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Research Article

The Relationship between Big Data Analytic-Artificial Intelligence and Environmental Performance: A Moderated Mediated Model of Green Supply Chain Collaboration (GSCC) and Top Management Commitment (TMC)

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Academics and practitioners have shown growing interests in big data analytics and artificial intelligence (BDA-AI) in recent years. Despite this, research on the application of BDA-AI for green supply chain collaboration (GSCC) and its influence on environmental performance (EP) is still limited. The current research addresses this gap and extends organizational information processing theory by incorporating BDA-AI and exploring top management commitment (TMC) as a moderator. The current study developed a moderated mediation model based on 402 samples of data from Turkish manufacturing firms. The result revealed that the application of BDA-AI has a positive impact on GSCC and EP. The results also indicated that GSCC has a positive impact on EP. Our findings revealed that GSCC mediated the association between BDA-AI and EP. The results also revealed that TMC moderated the positive relationship between BDA-AI and GSCC, such that the strength of the positive relationship is further intensified at higher levels of TMC. The results also show that TMC moderated the positive relationship between BDA-AI and EP, such that the strength of the positive relationship is dampened at lower levels of TMC; significant findings have not been outlined in the extant literature. The current research will assist supply chain and logistics managers and top management in deploying BDA-AI technology to support GSCC and improve EP.

1. Introduction

The application of big data analytics has drawn a lot of interest in both theory and practice in the last decade [1]. Papadopolous and Gunasekaran [2] attributed this to the rapid growth of information technology, which has enabled big data to gain key relevance and has grown to be among the most beneficial resources in several organizations. Additionally, organizations are going digital, and as a result, their supply chains are generating a large volume of data [3, 4]. According to Papadopolous et al. [5], the growth in data has prompted several organizations to build data analytics techniques such as big data analytics (BDA) to turn the data into meaningful information that would aid decision-making and boost their supply chain efficiency. However, for the environmental dimension, studies examining the impacts of BDA on the supply chain are still in their early stages [6]. With a few notable exceptions [6, 7], the number of empirical studies that have shown the effects of big data on green supply chain collaboration (GSCC) and environmental performance (EP) are still limited.

According to numerous researchers, integrating the environment into the supply chain provides organizations with a competitive advantage [8, 9]. However, the process is complex [9] and requires the collaboration and coordination of numerous organizations working together to achieve their desired goals [10]. It is important for all industries to improve their environmental performance (EP), but it is especially important for the manufacturing industry, which is a major source of pollution all along its supply chain.

The Turkish manufacturing industry is an important aspect of the country's economic development, acting as a catalyst for modernization and generating multiplier effects. However, several studies have indicated that the manufacturing sector generates emissions that cause environmental pollution [11, 12]. Thus, the manufacturing sector must identify ways to optimize material usage and improve operational processes [13]. When aiming for green initiatives, organizations must think from the perspective of their supply chain [14], especially in the manufacturing sector. A significant challenge that makes it more difficult to achieve green initiative results is the supply chain's members' involvement and participation [15]. So, managing the supply chain well is a key part of making sure that green initiatives in the manufacturing sector work.

BDA capabilities, powered by artificial intelligence, will drive the future of supply chain computerization to increase the visibility of green supply chains [16, 17]. This would make it highly helpful for the manufacturing sector to gain knowledge on how to apply big data analytics approaches and concepts in establishing environmental initiatives. Additionally, big data analytics can facilitate large-scale group decision-making techniques in a circular economy [18]. From this point of view, it makes sense to think that GSCC may be a link between BDA-AI and EP.

Despite the numerous studies on the importance of BDA-AI in manufacturing research, which aids organizations in cost reduction [19], increasing production speed [20], and developing new services or products in response to changes in the needs of consumers [21, 22], research on using BDA-AI in promoting manufacturing supply chain processes, especially green practices, is still very limited. Therefore, the current study focuses on the impact of BDA-AI in improving environmental performance in the manufacturing sector, an area that, to our knowledge, has received little research attention.

Furthermore, as a result of mounting pressure from both internal and external stakeholder groups, organizations' leaders are now held accountable for establishing cleaner operations [23]. This further demonstrates that environmental concerns have clearly become top priorities for corporations [24]. Additionally, top management's roles in green supply chain initiatives have received little attention [25]. In relation to sustainable supply chain management, the extent to which top management commitment plays a role in the link between BDA-AI technology and EP has not been rigorously empirically explored [6], especially in Turkey. To address these gaps, the current study developed a moderated mediation model that tested the mediating role of GSCC and the moderating role of top management commitment in the relationship between BDA-AI and EP in the context of the Turkish manufacturing sector. Figure 1 shows the conceptual model of the study and the proposed hypotheses.

2. Theoretical Rationale and Hypotheses Development

2.1. BDA. It is challenging to come to an agreement on a definition given the current widespread acceptance of BDA and the usefulness of its applications. According to Mikalef et al. [26], there is a new generation of technologies and architectures that facilitate high-velocity data capture, discovery, and analysis with the aim of economically extracting value from very large amounts of a wide variety of data. It uses innovative algorithmic methods and practices that enable organizations to analyze and make sense of crucial business data in order to better understand their operations and the market [2]. Therefore, it enabled them to gain a competitive advantage [19]. Among these advantages, there are supply chain and logistics management [2]. So, it is not surprising that researchers in management science and supply chain and logistics management have started to pay attention to BDA. Brynjolfsson et al. [27] attributed this to its ability to employ techniques that allow decision makers to arrive at improved decisions founded on evidence as opposed to intuition or human judgement. It necessitates the establishment of proper tools to handle the potential amount of data and, as a result, detect trends and uncover models to obtain advantageous outcomes [17]. The study by Choi et al. [28] distinguished three types of data processing schemes, namely, batch processing, real-time flowing processing, and interactive processing. BDA-related systems can be used in various areas of analysis, including descriptive, predictive, and normative analysis [29].

Through the combination of methods, tools, and processes, BDA helps firms make effective decisions regarding green initiatives in their supply chain [30]. Even so, the impact of BDA on GSCC and EP's decision-making processes is not well understood or established in the literature.

2.2. Green Supply Chain Collaboration in the Manufacturing Sector. Green supply chain management (GSCM), which combines studies on green management and supply chain management, is used to address environmental issues in organizations and their supply chains [31]. Every day organizations are confronted with pressures from the media, surrounding communities, nongovernmental organizations, and legal requirements enforced by environmental legislation [32]. Additionally, consumers are calling for greater accountability and transparency regarding the circumstances surrounding the manufacture and distribution of their goods. They also call for greater environmental sensitivity [32]. As a result, organizations are compelled to make significant efforts to create a more sustainable supply chain and reevaluate how they conduct their business as they become more aware of their obligation to ensure the long-term survival of humanity [33, 34]. So, for green

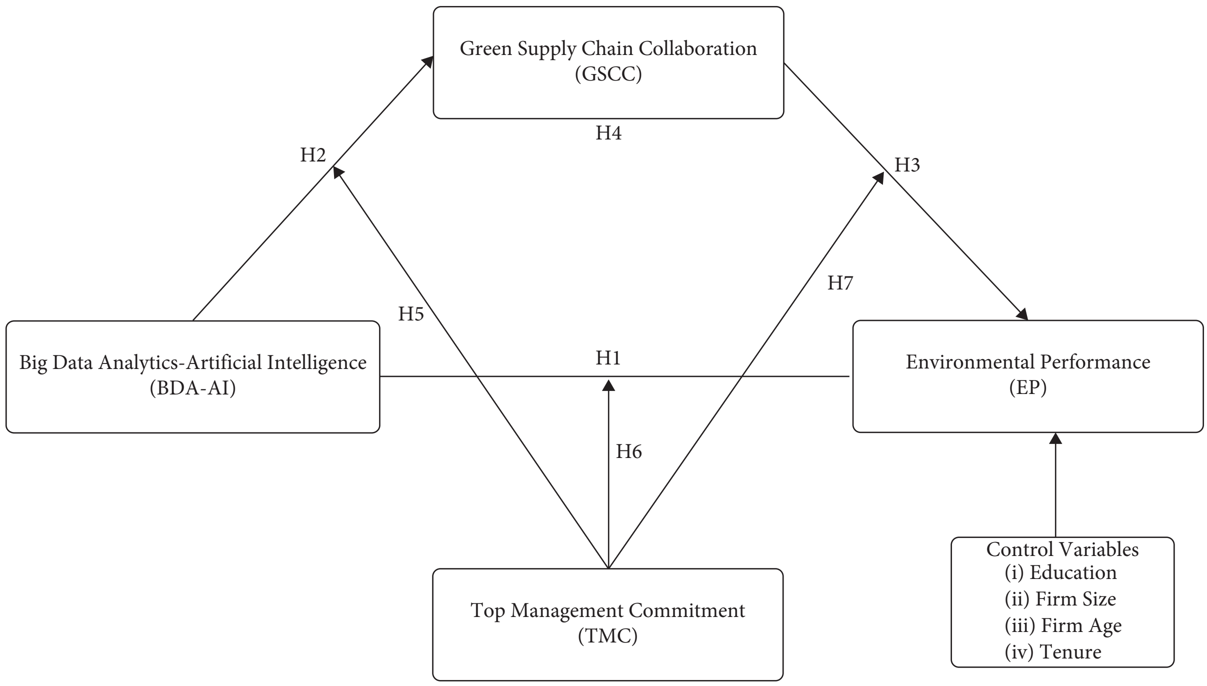

Figure 1: Conceptual framework.

management to happen, companies need to focus on the supply chain instead of the organizations themselves [14]. This is especially important in the manufacturing sector, where pollution has a big effect on the environment.

In a circular economy, GSCC relates to the degree to which organizations and their suppliers contribute to enhancing environmentally friendly decision making and performance, such as through the design of environmentally friendly products, the production and recycling of materials, the handling of waste, and the reusing of materials all through the life cycle of flow [35]. In the manufacturing sector, GSCC requires the synchronization and collaboration of several organizations [36]. Thus, the probability of achieving green initiatives within the supply chain increases with the degree of consultation and collaborative relationship between supply chain partners [37]. Also, the earlier study by Chen and Chen [38] advocated the use of collaboration among supply chain members so as to share knowledge, rationalize core business processes, and streamline interorganizational operations. However, Corso et al. [39] emphasized that several organizations are yet to comprehend the primary factor that allows organizations to implement green supply chain collaborative efforts. This study, however, proposes that the use of advanced technology (BDA-AI) can equip the manufacturing supply chain with the capacity to enhance flow management, processes, and cross-organizational relationships with the aim of attaining environmental performance.

2.3. Big Data Analytic-Artificial Intelligence in the Manufacturing Sector. Although there is a significant amount of literature on the adoption of emerging technologies [7], the research on the role of the adoption of emerging technologies (BDA and BDA-AI) on environmental performance remains relatively scarce in the manufacturing sector. Artificial intelligence and its technologies have been extensively utilized in the supply chain context since SCM has become more data intensive and its concerns have been aimed toward the substitution of assets (such as inventory, warehouses, and transport equipment). The benefits acquired in this domain in the manufacturing sector are abundant, including faster production, cost optimization, and the creation of new products [19, 21, 22]. Apart from its operational benefits, the combination of BDA and AI provides an encouraging window of opportunity for manufacturing sector studies. The combination of BDA and AI has already been proven efficient in the manufacturing sector, most notably in the creation of new products and services [22]. Thanks to the ability to process information faster, the manufacturing sector can better plan its resources. These benefits provide a significant benefit for controlling flows and procedures in the manufacturing supply chain, including transportation and warehousing, internal production, and waste handling sorting and treatment. In this study, the use of BDA-AI means using BDA mixed with AI to get more useful information so that organizations can improve their ability to make decisions [7].

Furthermore, the manufacturing supply chain has widely used organizational information processing theory [40]. The theory has not, however, been empirically applied in the particular research field of manufacturing green supply chains [6]. Given the complex nature of the manufacturing supply chain (such as inventory, warehouses, and transport equipment). The use of OIPT as a theoretical framework was appropriate. By using information processing mechanisms, the theory offers a sound foundation regarding the interpretation of the concept of organizational behavior in businesses [41]. Consequently, Galbraith [42] stated that technology infrastructure can enhance organizations' information processing capabilities. Based on this and considering the complexity of the manufacturing sector, we suggest BDA-AI techniques should develop information processing capacity to best support green decision-making. Dubey et al. [43] say that despite the opportunities that BDA-AI offers, many organizations have not been able to use it effectively to promote green supply chain operations.

2.4. BDA-AI and Environmental Performance. According to Wu and Pagell [44]; big data analytics powered by artificial intelligence play an important role in green supply chain management by removing information asynchronization and handling complex environmental data. Therefore, it offers insights for decision-making processes in order to promote green supply chain management and EP [45]. Chiarini's qualitative study (2021) found that AI and analytics are important for analyzing and finding patterns in data, predicting the effects on the environment, and reducing energy use, all of which improve environmental performance.

A number of researchers have suggested that the application of BDA is crucial in integrating environmental initiatives into several supply chain activities. For example, Lee and Klassen [46] argued that BDA can be very helpful in manufacturing, storing, and waste management, thus improving EP. The use of BDD-AI in the context of green supply chain management through eco-design and supplier selection has been reported to promote environmental performance [47]. Liu et al. [48] and Singh et al. [49] also say that BDA-AI improves internal green operations and supplier collaboration, which both reduce waste, emissions, and environmental risks.

Most of the abovementioned studies only offered a theoretical explanation of the relationship between BDA-AI and EP, and several of these studies were conducted outside the manufacturing sector. Thus, building on the existing literature, we hypothesize that:

> H1: BDA-AI empowered decisions has a positive impact on EP.

2.5. BDA-AI and GSCC. Recent years have seen a significant increase in the use of BDA in the green supply chain across a wide range of fields [5, 50]. Fernando et al. [51] pointed out that effective data synchronization in supply chain management has become a challenge. In order to achieve business objectives, supply chain partners are constantly willing to integrate and coordinate business processes [52]. However, difficulties with the sharing of information in the supply chain have always existed, including information delay, information distortion, and information loss [53]. From this standpoint, Song et al. [54] suggested that the application of big data analytics promotes visibility and green integration in supply chain management as well as the accessibility of valuable information.

BDA can aid in effective data collection, assimilation, and reporting [55] and enhance sustainability when designing products [43]. Singh et al. [49] combined big data analytics, cloud computing, and operations research techniques (AHP, TOPSIS, and DEMATEL) to create a new tool for decision-making that can measure carbon footprints and greenhouse gas emissions when choosing suppliers. Additionally, in the hospital sector, Benzidia et al. [6] reported that BDA-AI-empowered decisions are positively related to GSCC.

In line with the reasoning above and empirical evidence, we endorse the notion that the use of new BDA-AI technologies can help the manufacturing sector in processing data from intra- and cross-organizational sources, as well as creating avenues for collaboration with suppliers in the process of making environmental decisions. Thus, we hypothesize that:

> H2: BDA-AI empowered decision has a positive impact on GSCC.

2.6. Green Supply Chain Collaboration and EP. Previous research [56, 57] has shown the link between environmental integration and supplier collaboration to ensure long-term environmental performance. However, no research has focused on this link in the context of the Turkish manufacturing sector, even though this topic has become more important in recent years.

Supplier collaboration relates to a common understanding that includes resource sharing and decision-making with the aim of reducing environmental impact on the product development process [58]. From this standpoint, Zhu et al. [35] suggested that organizations should allocate more resources to research and development and collaborate with suppliers to attain environmental performance. Supplier collaboration, which has been empirically demonstrated by a number of studies [58, 59], is a critical factor for firms looking to integrate low-carbon emission resources and operations and minimize their energy and environmental footprint. In a similar way, Zhu et al. [35] said that a cross-collaboration strategy can help businesses cut down on waste, improve their environmental performance, and build a reputation for being green.

A GSCC improves the level of monitoring of suppliers who promise to provide and use environmentally friendly equipment and raw materials [60]. Furthermore, adopting a collaborative approach with suppliers in the manufacturing sector appears to be crucial in order to promote green purchasing and supply practices as well as manage potential demands and transportation. These procedures can enhance inventory management, warehouse storage, and transportation while minimizing manufacturing waste disposal. Thus, we hypothesize that:

> H3: Green supply chain collaboration has a positive impact on EP.

2.7. The Mediating Role of GSCC. Due to growing pressures, increasing challenges, and the desire to meet ever-changing customer needs, manufacturing companies are forced to think about implementing green supply chain practices with the aim of improving their EP [61]. Laosirihongthong et al. [62] pointed out that the design stage is the most crucial phase of the product lifecycle because it is where environmental concerns can be addressed. Designing re-useable and recyclable items through the use of low-energy processes will enhance waste management and minimize hazardous materials and toxic emissions [63], thus promoting environmental performance. With respect to green operations, organizations can collaborate with their suppliers to match environmental requirements with product design, manufacturing processes, and transportation [64]. Also, Benzidia et al. [6] pointed out that BDA-AI can help make green decisions and is an important tool for managing environmental concerns within and across organizations.

Prior studies [47, 49] suggested that BDA-AI enables intra-organizational green initiatives and suppliers' collaborations, leading to minimized waste, carbon emissions, and environmental concerns. To summarize, it is reasonable to infer that BDA-AI can trigger GSCC and that green supply chain collaboration would result in environmental performance. That is, GSCC may mediate the link between BDA-AI-powered decisions and EP. To date, no prior studies have investigated the mediating role of GSCC in the link between BDA-AI-empowered decisions and EP. In line with theoretical and empirical evidence, we posit that:

> H4: Green supply chain collaboration mediates the association between BDA-AI empowered decisions and environmental performance.

2.8. Moderating Role of TMC. The concept of TMC resonates with the Theory of Planned Behavior (TPB), which describes behavior based on an individual's will [65]. When an individual's activity has a goal and purpose, TBP behavioral performance occurs. An individual's behavior is the result of a logical cognitive process in which the individual assesses information internally before applying it to its external behavior [65]. From this point of view, it has been said that the knowledge and beliefs of top management affect how organizations use new technologies like big data analytics [66] and that managers' concerns about the environment affect how much green innovation operations affect EP and competitive capabilities [67].

It is one thing for organizations to portray themselves as eco-friendly while carrying out their usual activities [68]. However, it is another thing for top management to commit to the economic and environmental effects of their activities [69]. Li et al. [70] suggested that top management leaders must genuinely believe in sustainability if they are to translate the call of stakeholders for green operations into an efficient response with lasting results. Furthermore, a strong top management moral stance and its perceptions regarding the environment [71, 72] may largely instill positive ideologies on green practices in their supply chain practices and EP [24]. Therefore, the key components for the success of green practices are top management's "support for, leadership in, and commitment to sustainability" [23, 73].

Genuine leaders discover opportunities, provide purposeful vision, and amend the code of conduct of their operations in their respective fields [74]. From this standpoint, Wisner et al. [75] stated that commitment has to start at the upper echelons of management. Consequently, establishing appropriate strategic guidelines and building a green operation will certainly be impossible without TMC [25]. Indeed, numerous studies reported that several green initiatives had strongly failed due to a lack of support from top management [76, 77]. Thus, in order to establish green initiatives, management should incorporate sustainable initiatives into daily supply chain activities [78] to instigate environmental reasoning throughout the company [79].

In line with the arguments above, we hypothesize the following;

> H5: Top management commitment moderates the relationship BDA-AI and GSCC, such that the positive relationship is stronger for higher than lower level of top management commitment.
>
> H6: TMC moderates the relationship between BDA-AI and EP, such that the strength of the positive relationship is reduced for lower level of TMC.
>
> H7: TMC moderates the relationship between GSCC and EP, such that the strength of the positive relationship is further enhanced for higher level of top management commitment.

3. Methods

3.1. Sample and Procedures. Data collected through the cross-sectional method was utilized to examine the current research's conceptual model. With the help of nine (9) experts from manufacturing firms in Turkey, the questionnaire survey was pre-tested for face validity. These experts, who were well experienced in manufacturing supply chain management and logistics, participated in the pre-test we conducted. We asked these experts to assess the survey's structure, comprehensibility, imprecision, and wholeness [43]. This enabled us to clarify some questions regarding the measurement items. The inputs and suggestions from the experts were included in the final questionnaire. In order to prevent difficulty in understanding the questions, participants were given a glossary of key terms. The participants were then told that their information would be kept secret and that the data collected would only be used for academic research.

Consistent with Chen et al. [38]; in developing the measurement scale, a number of measures were followed, and a pre-test was carried out, as mentioned earlier. We had to make sure the measurement scale's content was valid as a first step. The purpose of content validity was to determine if or not the various questionnaire items sufficiently represented the phenomenon under examination. In doing so and before purification, we developed a questionnaire and measurement scales for our study's observed variables using the academic literature as a guide. All the constructs of the current research were evaluated on a 5-point Likert scale, from strongly disagreeing (=1) to strongly disagreeing (=5).

A total of 994 questionnaires were sent out, and 402 complete responses were retrieved, yielding a response rate of 40.44%.

Prior to administering the questionnaire survey, each participant was pre-selected through the use of closed-ended questions regarding their knowledge of BDA capabilities with respect to the supply chain. The questionnaire survey was sent out to participants who were in charge of supply chain and logistics activities within the manufacturing firms in Turkey. The survey was administered online via a Google form.

The demographic information is outlined in Table 1. Regarding gender, 341 (84.90%) of the participants were male and 61 (15.10%) were female. The majority (280, or 69.6%) of the participants had at least a bachelor's degree. Majority 344 (85.6%) of the firms surveyed had above 20 employees. The majority of 375 (93.0%) of the participants have been with their company for over 6 years, implying that they have the required experience to evaluate the survey. Based on the type of business their firm conducts: food and consumer goods 113 (28.10%), machinery and industrial equipment 110 (27.40%), chemicals 68 (16.90%), automotive components 56 (13.90%), and pulp and paper 55 (13.70%).

3.2. Measures. BDA-AI was measured using four items developed by Srinivasan and Swink [30] and Dubey et al. [43].

GSCC was measured using four items developed by Singh and El-Kassar [80].

TMC was measured using five items developed by Chen and Paulraj [81] and Dubey et al. [82].

EP was measured using six items developed by Longoni et al. [83]; and Singh and El-Kassar [80].

3.3. Data Analyses. The Statistical Package for Social Science (SPSS) 28.0 and AMOS 28 software were employed to analyze the data collected for this study. AMOS 28 was employed for confirmatory factor analysis (CFA) to examine the measurement model for all the constructs in our research. SPSS 28 was used to do Pearson correlation, common method bias, descriptive statistics, and PROCESS (the plug-in) by Hayes.

Consistent with Hayes [84]; PROCESS macro (Model 4) and (Model 59) were chosen to examine the mediation model and the moderated mediation model, respectively. A 5000 bootstrap resample with 95% confidence intervals (CIs) indicates whether or not the effects in the selected Model 4 and Model 59 are significant [84]. That is, where 95% CIs exclude zero, a significant effect is established. Before the data analyses, all the constructs in the study were standardized in Model 4 and Model 59.

4. Results

4.1. Common Method Variance (CMV). In order to prevent the presence of CMV, we adhere to the two common method biases frequently utilized in supply chain management research [1]: process control and Harman's one single factor test. While collecting data through a questionnaire survey, we adhere to the principles of confidentiality and anonymity, and the data gathered will be used for academic research purposes only. The Harman's single factor results indicate the first factor accounted for 38.18%. This is less than the critical criterion of 50%, which means that CMB is not a big problem in the research being done [85].

Additionally, the aforementioned test was supplemented with a test for collinearity. Variance inflation factor (VIF) estimates regarding correlation among the constructs in this study were below the recommended cutoff of 3.3 [86]. Hence, the result is not clouded by multicollinearity issues [87].

4.2. Measurement Model. To check whether the data collected followed normal distribution, Lei and Lomax [88] suggested that (skewness $< |2|$ and kurtosis $< |3|$; as demonstrated in Table 2, skewness lies inside the cut-off range (0.023 and 0.641) and kurtosis lies inside the cut-off range (0.409 and 1.515), indicating that the data collected can be said to be normally distributed.

All measurement items were tested for validity and reliability. The results revealed that every factor loading was greater than 0.6. The AVE of each variable was estimated to satisfy convergent validity [89]. The recommended lower limit of 0.5 for AVE [90]. Construct reliability (CR) estimates were made for each construct in order to examine composite reliability. 0.7 should be the lower limit [91]. The factor loadings (0.631 to 0.884), CR (0.833 to 0.958), and (0.549 to 0.838) as outlined in Table 3 Therefore, the items are appropriate, and the constructs are consistent and reliable.

To estimate discriminant validity, Fornell and Larcker [89] indicated that the square root of each AVE should be larger than the surrounding correlations. Table 4 demonstrates that the square root of AVEs (in parenthesis, in bold) is found to be larger than the surrounding correlations, demonstrating evidence of discriminant validity.

The research model's CFA is shown in Table 5. We estimated the model fit indices by various statistics: TLI, IFI, NFI, CFI, and RMSEA. NFI, TLI, and IFI values should be greater than 0.8; CFI values should be greater than 0.9; and RMSEA values should be less than 0.08 [92]. The results showed that all of them fell within the acceptable limits, which means that our chosen model fits the data well.

4.3. Mediation Model. It was hypothesized that green supply chain collaboration would mediate the relationship between BDA, AI, and EP in hypothesis 4. To validate this hypothesis, the current research followed a 4-step process for evaluating the mediation effect [93]. The 4-step process was as follows: (1) a significant relationship between BDA-AI and EP; (2) a significant relationship between BDA-AI and GSCC; (3) a significant relationship between GSCC and EP after controlling for BDA-AI; and (4) a significant coefficient for the indirect path between BDA-AI and EP via GSCC. The bias-corrected percentile bootstrap approach was adopted to determine if the last process was fulfilled. Also, as covariates,

Table 1: Previous studies' findings associated with the constructs of this study.

Authors	Constructs examined	Findings
Dubey et al. [7]	Big data analytics and artificial intelligence, operational performance, entrepreneurial orientation, and environmental dynamism	The study reported that manufacturing firms that are entrepreneurially oriented have the potential to use digital technologies such as BDA-AI to enhance their decision-making capabilities, which can further promote operational performance. It was also reported that the positive impact of entrepreneurial orientation on operational performance is less pronounced in more dynamic environments
Kitsis and Chen [25]	Stakeholder pressures, green supply chain practices, and top management commitment	The study reported significant empirical support for the relationship between stakeholder pressures and top management commitment. The study further suggested that stakeholder pressure can promote top management's commitment and efforts to undertake green operations
Benzidia et. al. [6]	Big data analytics and artificial intelligence, green supply chain integration, and hospital environmental performance	The study reported that the use of BDA-AI has a significant positive effect on green supply chain collaboration in the hospital sector. It was suggested that the application of BDA-AI can promote better collaboration between supply chain stakeholders. It was also suggested that the use of BDA-AI systems enable managers to put in place new methods in real-time to enable them to visualize and comprehend knowledge on environmental initiatives
	Big data analytics-artificial intelligence, green supply chain collaboration, top management commitment, and environmental performance	The current study found a significant positive relationship between BDA-AI and EP. Green supply chain collaboration was found to play a mediating role between BDA-AI and EP. Our findings also revealed that the positive impact of BDA-AI on GSCC is further enhanced by the level of top management commitment and that the positive impact of BDA-AI on EP is dampened when the level of top management commitment is low. Our findings provide important practical implications for managers in the manufacturing industry seeking to explore and implement BDA-AI in their environmental efforts. They should intensify TMC to develop efficient green supply chain collaborative efforts that enhance environmental performance

Table 2: Participant characteristics.

Demographic information ($n = 402$)	Frequency	%
Gender		
Male	341	84.90
Female	61	15.10
Education		
Bachelor	106	26.40
Master	132	32.80
Doctorate	42	10.40
Others	122	30.30
Firm size (number of employees)		
Less than 20	58	14.40
21–40	102	25.40
41–60	108	26.90
61–80	63	15.70
Above 81	71	17.70
Business type		
Chemical	68	16.90
Machinery and industrial equipment	110	27.40
Food/Consumer goods	113	28.10
Pulp and paper	55	13.70
Automotive components	56	13.90
Tenure (years)		
Less than 5	27	6.70
6–10	59	14.70
11–15	128	31.80
Above 15	188	46.80

Table 3: Measurement model.

Construct	Items	SFL	Distribution (normal)	
		(λ)	Skewness	Kurtosis
Big data analytics-artificial intelligence	∝ = 0.866			
	CR = 0.869 AVE = 0.609			
	BDAA1	0.822	0.061	−1.404
	BDAA2	0.789	0.163	−1.515
	BDAA3	0.772	−0.040	−1.461
	BDAA4	0.702	−0.112	−1.306
Green supply chain collaboration	∝ = 0.928			
	CR = 0.895 AVE = 0.838			
	GSC1	0.803	0.343	−1.245
	GSC2	0.866	0.221	−1.217
	GSC3	0.841	0.281	−1.219
	GSC4	0.852	0.480	−1.088
Top management commitment	∝ = 0.847; CR = 0.864; AVE = 0.763			
	TMC1	0.843	0.517	−0.409
	TMC2	0.880	0.255	−1.099
	TMC3	0.884	0.302	−1.009
	TMC4	0.874	0.341	−1.082
	TMC5	0.881	0.352	−1.098
Environmental performance	∝ = 0.829; CR = 0.811; AVE = 0.549			
	EP1	0.740	−0.023	−1.264
	EP2	0.712	0.183	−1.401
	EP3	0.631	0.642	−0.705
	EP4	0.739	0.308	−1.118
	EP5	0.783	0.515	−1.018
	EP6	0.701	0.209	−1.016

Note: (1) BDAA = big data analytics-artificial intelligence; GSC = green supply chain collaboration; TMC = top management commitment; EP = ; environmental performance; (2) λ = standard factor loading; AVE = average variance extracted; CR = composite reliability; ∝ = cronbach alpha.

Table 4: Descriptive statistics, correlation analysis and discriminant validity.

Construct	M	SD	BDAA	GSC	TMC	EP	Education	Firm size	Firm age	Tenure
BDAA	3.805	1.012	**0.780**							
GSC	3.717	0.998	0.501**	**0.914**						
TMC	2.001	0.669	0.619**	0.622**	**0.873**					
EP	3.980	1.271	0.488**	0.531**	0.562**	**0.740**				
Education	3.127	0.821	0.581**	0.599**	0.588**	0.517**	—			
Firm size	3.101	0.802	0.504**	0.631**	0.503**	0.600**	0.157**	—		
Firm age	3.364	0.911	0.526**	0.657**	0.481**	0.513**	0.022**	0.109**	—	
Tenure	2.662	0.727	0.472**	0.516**	0.499**	0.524**	0.265**	0.029**	0.029**	—

Note: (a) M = mean, SD = standard deviation; (b) correlations (two-tailed) were significant at $^{**}p < 0.01$; (c) boldface indicates that the square root of AVEs is larger than the off-diagonal (nearby) correlations.

Table 5: Model fit estimate.

Goodness of fit index	CMIN/df (<3)	IFI (>0.9)	CFI (>0.9)	NFI (>0.9)	RMR (>0.9)	TLI (>0.9)	RMSEA (<0.08)
	564.183/284 = 1.987	0.966	0.959	0.961	0.119	0.940	0.050

education, firm size, firm age, and tenure were added to the analyses that were just talked about.

As illustrated in Table 6, in Model 1, the results indicated that big data analytics and artificial intelligence significantly and positively predicted environmental performance ($\beta = 0.299$; $p < 0.001$). In Model 2, the second step results indicated that BDA-AI is a significant and positive predictor of green supply chain collaboration ($\beta = 0.504$; $p < 0.001$). In Model 3, after controlling for BDA-AI, GSCC was revealed to be a significant and positive predictor of environmental performance ($\beta = 0.305$, $p < 0.001$). Finally, the results for bias-corrected percentile bootstrap for indirect effect of BDA-AI on environmental performance through GSCC were significant ($\beta = 0.149$, SE = 0.018, CIs 95% = [0.106, 0.264] confidence interval excludes zero as shown in Table 7. Therefore, hypotheses 1, 2, 3, and 4 (mediation effect) were all validated.

4.4. Testing for Moderation Model. Model 59 in Hayes' PROCESS macro assumes that the moderator affects all three paths of the mediated model, which is consistent with our study's conceptual model. To explore the moderating role of top management commitment in the relationship between BDA-AI and GSCC (hypothesis 5), BDA-AI and EP (hypothesis 6), and GSCC and EP (Hypothesis 7), Model 59 of the PROCESS macro was used.

Our research examines the moderating effect of top management commitment on (a) the association between BDA-AI and GSCC (Model 1 of Table 8); (b) the association between BDA-AI and EP (Model 2 of Table 8); and (c) the relationship between GSCC and EP (Model 2 of Table 8). Similar to the mediation analysis in the previous section, education, firm size, firm age, and tenure were added as covariates. Consistent with Hayes [84]; a moderated mediation model will be established should one or both of the following paths be supported: (a) the path between BDA-AI and GSCC was moderated by top management commitment; or (b) the path between GSCC and EP was moderated by top management commitment.

As illustrated in Model 1 of Table 8, the results indicated that the main effect of BDA-AI on GSCC was statistically significant ($\beta = 0.120$, $p < 0.001$) and that this effect was moderated by top management commitment ($\beta = 0.017$, $p < 0.05$) with a 95% CI of [0.088, 0.141], implying that top management commitment moderated the positive relationship between BDA-AI and GSCC, validating hypothesis 5. Consequently, as illustrated in Model 2 of Table 8, the main effect of BDA-AI on EP was statistically significant ($\beta = 0.221$, $p \leq 0.001$) but this effect was moderated by top management commitment ($\beta = 0.078$, $p \leq 0.05$) with a 95% CI of [0.103, 0.152] validating hypothesis 6. Finally, still in Model 2 of Table 7, there was a significant main effect of GSCC and EP ($\beta = 0.113$, $p < 0.001$), but this particular effect was not moderated by top management commitment ($\beta = 0.059$, $p > 0.05$) with a 95% CI of [−0.064, 0.125] implying that top management commitment did not moderate the positive relationship between GSCC and EP, rejecting hypothesis 7.

The two significant effects of the interactions were further examined via simple slope analysis. For hypothesis 5, interactions were plotted at +1 and −1 SD from the mean of top management commitment (see Figure 2). For both high and low levels of top management commitment, we created a simple slope to assess the strength of the relationship between BDA-AI and GSCC. The result of the conditional direct effect of BDA-AI on GSCC showed that the strength of the positive relationship is stronger for higher levels of top management ($\beta = 0.194$, $t = 3.272$, $p \leq 0.001$), while the relationship is weaker ($\beta = 0.061$, $t = 1.612$, $p \leq 0.001$) at lower levels of top management commitment to strategic performance. Therefore, further supporting hypothesis 5.

For hypothesis 6, +1 and −1 SD from the mean of top management commitment were used to plot the interactions (see Figure 3). For both high and low levels of top

Table 6: Direct and mediation effects GSCC partially mediated the relationship between BDA-AI and environmental performance (PROCESS model 4, CI = 95%).

Predictor	Model 1 (EP)		Model 2 (GSC)		Model 3 (EP)	
	B	t	B	t	B	t
BDAA	0.299	5.998***	0.504	10.104***	0.305	4.694***
GSC					0.184	4.981***
Education	0.018	0.611	0.050	1.168	0.029	1.117
Firm size	0.039	1.302	0.020	0.700	0.041	1.027
Firm age	0.021	1.001	0.011	0.521	0.023	1.099
Tenure	0.026	1.102	0.012	0.223	0.024	1.042
R^2	0.155		0.187		1.938	
F	11.224***		19.991***		13.557***	

Note: (1) each column demonstrates a regression model that predicts the criterion at the column's top; (2) *** $p < 0.001$.

Table 7: Bootstrap results for the indirect effect (indirect effect of BDA-AI on EP via GSCC).

Bootstrap resamples = 5000	B	SE	LLCI	ULCI
The indirect effect of (BDA-AI ion EP via GSCC)	0.149	0.018	0.106	0.264

Table 8: Testing for moderated mediation: top management commitment moderates the direct and indirect relationship between BDA-AI and environmental performance (PROCESS model = 59, CI = 95%).

	Bootstrapped CI 95%						
	B	SE	t	p	LLCI	LLCI	R^2
Model 1: Mediator variable model	Outcome: green supply chain collaboration						
Big data analytic-artificial intelligence	0.120	0.024	4.911	≤0.001	0.103	0.209	0.806
Top management commitment	0.799	0.021	30.228	≤0.001	0.802	0.913	
Big data analytic-artificial intelligence X top management commitment (interaction)	0.017	0.019	1.995	0.012	0.088	0.141	
Co: education	−0.019	0.020	−1.221	0.173	−0.071	0.052	
Co: firm size	−0.009	0.010	−0.097	0.863	−0.026	0.025	
Co: firm age	0.022	0.011	2.003	0.027	0.010	0.062	
Co: tenure	−0.008	0.015	−0.501	0.707	−0.064	0.018	
The conditional direct effect of BDA-AI on GSCC							
Top management commitment (-1SD)	0.061	0.099	1.612	≤0.001	0.094	0.180	
Top management commitment (+1SD)	0.194	0.044	3.272	≤0.001	0.181	0.303	
Model 2: Dependent variable model dependent: environmental performance							
Big data analytic-artificial intelligence	0.221	0.051	4.642	≤0.001	0.127	0.318	0.228
Green supply chain collaboration	0.113	0.042	3.928	≤0.001	0.201	0.494	
Top management commitment	0.195	0.082	2.531	0.012	0.134	0.312	
Big data analytic-artificial intelligence X top management commitment (Interaction)	0.078	0.032	2.244	0.028	0.103	0.152	
Green supply chain collaboration X top management commitment (Interaction)	0.059	0.037	0.726	0.311	−0.064	0.125	
Co: education	−0.028	−0.033	−1.010	0.355	−0.092	0.0	
Co: firm size	−0.041	0.022	−1.492	0.119	−0.088	0.010	
Co: firm age	0.019	0.014	0.699	0.436	−0.024	0.049	
Co: tenure	0.021	0.032	−0.591	0.493	−0.114	0.088	
The conditional direct effect of BDA-AI on environmental performance							
Top management commitment (-1SD)	0.089	0.058	1.611	0.023	0.094	0.144	
Top management commitment (+1SD)	0.311	0.069	4.649	≤0.001	0.292	0.466	

Note: $n = 402$; B = unstandardized regression coefficients; bootstrapping resample size = 5000; LLCI = confidence interval (lower level); ULCI = confidence interval (upper level).

management commitment, we created a simple slope to assess the strength of the positive relationship between BDA-AI and EP. The result of the conditional direct effect demonstrated that the association is weaker ($\beta = 0.089$, $t = 1.611$, $p < 0.05$) when top management commitment is low, while the association is stronger ($\beta = 0.311$, $t = 4.649$, $p < 0.001$) at high levels of top management commitment. Therefore, further validating hypothesis 6.

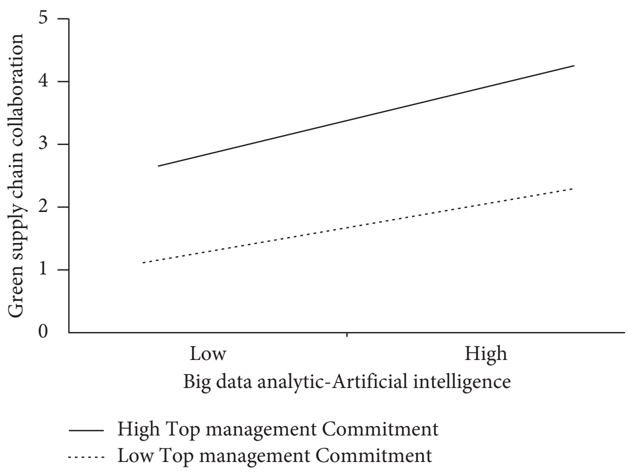

Figure 2: The moderating effects at different levels of TMC on the relationship between BDA-AI and GSCC.

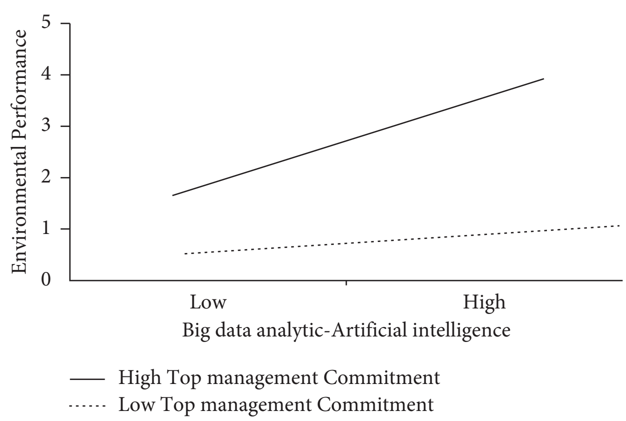

Figure 3: The moderating effects at different levels of TMC on the relationship between BDA-AI and EP.

5. Discussion

The current research examined a moderated mediation model based on a Turkish sample and uncovered the underlying mechanisms in the association between BDA-AI and environmental performance in the context of the Turkish manufacturing sector. First, it was revealed that BDA-AI-empowered decisions have a positive impact on EP. This particular result provides empirical evidence for the arguments of Chiarini [94]; Dubey et al. [45]; and Raut et al. [47]; who argued that the BDA-AI in the context of green supply chain management can promote EP. The observation here is that the use of new technologies such as BDA-AI in the manufacturing sector can suppress information asynchronization in the supply chain and manage complex environmental data with the aim of improving environmental performance. Second, it was discovered that BDA-AI-empowered decisions are a determinant of GSCC. This result aligns with the recent findings of Benzidia et al. [6] and the conclusions of Liu et al. [48]; Singh et al. [49]; and Raut et al. [47]. The discovery of BDA-AI as a determinant of GSCC indicates that such a relationship is not exclusive to the western context only. The consistency of this pattern of results could imply that the manufacturing sector needs to establish supporting IT infrastructure, such as BDA-AI, to develop collaborative relationships for green supply chain operations. Third, GSCC was discovered to have a positive impact on EP. This result confirms the findings of Benzidia et al. [6] and Seman et al. [60]; who reported that green supply chain collaboration leads to enhanced environmental performance. Clearly, manufacturing firms should collaborate with their suppliers to attain improved green performance. Fourth, it was discovered that GSCC mediated the direct relationship between BDA-AI and EP.

Fifth, top management commitment moderates the relationship between BDA-AI and GSCC, such that the positive relationship is stronger for higher than lower levels of top management commitment. Sixth, TMC moderates the relationship between BDA-AI and environmental performance so that when top management commitment is low, the strength of the positive relationship is less.

Lastly, the role of TMC as a moderator in the link between GSCC and EP was not supported by our results.

5.1. Theoretical Implication. The current study developed and empirically examined a research framework that demonstrates how BDA-AI technology enhances environmental performance. Our research provided empirical evidence that using innovative technologies (e.g., BDA-AI) for decision making promotes the information processing capabilities of manufacturing firms. The finding backs up our belief that manufacturing firms with advanced technological infrastructure and smart analytical capacity can improve their environmental performance. This extends organizational information processing theory (OIPT) to the Turkish manufacturing industry, which has not gotten much attention.

The current study also demonstrates how integrating innovative technologies such as BDA-AI enables GSCC and further promotes green operations. However, the relationship between BDA-AI and GSCC has not been empirically proven in the context of Turkish manufacturing firms. Further, the manufacturing industry is made up of various parties with varying desires; thus, making decisions requires consensus among stakeholders who share the philosophy of a circular economy [95]. Particularly, the OIPT emphasizes the synchronization of information processing capacities at both intra-organizational and cross-organizational levels in order to promote environmental performance. Therefore, the current study offers a novel contribution on how the application of BDA-AI technological systems impacts GSCC in the manufacturing industry. This current study also offers important knowledge on how GSCC impacts EP.

The current study also provides new evidence and reveals green supply chain collaboration as an important mechanism in the association between BDA-AI and environmental performance. Our study shows how this mechanism is involved in the process of enhancing the environmental performance of manufacturing firms, moving from the use of advanced technologies with information processing capabilities (BDA-AI) through GSCC to achieving environmental performance. This result could mean that manufacturing companies that use BDA-AI to handle out-of-sync information and complicated data about the environment are more likely to work with their suppliers and improve their green operations.

Furthermore, a key finding that has not been reported in the existing literature is that the current study provides new evidence on how TMC moderates the association between BDA-AI and EP. Contrary to previous studies that explored top management commitment as a predictor (Bag et al., 2020) or as a mediator [25], our study examined top management commitment as a moderator. To our knowledge, our study was the initial study that investigated the role of TMC in the relationship between BDA-AI and EP, revealing that TMC moderates the relationship between BDA-AI and green supply chain collaboration, such that the positive relationship is stronger for higher than lower levels of top management commitment, and that TMC moderates the relationship between BDA-AI and EP, such that the strength of the positive relationship is reduced for lower levels of top management commitment. A more logical explanation would be that top management support is necessary for successful green initiative operations. Thus, top management actions are critical in laying the groundwork for green operations. This pattern of results aligns with extant literature that indicates that green operations are majorly influenced by the choices of top management [96]. So, the current research adds a lot to what we already know by using a new method that goes beyond the direct link between BDA-AI and environmental performance and takes into account how complicated real life is.

5.2. Practical Implications. The research offers important practical implications that the manufacturing industry should be aware of, especially policy makers. First, there is a chance for policy makers in the manufacturing industry to take advantage of BDA-AI's technological capabilities to implement an ardent environmental policy that covers the entire operations of the manufacturing supply chain. Precisely, decision makers can administer new indicators and measures in real time by using BDA-AI technologies, which can help improve visualization and comprehend information on environmental initiatives.

Second, our findings suggest that GSCC is a crucial element in the manufacturing industry. Therefore, organizations' leaders should not only depend on the use of IT infrastructure to implement green initiatives but also collaborate with suppliers within the supply chain if they are to meaningfully contribute to a cleaner environment and a better society.

Third, our findings also suggest that manufacturing firms cannot succeed in the present era of big data if they only have access to good data and effective information processing; a strong top management commitment to sustainable initiatives can intensify communication and collaboration with the suppliers and enhance the establishment of shared beliefs and actions for green operations. Therefore, TMC is a crucial driver of green operations and EP. But the current study wants to add that organizations' leaders should pay enough attention to TMC and understand how different levels of top management commitment can affect BDA-AI on GSCC and, as a result, environmental performance.

Finally, the findings of this study indicate that the positive impact of BDA-AI on GSCC is further enhanced by the level of top management commitment. Hence, manufacturers' decision-makers seeking to explore and implement BDA-AI in their environmental initiatives should intensify TMC to develop efficient green supply chain collaborative efforts that promote environmental performance.

6. Conclusion

The empirical findings of the current study provide a more nuanced understanding of the use of BDA-AI technology in achieving environmental performance, which in turn helps to clarify the role green supply chain collaboration and, most importantly, top management commitment play in these relationships. So, the data-driven research we did for this study offers more benefits by giving business leaders who agree with our suggestions more information they can use to evaluate how well they are being put into practice.

To the best of our knowledge, based on OIPT, the current research is the first academic effort to demonstrate the relationships between the application of BDA-AI through GSCC and enhanced environmental performance in the context of the Turkish manufacturing industry. In general, our study adds to the small but growing amount of information about how BDA-AI systems can be used in a circular economy.

7. Limitations and Future Research Directions

The current study offers important contributions, but it also has some limitations that may open up a new research direction. First, because the sample was limited to the manufacturing industry in Turkey, our conclusions may not apply to other nations' supply chains depending on their technological capabilities and national cultures that support sustainability. Future studies could examine manufacturing firms in other developing nations to complement and solidify our findings. Second, though this research has demonstrated the crucial role of green supply chain collaboration as a mediator in the link between BDA-AI and EP, future research examining the moderating effect of green supply chain collaboration could yield more useful insights. Could it be that, for example, when GSCC is high, the relationship between BDA-AI and EP is stronger? Third, future studies could also look into other constructs, such as stakeholder pressure in the abovementioned relationships. Fourth, we urge future studies to validate the empirical results from our study using a larger sample size, as well as in other sectors and nations. Finally, there still exists a sparse body of knowledge or information regarding the application of BDA-AI in attaining improved environmental performance; more study should be carried out to promote its effectiveness in green operations.

Data Availability

The data used to support the findings of this study are available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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