory Factor Analysis (CFA) are detailed in Table 3, which evaluates the adequacy of the measurement model by examining each latent construct separately. Summarized in the same table, all constructs demonstrate convergent validity, supported by statistically significant ($p < 0.001$) factor loadings (≥ 0.5). Additionally, the Average Variance Extracted (AVE) values surpass the suggested minimum threshold of 0.50 (Hair et al., 2009; Zainudin, 2012; Fornell & Larcker, 1981). Moreover, R2 values exceed 0.5, as advocated by Easterby-Smith (1991). Furthermore, both composite reliability and Cronbach's alpha values for all constructs exceed the recommended threshold of 0.70 (Hair et al., 2009).

Table 3 Convergent validity

Construct	Item Code	Convergent Validity				Squared Multiple Correlations (>0.5)
		Standardized Regression Weight (> 0.5)	Average Variance Extracted (≥ 0.5)	Cronbach's Alpha (≥ 0.7)	Composite Reliability (≥ 0.7)	
BDA Management Capabilities	BMC1	.791	.622	.908	.908	.626
	BMC2	.779				.607
	BMC3	.739				.546
	BMC4	.786				.619
	BMC5	.826				.682
	BMC6	.810				.655
BDA Talent Capabilities	BTC1	.816	.696	.954	.954	.666
	BTC2	.797				.636
	BTC3	.796				.634
	BTC4	.855				.731
	BTC5	.841				.708
	BTC6	.853				.727
	BTC7	.878				.771
	BTC8	.816				.666
	BTC9	.850				.722
RL Innovation	RLI1	.835	.683	.915	.915	.697
	RLI2	.825				.680
	RLI3	.839				.703
	RLI4	.814				.663
	RLI5	.818				.670
Sustainable RL Performance	SRP1	.859	.679		.927	.737
	SRP2	.802				.642
	SRP3	.790				.624
	SRP4	.796				.634
	SRP5	.839				.703
	SRP6	.855				.731

Source: Constructed by the authors based on primary data
n=241

Discriminant validity is assessed through Pooled Confirmatory Factor Analysis (CFA), with the findings outlined in Table 4. The inter-correlation values among the exogenous constructs are maintained below .85, as recommended by Zainudin (2012).

Table 4 Inter-correlation Values among Exogenous Constructs

Constructs	Inter Correlation	
	BDA Management Capabilities	BDA Talent Capabilities
BDA Management Capabilities	-	
BDA Talent Capabilities	.151	-

Source: Constructed by the authors based on primary data
n=241

Additionally, as depicted in Table 5, the Average Variance Extracted (AVE) values surpass the squared inter-correlation values, aligning with the recommendations established by Hair et al. (2009) and Fornell & Larcker (1981), thereby ensuring discriminant validity.

Table 5 Average Variance Extracted (AVE) and Squared Inter-correlation Values among Exogenous Constructs

Constructs	Square of Inter Correlation		AVE
	BDA Management Capabilities	BDA Talent Capabilities	
BDA Management Capabilities	-		.622
BDA Talent Capabilities	.023	-	.696

Source: Constructed by the authors based on primary data
n=241

After confirming the assumptions of Structural Equation Modeling (SEM), the validity and reliability of the constructs are evaluated, and the results show that the values are within the recommended threshold

limits. The fitness indices for latent constructs, detailed in Table 6, indicate that GFI, AGFI, NFI, RFI, IFI, TLI, and CFI all exceed 0.90. Additionally, both RMSEA and SRMR values are below 0.08, in accordance with the guidelines from Hu and Bentler (1999) and Hair et al. (2009).

Table 6 Fitness Indices for Latent Constructs

Construct	CMIN/DF	χ^2	RMSEA	SRMR	GFI	AGFI	NFI	RFI	IFI	TLI	CFI
BDA Management Capabilities	.830	7.473	.000	.018	.990	.976	.991	.985	1.002	1.003	1.000
BDA Talent Capabilities	1.626	43.893	.051	.031	.963	.938	.977	.969	.991	.988	.991
RL Innovation	2.884	14.418	.08	.055	.977	.930	.982	.964	.988	.976	.988
Sustainable RL Performance	1.851	16.663	.060	.027	.979	.950	.984	.973	.993	.987	.992

*Source: Constructed by the authors based on primary data
n=241*

Model Fit

As depicted in Table 7, the model exhibits commendable suitability for testing hypotheses, demonstrated by a χ^2 value of 513.697 and a CMIN/DF value of 1.753. Notably, the CMIN/DF values fall below the accepted threshold of 5.0, as stipulated by Marsh and Hocevar (1985). Furthermore, both the RMSEA and SRMR values remain below the recommended limit of 0.08, in accordance with guidelines outlined by Hair et al. (2009) and Hu & Bentler (1999). Moreover, the GFI, AGFI, NFI, RFI, IFI, TLI, and CFI all exceed the recommended threshold of 0.90, aligning with criteria established by Hair et al. (2009) and Hu & Bentler (1999).

Table 7 Model fit summary

CMIN/DF	χ^2	RMSEA	SRMR	GFI	AGFI	NFI	RFI	IFI	TLI	CFI
1.753	513.697	.056	.062	.864	.837	.904	.894	.957	.952	.956

*Source: Constructed by the authors based on primary data
n=241*

Figure 2 illustrates the structural model used to investigate the impact of BDA capabilities on Sustainable RL Performance, taking into account the influence of RL Innovation.

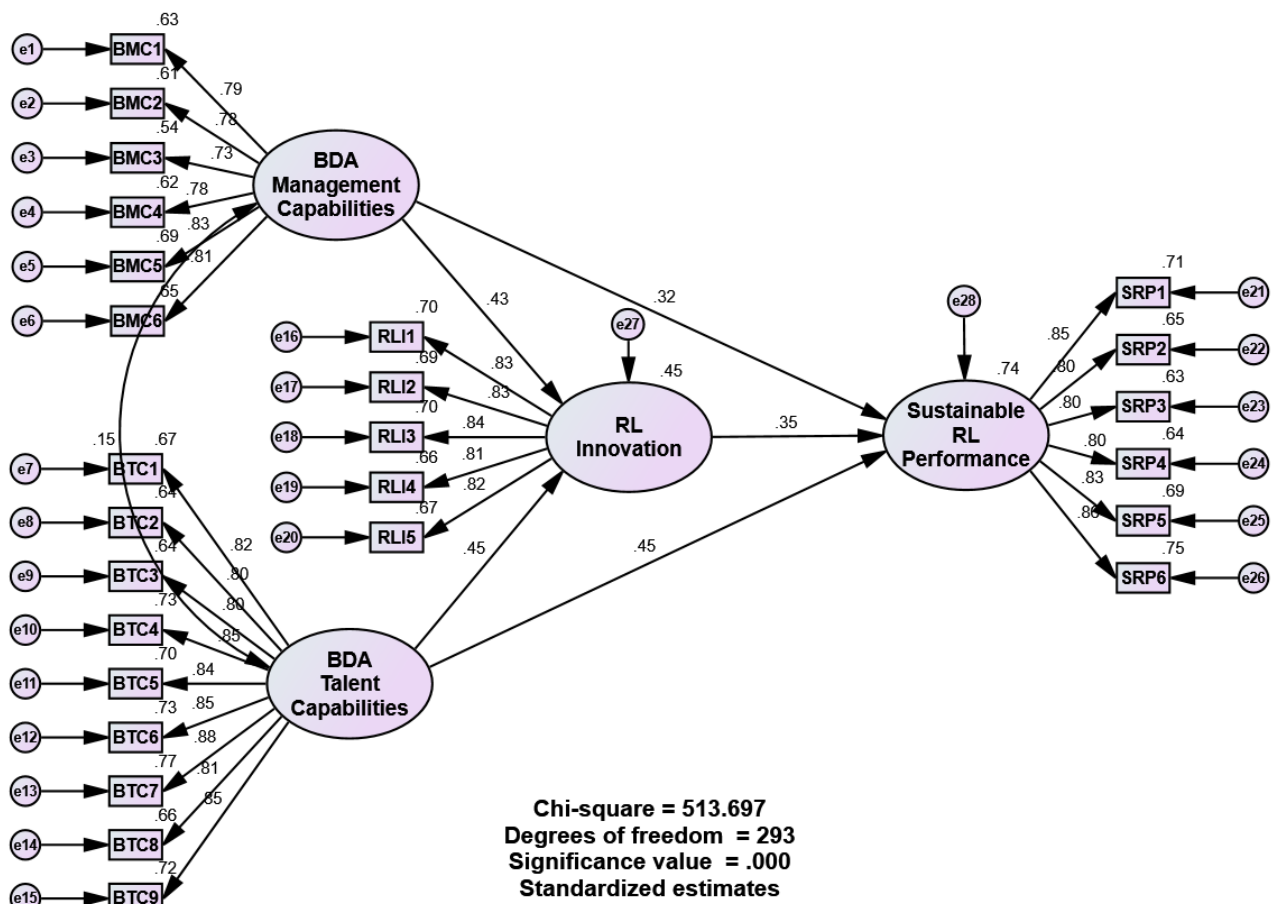


Figure 3 Tested Structural Model (Source: Constructed by the authors based on primary data)

Testing of Hypothesis

Table 8 illustrates a significant relationship between BDA Capabilities and RL Innovation. The results clearly indicate a significant positive relationship between BDA Management Capabilities and RL Innovation, evidenced by a standardized regression weight of 0.430, with a significance level below 0.001 (S.E. = 0.101, t Value (C.R.) = 6.870***). Therefore, hypothesis H1a is confirmed.

Additionally, the study reveals a significant positive relationship between BDA Talent Capabilities and RL Innovation, evidenced by a standardized regression weight of .449, with a significance level below 0.001 (S.E. = .078, t Value (C.R.) = 7.323***). Consequently, hypothesis H1b is accepted.

Similarly, the results indicate a significant positive relationship between BDA Management Capabilities and Sustainable RL Performance, as evidenced by a standardized regression weight of .317, with a significance level below 0.001 (S.E. = .062, t Value (C.R.) = 5.924***). Therefore, we accept hypothesis H2a.

Moreover, the findings demonstrate a significant positive relationship between BDA Talent Capabilities and Sustainable RL Performance, supported by a standardized regression weight of .452, with a significance level below 0.001 (S.E. = .051, t Value (C.R.) = 8.130***). Accordingly, hypothesis H2b is accepted.

Table 8 Testing of hypothesis H1a, H1b, H2a and H2b

Hypothesis	Relationship (Structural Path)	Standardized path coefficient (Standardized Regression Weight)	S.E.	t Value (C.R.)	Comments
H1a	BDA Management Capabilities → RL Innovation	.430	.101	6.870***	Supported
H1b	BDA Talent Capabilities → RL Innovation	.449	.078	7.323***	Supported
H2a	BDA Management Capabilities → Sustainable RL Performance (Standardized Direct Effect)	.317	.062	5.924***	Supported
H2b	BDA Talent Capabilities → Sustainable RL Performance (Standardized Direct Effect)	.452	.051	8.130***	Supported

Source: Constructed by the authors based on primary data

n=241

*** $p < 0.001$

Shifting focus to the outcomes, Table 9 illustrates a noteworthy indirect correlation between BDA Management Capabilities and Sustainable RL Performance, mediated by RL Innovation, as indicated by a standardized regression weight of .149, with a significance level below 0.001 ($p = .000$). Hence, hypothesis H3a is accepted.

Similarly, there exists a significant indirect relationship between BDA Talent Capabilities and Sustainable RL Performance through the mediating role of RL Innovation, supported by a standardized regression weight of .155, with a significance level below 0.001 ($p = .000$). Consequently, hypothesis H3b is accepted.

Both hypotheses H3a and H3b provide evidence for the partial mediation effect of RL Innovation in the relationships between BDA Management Capabilities and BDA Talent Capabilities on Sustainable RL Performance, as both the direct and indirect relationships are statistically significant.

Table 9 Testing of hypothesis H3a and H3b

Hypothesis	Relationship (Structural Path)	Standardized path coefficient (Standardized Regression Weight)	Comments
H3a	BDA Management Capabilities → RL Innovation → Sustainable RL Performance (Standardized Indirect Effect)	.149 ($p = .000$)	Supported
H3b	BDA Talent Capabilities → RL Innovation → Sustainable RL Performance (Standardized Indirect Effect)	.155 ($p = .000$)	Supported

Source: Constructed by the authors based on primary data
n=241

Discussion

The literature review distinctly emphasizes the significant potential benefits linked to the impact of big data analytics in Reverse Logistics, despite a scarcity of empirical research and practical insights in this domain (Richey et al., 2016). The study holds importance in its comprehensive investigation of the connections between Big Data Analytics (BDA) Management and Talent Capabilities and their influence on Reverse Logistics (RL) Innovation and Sustainable RL Performance. The identified connections outlined in hypothesis H1a between BDA Management Capabilities and RL Innovation, and in hypothesis H1b between BDA Talent Capabilities and RL Innovation, underscore the role of BDA in fostering innovation within organizations. This emphasizes the relevance of leveraging data analytics competencies for driving novel solutions and practices. The observed significant relationship between BDA Management Capabilities and Sustainable RL Performance (H2a) emphasizes the pivotal role of effective data management strategies in fostering sustainable business practices. This underscores the relevance of incorporating robust BDA frameworks within organizations aiming for enduring performance outcomes. The substantial connection found between BDA Talent Capabilities and Sustainable RL Performance (H2b) highlights the importance of nurturing talent equipped with advanced data analytics skills. This underscores the relevance of human capital development in achieving sustainable business performance through data-driven decision-making. The acceptance of hypotheses H1a, H1b, H2a and H2b anticipates positive outcomes for organizations that prioritize and invest in enhancing both management and talent capabilities in the realm of data analytics. Enhanced BDA capabilities make a substantial contribution to both sustainable performance and innovation, as indicated by the results. Recognizing the indirect connections in hypotheses H3a and H3b foresees a nuanced comprehension of how RL Innovation serves as a mediator in the relationship between BDA capabilities and Sustainable RL Performance. This implies that cultivating innovation through data analytics acts as a crucial intermediary step towards achieving sustainable outcomes.

Conclusion

The research offers practical guidance for managers by presenting empirical evidence of the substantial relationships among BDA capabilities, RL Innovation, and Sustainable RL Performance. Through an examination of both management and talent capabilities, this research enhances our understanding of the comprehensive role of BDA in the reverse logistics domain. The recognition of RL Innovation as a partial mediator in the relationships between BDA Management and Talent Capabilities with Sustainable RL Performance adds a nuanced layer to the existing knowledge. Moreover, this research contributes valuable insights to guide organizations in aligning their strategies with the evolving landscape of sustainable business practices, emphasizing the pivotal role of BDA capabilities and innovation in achieving enduring performance outcomes. The expected contributions of the proposed study span both societal and operational dimensions. Ultimately, this research is anticipated to make a substantial contribution to the body of knowledge in supply chain and logistics management by formulating and validating a theoretical model.

The proposed outputs from this research encompass actionable insights for organizations seeking to enhance their performance, sustainability, and innovation strategies. The identification of significant relationships between BDA capabilities and RL Innovation encourages organizations to integrate data-driven approaches in fostering innovative solutions. Organizations can leverage the evidence-supported connection between BDA Management Capabilities and Sustainable RL Performance to refine their data management practices, promoting long-term sustainability. Recognizing the impact of BDA Talent Capabilities on Sustainable RL Performance suggests that investing in talent development in data analytics is a key strategy for achieving sustainable business outcomes. The highlighted mediation effects in hypotheses H3a and H3b provide a roadmap for organizations to understand and strategically leverage RL Innovation as a key driver in the relationship among BDA capabilities and sustainable RL performance. Organizations should strategically invest in developing both BDA Management and Talent Capabilities to enhance RL Innovation, thereby positively impacting Sustainable RL Performance. Recognizing the substantial influence of BDA Talent Capabilities on RL Innovation, managers should focus on talent development programs to cultivate analytical skills within their workforce. Managers should adopt integrated approaches that leverage both management and talent capabilities in BDA for optimal results in RL Innovation and Sustainable RL Performance.

Limitations of the Research and Implications for Further Research

The study's findings are based on a specific context, limiting the generalization of results to diverse industries or regions. The study's cross-sectional nature may not capture temporal dynamics, highlighting the need for longitudinal studies to achieve a more comprehensive understanding. Despite rigorous methodologies, measurement biases may exist, urging caution in the interpretation of results. Future studies could address these limitations for a more robust analysis.

Future research could explore the dynamic nature of BDA capabilities over time and its impact on RL Innovation and Sustainable RL Performance. Investigating how BDA capabilities influence reverse logistics in different industries could provide insights into industry-specific nuances. Exploring the integration of emerging technologies with BDA in reverse logistics may uncover additional dimensions for improvement.

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