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Big Data Management Capabilities and Green Innovation: A Dynamic Capabilities View

Hongyi Mao and Jiang Lu *

School of Business Administration, Guizhou University of Finance and Economics, Guiyang 550025, China; mao@mail.gufe.edu.cn
* Correspondence: jianglu0819@outlook.com

Abstract: In recent years, both industry professionals and scholars have shown increased interest in the ability of big data management capabilities (BDMCs) to drive green innovation, emphasizing their potential in fostering environmentally sustainable practices. While many studies highlight the positive influence of big data technology on green innovation, there is a notable gap in understanding the managerial process required for such innovation. Moreover, the roles of green dynamic capabilities and environmental turbulence in this context are underexplored. This study aims to contribute to the existing literature by examining the mechanisms and boundary conditions of the relationship between BDMCs and green innovation. We gathered data from 266 Chinese manufacturing enterprises using questionnaires and analyzed the results using Partial Least Squares Structural Equation Modeling (PLS-SEM). Our findings indicate that, despite the inherent qualities of BDMCs such as rarity, applicability, nonreplicability, and non-substitutability, their influence on green innovation is reduced in the absence of effective green dynamic capabilities. Furthermore, our study suggests that environmental turbulence does not weaken the influence of BDMCs on green dynamic capabilities; rather, it amplifies the effects of BDMCs on green dynamic capabilities and their impact on two types of green innovation. This study provides new insights for manufacturing enterprises aiming to achieve green transformation. We also discuss the theoretical and practical implications of the research, along with its limitations.

Keywords: sustainable development; big data management capabilities; green innovation; green dynamic capabilities; environmental turbulence

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1. Introduction

The urgency of addressing environmental challenges has heightened the need for sustainable development, prompting organizations to explore novel solutions to minimize their ecological footprint [1]. Green innovation stands at the forefront of these efforts, as it encompasses the creation, adoption, and integration of eco-friendly products, processes, and practices; thus, it ultimately contributes to environmental preservation [2]. As the world increasingly becomes data driven, big data management capabilities (BDMCs) have emerged as a vital determinant of organizational competitiveness and growth [3,4]. BDMCs accentuate the significance of consolidating big data assets with various resources and capabilities, thereby maximizing their potential value to organizations [5,6]. The proliferation of data sources and the increasing availability of advanced data analytics tools have created new opportunities for organizations to leverage data-driven insights to develop informed decision-making and drive innovation. In this context, BDMCs have the potential to play a transformative role in enabling organizations to develop and implement green innovations that address environmental challenges [7,8]. Nevertheless, the existing literature remains divided on the actual effectiveness of BDMCs in fostering green innovation; in particular, some studies highlight the merits of BDMCs [1], whereas others point out their limitations [9]. This disparity underscores the need for a comprehensive understanding of the mechanisms through which firms leverage BDMCs to achieve green innovation.

The present paper study aims to address this research gap by delving into the intricate process of utilizing BDMCs to attain green innovation. In this study, the influence of a firm's green dynamic capabilities (DCs) and the role of environmental turbulence (ET) are considered. Green DCs, a concept derived from DC theory, refer to the ability of enterprises to utilize existing resources and knowledge to refresh and enhance their green organizational capabilities in response to the demands of sustainable development [10–12]. Scholars suggest that green DCs may serve as a crucial link between BDMCs and green innovation [13]. On the one hand, leveraging BDMCs can enhance innovation and promote green DCs [14]. In particular, BDMCs enable firms to harness the power of big data analytics and generate valuable insights for environmental sustainability, allowing firms to respond swiftly to emerging environmental challenges and capitalize on opportunities for green innovation [4]. On the other hand, the degree of success that enterprises achieve in their pursuit of green innovation is contingent upon their adept responsiveness to green DCs [15]. Green DCs encompass the firm's agility and adaptability in the face of environmental challenges and opportunities [12]. Firms with strong green DCs can swiftly reconfigure their resources and processes to capitalize on emerging opportunities for green innovation [16]. Therefore, incorporating green DCs as a mediator for BDMCs can be a feasible strategy for advancing green innovation [12,13].

Moreover, we acknowledge the potential influence of external factors on the impact of BDMCs on green innovation. The traditional resource-based view (RBV) has faced criticism for its oversight of this aspect [17]. In response to this criticism and the call for research on external factors affecting green innovation [8,18], we introduce ET as an important exogenous factor that may influence the relationship between BDMCs, green DCs, and green innovation. ET refers to the degree of unpredictability and instability in the external environment [19]. The impacts of ET on the effectiveness of BDMCs and green innovation have been the subject of various debates among scholars. Some researchers argue that ET enhances the role of big data management by increasing the demand for information within enterprises, thereby facilitating informed decision-making and fostering innovation [20]. In this view, ET creates opportunities for organizations to leverage BDMCs to identify and respond to emerging environmental trends and challenges, ultimately driving green innovation. Conversely, other scholars indicate the uncertainty and risk that ET brings to the ability of enterprises to function effectively [21]. High levels of ET can create a volatile and unpredictable business landscape, thereby complicating the planning and execution of long-term strategies for organizations. In such an environment, the effective utilization of BDMCs may be hindered by rapidly changing conditions, and the potential benefits of green innovation may be offset by the challenges of navigating an uncertain external context. Thus, the relationship between BDMCs, green DCs, and green innovation may be contingent upon the level of ET the organization faces.

In light of the research themes related to sustainable development and innovative science and technology, we pose the following research questions:

RQ1. Can the mediating impact of green DCs explain the link between BDMCs and green innovation?

RQ2. How does ET affect the relationship between BDMCs, green DCs, and green innovation?

These questions serve to elucidate the intricate multifaceted nature of Green Innovation and the role of ET in the utilization of BDMCs for facilitating enterprises' green transformation and implementation. This study examines the role of BDMCs in facilitating green innovation among enterprises. By empirically analyzing data from 266 manufacturing companies, we address the research gap concerning the tangible effects of BDMCs in green innovation. The findings contribute to revealing the mechanisms through which BDMCs influence green innovation, providing empirical support for organizational sustainable development. Furthermore, the introduction of external ET as a research factor extends the understanding of the relationship between BDMCs and green innovation. The study uncovers how ET impacts the role of BDMCs in green innovation to varying degrees, further enriching the existing theoretical framework concerning the connection between BDMCs and green innovation. In the subsequent sections, we delve into a comprehensive examination of the research topic. Section 2 provides the theoretical background, laying the foundation for the study. In Section 3, we present our research models and hypotheses, outlining the framework guiding the empirical analysis. Section 4 details the research methodology, elucidating the process of data collection and analysis. In Section 5, we engage in a thorough discussion of the findings and their implications. Section 6 addresses the limitations of the study and identifies potential avenues for future research. Finally, in Section 7, we draw conclusions, summarizing the key insights gained from this research.

2. Theoretical Background

2.1. Green DCs

DCs are a pivotal concept in understanding how firms navigate external environmental changes by adjusting their internal resources and capabilities [22]. They play a crucial role in fostering organizational agility, enabling companies to swiftly adapt and reorganize resources and capabilities in response to ever-evolving markets [23]. The maturity of a firm's utilization of DCs significantly influences its ability to deliver timely and high-quality products that align with customer needs [24]. However, developing these capabilities can be intricate, as they are often internally complex and path-dependent, leading to intricate cause-and-effect relationships [25]. Nonetheless, DCs offer the potential to confer competitive advantages and create an environment conducive to innovation [26].

Amidst the complexities of a rapidly changing landscape, firms can harness DCs to facilitate green innovation. By absorbing, sharing, and adjusting resources, firms and their partners can craft offerings tailored to customer demands [27]. This becomes particularly pertinent in the context of green development within manufacturing firms, where cultivating and enhancing green DCs takes center stage [28]. These green DCs encompass a firm's ability to update and cultivate green organizational capabilities, leveraging existing resources and knowledge to effectively respond to market shifts [12]. As corporate actions mirror market shocks, the concept of green DCs has gained prominence in the realm of green innovation.

The utilization of green DCs empowers firms to create sought-after green products and services, infusing environmentally friendly elements into design, packaging, and production processes [29]. Rapid recognition of environmental needs, adept explanation of phenomena, meticulous evaluation of consequences, exploration of measures, and adept response characterize this capability [12]. Leveraging green DCs, enterprises adeptly design new eco-friendly products and adapt existing production processes to swiftly and flexibly navigate volatile market conditions [13]. In this way, green DCs not only foster innovation but also enable firms to proactively address environmental demands and optimize their operations for long-term sustainability.

2.2. BDMCs and Green Innovation

Green innovation refers to the development of novel environmentally friendly products or processes aimed at enhancing an organization's ecological performance [30]. Within the realm of environmental protection, innovative strategies encompass various approaches that promote eco-conscious business practices, including the adoption of energy-efficient technologies, implementation of pollution control measures, utilization of recycling methods, creation of reusable products, and harnessing emerging sustainable technologies [31]. Scholars have delineated two central categories within green innovation: green product innovation (GPDI) and green process innovation (GPCI), which are conceptually distinct [30]. While GPDI focuses on refining product design to align with environmental goals and thus differentiate and increase the value of green products [32], GPCI is dedicated to minimizing energy consumption during production processes and advancing renewable technologies to mitigate negative environmental impacts [33]. This differentiation highlights that GPDI primarily involves material transformation and recycling, while GPCI centers on energy efficiency and renewable technology development [34].

Crucial to the innovation process, big data management capabilities (BDMCs) empower organizations to strategically restructure and optimize their big data resources [5]. Guided by the Resource-Based View (RBV), BDMCs are characterized by their rarity, mobility, nonreplicability, and irreplaceability, contributing to innovation and conferring competitive advantages [35]. In our study, we define BDMCs as a second-order construct encompassing four dimensions: BDMC planning, BDMC investment, BDMC coordination, and BDMC control [36]. BDMC planning identifies business opportunities and assesses the potential of leveraging big data management for performance enhancement [37]. BDMC investment entails cost estimation and benefit analysis to maximize returns [38], while BDMC coordination involves simultaneous analysis activities across departments and functions [39]. Finally, BDMC control ensures appropriate resource allocation and usage [40]. Prior studies proposed to examine the potential mechanisms that underlie the role of BDMCs in promoting green innovation (see the representative research in Table 1).

Table 1. Representative studies related to big data management capability and green innovation.

Reference	Research Method	Big Data Related Construct	Intermediate Capabilities	Green Innovation Related Construct	Boundary Conditions	Effect	Main Finding	Research Gap
[41]	Qualitative	Big data technologies	N/A	Green innovation processes	N/A	-	Companies that use big data as a strategic knowledge asset can promote green innovation	1. Previous studies present mixed conclusions on the effect of big data management capabilities in shaping high levels of green innovation. 2. The roles of green dynamic capabilities in the capabilities building processes differ. 3. The role of big data management capabilities and green dynamic capabilities in big data management capabilities-green innovation research is diverse and depends on certain boundary factors.
[42]	Qualitative	Big data technologies	N/A	Green applications	N/A	-	Big data would have high potential to support green targets in environmentally friendly future and sustainable development	
[43]	Quantitative	Big data and predictive analytics	N/A	Green innovation practices	N/A	Positive	Big data and predictive analytics positively influence green innovation	
[16]	Quantitative	Big data acceptance, routinization, assimilation	N/A	Sustainable performance	Green HR training	Positive	The assimilation of big data through acceptance and routinization has a positive impact on internal green practices	
[44]	Quantitative	Big data (volume, variety and velocity)	N/A	Innovation efficacy, Innovation efficiency	N/A	Positive	Big data are capable of changing the innovation landscape by effectively and efficiently increasing the fit between consumers' preferences and product features	
[45]	Quantitative	Big data analytics management capability	N/A	Green product innovation	N/A	Positive	Big data analytics management capability is positively related to innovative green product development	
[6]	Quantitative	Big data analytics capability	N/A	Green innovation	organizational commitment	Positive	Organizational commitment positively moderates the link between big data analytics capability management and green innovation	
[46]	Quantitative	Big data analytics	N/A	Green innovation	N/A	Positive	Big data analytics positively influence green innovation	
[47]	Quantitative	Big data analytics capabilities	Green innovation	Green supply chain performance	Technological intensity	Positive	Green innovation positively moderates big data analytics capabilities on green supply chain performance	
[48]	Quantitative	Big data capability	Green innovation intention	Green process innovation	N/A	Positive	Green innovation intention mediates the effect of big data capability on green process innovation	

Table 1. *Cont.*

Reference	Research Method	Big Data Related Construct	Intermediate Capabilities	Green Innovation Related Construct	Boundary Conditions	Effect	Main Finding	Research Gap
[49]	Quantitative	Big data analytics capabilities	N/A	Green radical/ incremental intention	N/A	Positive	There is a positive relationship between big data analytics and green radical and incremental intention	
[50]	Quantitative	Digital transformation	Research and development investment, police support	Green innovation	N/A	Positive	Digital transformation has a critical role in promoting enterprise green innovation.	
[51]	Quantitative	Big data application	Capital/labor allocation efficiency	Green innovation	N/A	Positive	The application of big data can significantly promote green innovation by manufacturing enterprises.	

Although BDMCs alone cannot directly foster green innovation, their integration with other organizational capabilities can facilitate this process [43]. Bag et al. [45] further suggested that the support of BDMCs and the degree of improvement in core competitiveness can account for the outcomes of green innovation. BDMCs can impact green innovation only through interaction and integration with other capabilities, particularly green DCs [4,52,53]. Researchers can gain a deep insight into the role of BDMCs in green innovation and provide valuable guidance for practitioners in devising, modifying, and optimizing BDMC strategies by linking BDMCs with specific green DCs.

The impact of exogenous variables as moderators on enterprise green innovation through the potential mechanism of BDMCs has been studied [33,54,55]. Lin and Chen [13] emphasized that achieving innovation in an organization depends on appropriately matching specific internal and external variables. According to previous studies, enterprises can develop new strategies to match resources and reduce the threat of exogenous environmental factors when identifying business opportunities [56,57]. Furthermore, Gupta and George [5] found that the extent to which enterprises satisfy their industries' needs can be used to measure the influence of BDMCs on green innovation. Recent research has supported the view that external environmental factors, such as ET, are crucial in BDMCs' effect on green innovation [58]. Given the limited existing knowledge of environmental constraints in BDMCs, we comprehensively examined the role of green DCs and ET, aiming to provide a broad perspective on how BDMCs can facilitate green innovation in an uncertain environment.

3. Research Models and Hypotheses

This research paper presents a novel model suggesting that BDMCs indirectly impact green innovation, with green DCs as the mediating factor. Additionally, our model posits that the effects of BDMCs on green DCs, green DCs on GPDI, and green DCs on GPCI are moderated by ET. We depict the proposed relationships in Figure 1.

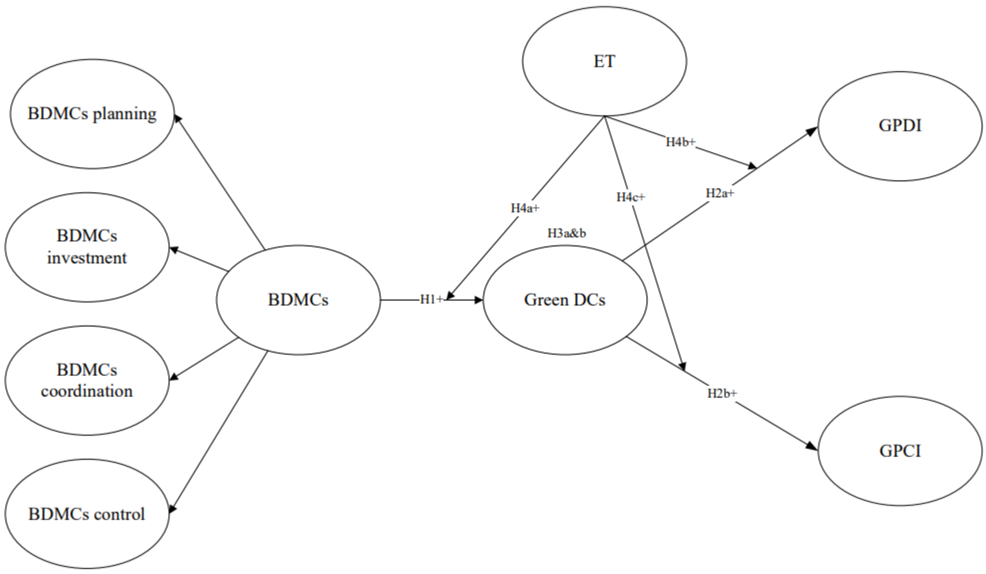


Figure 1. Research model.

3.1. BDMCs and Green DCs

BDMCs can enable manufacturing enterprises to enhance their green DCs in three crucial ways: (1) by identifying emerging environmental threats and opportunities, (2) by fostering adaptability and flexibility in green DCs, and (3) by facilitating green DC transformation to align it with sustainability goals [7].

According to the RBV, from a dynamic perspective, firms have two critical processes for acquiring resources and gaining a competitive advantage: resource selection and capability development [59]. Manufacturing enterprises must use their existing resources to meet the ever-changing market demands by identifying potential threats and opportunities and seeking DCs [60]. In this context, BDMCs can play a vital role in enabling enterprises to actively and flexibly select the valuable resources and capabilities suitable for organizational growth, make good decisions, and achieve green development [61]. In particular, BDMCs can enhance operational efficiency and optimize processes by facilitating the development, deployment, and reallocation of internal resources [36]. Companies that frequently use BDMCs can effectively absorb and adjust their internal resources, whereas those that ignore them vaguely tend to identify opportunities and guide their organization to adjust resources flexibly; thus, the latter falls behind competitors in operations [45].

Given the rapid pace of change in today's business environment, companies must have the flexibility to allocate resources and optimize capabilities effectively; this approach can help them maintain competitiveness [62]. El-Kassar and Singh [43] proposed that organizations with high utilization capabilities can develop reliable information sources; moreover, BDMCs can help enterprises identify potential business opportunities to develop other capabilities needed for growth [63]. Therefore, BDMCs are critical resources that support companies' successful operations in rapidly changing environmental and market conditions; they also play a vital role in developing a company's DCs [35]. When the threats and opportunities are identified, BDMCs can be used to update or adjust the existing data resources and capabilities fundamentally; thus, the enterprises' ability to seize opportunities and realize green DC transformation can be enhanced [52,64]. Thus, we propose the following hypothesis:

H1: *BDMCs have a significant positive impact on green DCs.*

3.2. Green DCs and Green Innovation

The concept of green DCs emphasizes a company's ability to utilize existing resources and knowledge to update and develop its green organizational capabilities in response to sustainable development demands [12]. The GPDI focuses on improving product design by developing environmentally friendly products using low-carbon technology or recyclable materials to address environmental protection [16]. Yu et al. [65] emphasized that manufacturing companies can grab opportunities to increase the eco-friendliness of their products by integrating existing resources and optimizing their capabilities to respond to environmental demands. The development of GPDI depends largely on a company's ability to quickly adopt the necessary changes related to environmental management, namely green DC [11]. Moreover, scholars argued that firms with robust green DC are adequately equipped to allocate resources and invest them in the research and development of green products [34]. Thus, enterprises can effectively respond to market opportunities related to green innovation by recombining resources and setting up new cross-functional teams for green product development [16].

H2a: *GPDI is significantly positively affected by the implementation of green DCs.*

The GPCI demands that manufacturing enterprises utilize novel ideas, techniques, and methods at every stage of the product lifecycle, from design and production to sales and disposal, to achieve minimal energy consumption and waste emission in response to sustainable development policies [12]. According to DC theory, enterprises with strong DCs are sufficiently equipped to allocate resources and optimize abilities in a constantly changing environment; thus, the production processes are simplified while reducing innovation risks and production costs [53]. Yuan and Cao [28] asserted that as a driving force for organizations to respond to the environment and sustainable development, green DCs guide efforts to improve the process of protecting the ecosystem. Green DCs can promote process-related green innovation, including reducing waste emissions, waste recycling, energy conservation, and improvements in raw materials [16]. Furthermore, enterprises possessing green DCs can respond to market opportunities for green innovation through resource restructuring, thereby achieving GPCI [48].

H2b: *GPCI is significantly positively affected by the implementation of green DCs.*

3.3. Mediating Role of Green DCs

Manufacturing firms with BDMCs can effectively promote green innovation, with green DCs mediating between BDMCs and green innovation. BDMCs enable enterprises to absorb knowledge from partners, integrate their resources, and engage in green development activities driven by customer and government demands. According to DC and RBV theories, manufacturing enterprises can transform environmental pressure into a driving force for green development by optimizing their big data capabilities [6,45,49]. When facing environmental pressure, manufacturing enterprises tend to focus their resources on identifying green innovation opportunities, mobilizing and allocating resources, developing capabilities suitable for green development, and translating opportunities into green innovation practices [11,66,67].

Hence, establishments that ardently cultivate BDMCs have the opportunity to augment their aptitudes incessantly for amalgamating resources, revamping resources, and gaining perspicacity regarding environmental information. Moreover, strengthening the green DCs of manufacturing enterprises empowers them to procure clients' predilections for consuming green products in the marketplace expeditiously and precisely; as a result, informative sustenance is provided for establishments to execute GPDI [34,68]. According to Shu et al. [69], companies that prioritize environmental sustainability in their DC tend to secure funding, attract skilled personnel and technology, and gain access to essential resources from the government and partners. Thus, ample support is provided for companies to pursue green innovation. Enterprises can reorganize their operations by integrating the functions of various departments to achieve GPCI when they obtain market information [28,33,48]. Hence, we propose two hypotheses:

H3a: *Green DCs mediate the relationship between BDMCs and GPDI.*

H3b: *Green DCs mediate the relationship between BDMCs and GPCI.*

3.4. Moderating Role of ET

Recent research has suggested that the integration of exogenous variables and internal mechanisms within enterprises can serve as a catalyst for promoting green innovation [33]. Conformity to such variables can influence internal procedures and impact overall innovation within a company [70]. ET characterizes an environment where market demands and environmental dynamics remain in a constant state of flux, defying predictability [71]. Furthermore, ET is a pivotal factor in shaping a firm's strategies and capabilities, as it simultaneously introduces opportunities and constraints for innovation [72]. Turbulence in this context not only refers to mere environmental changes but primarily indicates the degree of unpredictability and instability. As the degree of turbulence increases, strategic deployments within an organization are more susceptible to disruption [6]. Schilke [71] emphasized the dual role of market dynamics, which can both facilitate and constrain innovation. Similarly, the recalibration of a firm's capabilities can result in the restructuring of resource allocations. The impact of ET compels enterprises to adapt their existing resources within a dynamic capability framework that can effectively respond to environmental perturbations [73]. Notably, big data emerge as a driving force behind dynamic capabilities, particularly when navigating the realm of continuous and unpredictable changes [74].

H4a: *The association between BDMCs and green DCs can be positively influenced by ET.*

As pointed out by Chen et al. [75], ET introduces uncertainty and risks to an organization's effective functioning. In line with the information processing theory, when faced with uncertain environments, organizations require more data and higher information processing capabilities [76] to achieve greater agility through efficient sensing and responsive actions [77]. ET enhances the role of big data management by increasing the demand for information within enterprises, thereby facilitating informed decision making and fostering innovation [20]. From this viewpoint, ET creates opportunities for organizations to utilize BDMCs in identifying and addressing emerging environmental trends and challenges, ultimately driving green innovation. In uncertain environments, the capabilities of BDMCs and dynamic capabilities are more effective in leveraging resources and processing informational data within the organization. Our research findings suggest that the incorporation of ET actually strengthens the link between dynamic capabilities and green innovation.

Furthermore, the transformative impact of ET on innovation becomes evident as organizations respond to the growing call for sustainable practices. ET necessitates a reorganization of resources to elevate competitiveness. This transformative shift towards sustainability is instrumental in catalyzing the development of novel green products, optimizing production processes, and facilitating integration into new markets. Ultimately, these actions contribute to growth and the attainment of a competitive advantage [78,79]. Additionally, Porter and Linde [80] suggested that ET prompts a continuous enhancement of products and processes to effectively respond to evolving environmental circumstances. Building upon these insights, we posit the following hypotheses:

H4b: *The association between green DCs and GPDI can be positively influenced by ET.*

H4c: *The association between green DCs and GPCI can be positively influenced by ET.*

4. Research Methodology

4.1. Data Collection

Carbon neutrality is a new development-related area of focus in China, with many Chinese companies increasing their investment in green innovation. With the help of the Institute of Statistical Analysis of Big Data in Guizhou, China, we obtained the full contact information of 500 relevant manufacturing companies and sent them an email asking if they would like to participate in our study. The following arrangements were made to avoid possible nonresponse bias: we distributed and collected the questionnaires in two waves with a month-long distribution gap [81]. We compared the differences in the mean values of core variables in the questionnaires distributed before and after and found no substantial differences in BDMCs, green DCs, GPDI, and GPCI between the first and second waves. Hence, our study was unaffected by the nonresponse bias. We also selected 10 companies whose operations were in a Chinese city that served as the capital of its corresponding province. These companies were invited for a pretest where the questionnaire was adjusted based on their feedback to ensure linguistic accuracy. After 3 months, we received 266 valid responses out of 500 valid questionnaires with an acceptable response rate of 53.2%. Appendix A shows the information on our research sample.

4.2. Measurement Items

Chin et al. [82] proposed that reflective observation variables should be prioritized over formative observation variables during the testing of existing theories. Given this perspective, we selected scales validated by scholars and developed multi-item reflection measures by making slight modifications to tailor them to specific situations. Appendix B presents the measurement items of each construct.

We followed the reverse translation technique of Bhalla and Lin [83] to ensure the accuracy and equivalence of language. This technique involves a machine that translates the Chinese questionnaire into English and then back-translates the English sentences into Chinese sentences. The obtained Chinese sentences were compared with the original Chinese sentences. We invited one professor and two PhD students in the field of information systems to review and provide feedback. Thus, the questionnaire content can be validated, and its comprehensibility can be ensured. On the basis of their input, we made certain revisions to the final version.

BDMCs: In accordance with our theoretical framework, we followed the methodology proposed by Akter, Wamba, Gunasekaran, Dubey, and Childe [36] and treated BDMCs as a second-order structure with four dimensions: BDMC planning, BDMC investment, BDMC coordination, and BDMC control. We requested that managers evaluate the significance of the measured components in relation to those of other companies within the industry. We adopted a 7-point Likert scale to obtain item measurements. A score of 1 represented poorer performance than most, and a score of 7 represented exceptionally good performance.

Green DCs: Chen and Chang [12] defined green DCs as the ability of an enterprise to use existing resources and knowledge for updating and developing green organizational capabilities and managing random market changes. We utilized the 7-item scale developed by Chen and Chang [12] to measure the said variable and the effectiveness of green DCs.

Green innovation: In the domain of environmental management, green innovation has been widely recognized as an effective approach to enhancing the quality of products or processes. Green innovation holds significant potential to promote sustainable development and create value for businesses and society by reducing energy consumption, mitigating pollution, recycling waste, promoting eco-friendly product development, and leveraging cutting-edge technologies [30,84]. We employed a well-established measure of green innovation proposed by [85] to align our study with state-of-the-art research in this field.

ET: We utilized the scale of measure by Schilke [71] to assess the volatility and unpredictability of environmental factors. We employed a survey instrument to obtain information on the external factors that organizations face in their industry. In this survey, business managers were asked to evaluate these factors. The instrument employed a 7-point Likert scale to measure the items. A score of 1 indicated poorer performance than most, and a score of 7 indicated exceptionally good performance.

Control variables: The type and age of a firm are influential factors in the development of big data and the ability to transform. Enterprises with long operational cycles are adept at adjusting resources for innovative development. Thus, they gain a competitive advantage. Different types of firms have varying approaches and methods for achieving green innovation [47]. Moreover, companies that have utilized BDMCs for an extended period possess a competitive advantage in implementing green innovation [6]. Hence, the age and type of organization were treated as our control variables in this study.

4.3. Data Analysis and Results

Convergent validity: We utilized confirmatory factor analysis (CFA) to determine convergence validity. Our study employed a five-construct CFA model by utilizing SmartPLS 4.0. This model included BDMCs (represented as a reflection of second-order factors), green DCs, ET, GPDI, and GPCI. The results of our analysis can be found in Table 2, which presents compelling evidence of convergent validity. All four first-order factor path coefficients associated with BDMCs were statistically significant, surpassing the recommended critical value of 0.70. These findings demonstrate that BDMCs possess strong convergent validity as a reflective second-order factor.

Table 2. Finalized confirmatory factor analysis results for the constructs.

Model Construct	**Item**	**Standardized Loading**	**Cronbach's α**	**AVE**	**Second-Order Factor Loading [a]**
Big data management capabilities (BDMCs)					
BDMC planning	BMP1	0.82	0.85	0.69	0.82
	BMP2	0.84			
	BMP3	0.86			
	BMP4	0.81			
BDMC investment	BMI1	0.88	0.88	0.74	0.82
	BMI2	0.87			
	BMI3	0.86			
	BMI4	0.84			
BDMC coordination	BMC1	0.86	0.88	0.74	0.80
	BMC2	0.86			
	BMC3	0.87			
	BMC4	0.86			
BDMC control	BMT1	0.83	0.85	0.69	0.83
	BMT2	0.86			
	BMT3	0.83			
	BMT4	0.80			
Green dynamic capabilities	DC1	0.73	0.90	0.64	-
	DC2	0.80			
	DC3	0.83			
	DC4	0.80			
	DC5	0.83			
	DC6	0.79			
	DC7	0.80			
Green product innovation	GPDI1	0.80	0.85	0.70	-
	GPDI2	0.88			
	GPDI3	0.84			
	GPDI4	0.81			
Green process innovation	GPCI1	0.81	0.87	0.71	-
	GPCI2	0.84			
	GPCI3	0.85			
	GPCI4	0.87			
Environment turbulence	ET1	0.78	0.87	0.65	-
	ET2	0.80			
	ET3	0.84			
	ET4	0.79			
	ET5	0.83			

[a] Second-order factor loading from second-order factor (that is, BDMCs) to first-order factors (that is, BDMC planning, BDMC investment, BDMC coordination, and BDMC control).

Reliability testing: As summarized in Table 2, the internal consistency of the constructs was assessed using Cronbach's α scale. The results indicated that all constructs had a minimum α value above 0.85, exceeding the reliability threshold of 0.70 suggested by Bland and Altman [86]. These findings suggest that the constructs are reliable and can be used for further analysis.

Discriminant validity: We assessed the discriminant validity by employing the suggested method of analyzing the factor correlations and the average variance extracted (AVE) of each construct, as proposed by Gefen et al. [87]. Our findings are presented in Table 3, which indicates that none of the correlation coefficients between the constructs exceeded 0.80. This finding reveals a lack of a strong correlation. Furthermore, the square root of AVE for each construct was significantly higher than the correlation between any two factors, indicating strong evidence of discriminant validity for the scale.

Table 3. Descriptive statistics.

Variables	Mean	SD	1	2	3	4	5	6	7
1.BDMCs	4.92	1.03	**0.69**						
2.ET	4.87	1.24	0.22 **	**0.80**					
3.Green DCs	4.77	1.20	0.42 **	0.33 **	**0.81**				
4.GPDI	5.07	1.27	0.40 **	0.26 **	0.35 **	**0.83**			
5.GPCI	5.17	1.26	0.48 **	0.35 **	0.50 **	0.45 **	**0.84**		
6.Firm type	12.08	17.17	−0.04	−0.06	0.00	0.09	−0.05	**N/A**	
7.Firm age	1.67	0.47	−0.04	−0.06	−0.06	−0.03	−0.08	0.04	**N/A**

Notes: Diagonal elements are the square roots of average variance extracted; ** $p \leq 0.01$, (two-tailed).

Common methods variance: (CMV) Kock and Lynn [88] indicated that collinearity of the same source causes CMV, and if the variance inflation factor (VIF) exceeds 3.3, it may suggest the presence of common method bias, which could compromise the model. Therefore, an internal model's VIF values for all variables obtained through tests for perfect collinearity should be 3.3 or lower, indicating the absence of CMB [89]. In the present study, we employed SmartPLS 4.0 to examine the VIF values in our structural models and found that all values were less than 3. Hence, we can conclude that our models are free of CMV.

Testing of hypotheses: The method of testing the moderating relationship with hierarchical regression analysis yields an accurate estimate of the strength of the link between the interacting effects [90–92]. We developed several models in PLS starting from controlling variables to verify the direct, mediating, and moderating effects.

The following hierarchical research model is proposed: the BDMCs (big data management capabilities), green DCs (green dynamic capabilities), GPDI (green product innovation), GPCI (green process innovation), ET (environmental turbulence), C1 (Firm type), C2 (Firm Age), β (path coefficient), and ε (error). The sources and definitions of the variables used in our model are provided in Appendix C.

(1) Main Effect Test

$$\text{GPDI} = \text{a0} + \beta_1\ \text{C1} + \beta_2\ \text{C2} + \varepsilon(\text{M5a}) \tag{1}$$

$$\text{GPCI} = \text{a0} + \beta_1\ \text{C1} + \beta_2\ \text{C2} + \varepsilon(\text{M5b}) \tag{2}$$

$$\text{GPDI} = \text{a0} + \beta_1\ \text{C1} + \beta_2\ \text{C2} + \beta_3\ \text{BDMCs} + \varepsilon(\text{M6a}) \tag{3}$$

$$\text{GPCI} = \text{a0} + \beta_1\ \text{C1} + \beta_2\ \text{C2} + \beta_3\ \text{BDMCs} + \varepsilon(\text{M6b}) \tag{4}$$

$$\text{GPDI} = \text{a0} + \beta_1\ \text{C1} + \beta_2\ \text{C2} + \beta_3\ \text{green DCs} + \varepsilon(\text{M8a}) \tag{5}$$

$$\text{GPCI} = \text{a0} + \beta_1\ \text{C1} + \beta_2\ \text{C2} + \beta_3\ \text{green DCs} + \varepsilon(\text{M8b}) \tag{6}$$

Model 5 was conducted to estimate the effects of two control variables on green innovation. The effects of BDMCs on green innovation (GPDI/GPCI) were evaluated in model 6. The effects of green DCs on green innovation (GPDI/GPCI) were evaluated in model 8.

(2) Mediating Role Test

$$\text{Green DCs} = \text{a0} + \beta_1\ \text{C1} + \beta_2\ \text{C2} + \varepsilon(\text{M1}) \tag{7}$$

$$\text{Green DCs} = \text{a0} + \beta_1\ \text{C1} + \beta_2\ \text{C2} + \beta_3\ \text{BDMCs} + \varepsilon(\text{M2}) \tag{8}$$

$$\text{GPDI} = \text{a0} + \beta_1\ \text{C1} + \beta_2\ \text{C2} + \beta_3\ \text{BDMCs} + \beta_4\ \text{green DCs} + \varepsilon(\text{M7a}) \tag{9}$$

$$GPCI = a0 + \beta_1\ C1 + \beta_2\ C2 + \beta_3\ BDMCs + \beta_4\ green\ DCs + \varepsilon(M7b) \quad (10)$$

Model 1 was conducted to estimate the effects of two control variables on green DCs. In model 2, we added the BDMCs to evaluate their influence on green DCs. And in model 7, we added the green DCs to evaluate their effect on green innovation (GPDI/GPCI).

(3) Moderating Role Test

$$Green\ DCs = a0 + \beta_1\ C1 + \beta_2\ C2 + \beta_3\ BDMCs + \beta_4\ ET + \varepsilon(M3) \quad (11)$$

$$Green\ DCs = a0 + \beta_1\ C1 + \beta_2\ C2 + \beta_3\ BDMCs + \beta 4\ ET + \beta_4 + BDMCs \times ET + \varepsilon(M4) \quad (12)$$

Model 3 estimated the direct effect of ET on green DCs. Model 4 estimated the effect of interaction terms between ET and BBDMCs on green DCs. Thus, model 3 and model 4 captured the quasi-moderating effect of ET.

$$GPDI = a0 + \beta_1\ C1 + \beta_2\ C2 + \beta_3\ green\ DCs + \beta_4\ ET + \varepsilon(M9a) \quad (13)$$

$$GPCI = a0 + \beta_1\ C1 + \beta_2\ C2 + \beta_3\ green\ DCs + \beta_4\ ET + \varepsilon(M9b) \quad (14)$$

$$GPDI = a0 + \beta_1\ C1 + \beta_2\ C2 + \beta_3\ green\ DCs + \beta_4\ ET + \beta_5\ green\ DCs \times ET + \varepsilon(M10a) \quad (15)$$

$$GPCI = a0 + \beta_1\ C1 + \beta_2\ C2 + \beta_3\ green\ DCs + \beta_4\ ET + \beta_5\ green\ DCs \times ET + \varepsilon(M10b) \quad (16)$$

Model 9 estimated the direct effect of ET on green innovation (GPDI/GPCI). Model 10 estimated the effect of the interaction terms between ET and green DCs on green innovation (GPDI/GPCI). Thus, model 9 and model 10 captured the quasi-moderating effect of ET.

The results of the regression analysis are presented in Table 4, which includes standardized path coefficients, the variance explained by the independent variables (R^2), the incremental change in R^2 (ΔR^2), the effect size (f^2), and the model's goodness of fit (SRMR). Considering the complexity of the model we developed, we also analyzed the data results under a hypothetical sequence.

In Model 1, firm age had a negative effect on green DCs, whereas the firm type had a positive effect on green DCs; however, neither of them was significant ($\beta = -0.29$, $p > 0.05$ and $\beta = 0.13$, $p > 0.05$). The equation's explanatory power was also not significant (R2 = 0.03, $p > 0.05$). However, model 2 showed that BDMCs had a significant positive impact on green DCs ($\beta = 0.43$, $p < 0.001$), and the equation's explanatory power was significant ($R^2 = 0.18$, $p < 0.001$). Thus, H1 is supported.

Table 4. Results of the regression analyses [a].

	Green Dynamic Capabilities				Green Product Innovation						Green Process Innovation					
	M1	**M2**	**M3**	**M4**	**M5a**	**M6a**	**M7a**	**M8a**	**M9a**	**M10a**	**M5b**	**M6b**	**M7b**	**M8b**	**M9b**	**M10b**
Control																
Firm age	−0.29	−0.10	−0.07	−0.04	−0.09	−0.04	−0.02	−0.02	−0.01	0.01	−0.19	−0.12	−0.10	−0.11	−0.09	−0.07
Firm type	0.13	0.02	0.03	0.03	0.12	0.10	0.10	0.09	0.10	0.10	−0.05	−0.02	−0.04	−0.06	−0.05	−0.05
Independent																
BDMCs		**0.43 *****	**0.37 *****	**0.37 ****		**0.42 *****	**0.32 *****					**0.48 *****	**0.33 *****			
Green DCs							**0.22 ****	**0.36 *****	**0.30 *****	**0.33 *****			**0.37 *****	**0.51 *****	**0.44 *****	**0.47 *****
ET			**0.25 ****	**0.27 *****					**0.18 ****	**0.17 ****					**0.21 ****	**0.20 ****
Interaction																
BDMCs × ET				**0.20 ****												
Green DCs × ET										**0.14 ***						**0.16 ****
R^2	0.03	0.18	0.24	0.30	0.02	0.18	0.22	0.14	0.17	0.20	0.01	0.24	0.35	0.27	0.31	0.35
ΔR^2		0.15	0.06	0.05		0.17	0.04	0.12	0.03	0.03		0.23	0.11	0.26	0.04	0.04
f^2		0.22	0.17	0.08		0.21	0.22	0.15	0.03	0.04		0.31	0.17	0.36	0.05	0.06
F		**19.56 *****	**20.95 *****	**21.76 *****		**19.43 *****	**18.19 *****	**13.98 *****	**12.99 *****	**12.60 *****		**27.88 *****	**35.13 *****	**32.30 *****	**28.77 *****	**27.63 *****
SRMR	0.14	**0.05**	**0.05**	**0.05**	0.06	**0.04**	**0.05**	**0.05**	**0.05**	**0.05**	0.07	**0.04**	**0.05**	**0.06**	**0.05**	**0.05**

[a] Tabled values are standardized regression weights. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$ (two-tailed).

Models 5a and 5b indicated the influence of firm age and firm type, respectively, on GPDI and GPCI. However, neither of them was statistically significant ($p > 0.05$), and the explanatory capability of the equation was not significant ($R^2 = 0.02$, $p > 0.05$ and $R^2 = 0.01$, $p > 0.05$). In model 6a, BDMCs had a significant positive impact on GPDI ($\beta = 0.42$, $p < 0.001$). In model 7a, BDMCs and green DCs exhibited positive and significant influences ($\beta = 0.32$, $p < 0.001$ and $\beta = 0.22$, $p < 0.001$). The explanatory power of our model deserves recognition ($R^2 = 0.218$, $p < 0.01$). In model 6b, BDMCs had a significant positive effect on GPCI ($\beta = 0.48$, $p < 0.001$). In model 7b, BDMCs and green DCs had positive and significant impacts ($\beta = 0.33$, $p < 0.001$ and $\beta = 0.37$, $p < 0.001$). The explanatory power of our model was significant ($R^2 = 0.350$, $p < 0.01$). Moreover, we adopted the bootstrapping method with 5000 samples proposed by Preacher and Hayes [84] to examine the comprehensive mediation relationship thoroughly. We also used SmartPLS 4.0. The results indicate that the direct effect of BDMCs on GPDI was significant under the control of green DCs ($\beta = 0.32$; t value = 4.015, $p < 0.001$). The 95% confidence interval for the indirect path (0.09) excluded zero (0.03, 0.17). Moreover, the direct effect of BDMCs on GPCI was significant under the control of green DCs ($\beta = 0.33$; t value = 4.397, $p < 0.001$). The 95% confidence interval for the indirect path (0.15) excluded zero (0.17, 0.46). Thus, both H2 and H3 are supported. The results suggest that green DCs play a mediating role between BDMCs and GPDI/GPCI. Therefore, H2a, H2b, H3a, and H3b are supported.

We used models 1–4 to test the moderating effect of ET between BDMCs and green DCs. According to the data from model 1, the explanatory power of the equation was not significant ($R^2 = 0.03$, $p > 0.05$). In model 2, BDMCs had a significant positive effect on green DCs ($\beta = 0.43$, $p < 0.001$). Additionally, model 3 indicated that the introduction of ET had a significant and positive impact on green DCs ($\beta = 0.25$, $p < 0.01$). Furthermore, model 4 supported H4a by demonstrating that the interaction terms between ET and BDMCs were positive and significant ($\beta = 0.20$, $p < 0.01$).

Models 5a, 8a, 9a, and 10a were used to test the moderating effect of ET between green DCs and GPDI. The results of model 5a indicated that the equation's explanatory power was not significant ($R^2 = 0.02$, $p > 0.05$). Additionally, model 8a indicated that the influence of green DCs on GPDI was positive and statistically significant ($\beta = 0.36$, $p < 0.001$). Furthermore, model 9a highlighted that GPDI was positively and significantly impacted by ET after its inclusion ($\beta = 0.18$, $p < 0.01$). Finally, the results of model 10a supported H4b. This finding revealed that the interaction between ET and green DCs was positive and significant ($\beta = 0.14$, $p < 0.05$).

Models 5b, 8b, 9b, and 10b were used to test the moderating effect of ET between green DCs and GPDI. The equation in model 5b had no significant explanatory power ($R^2 = 0.01$, $p > 0.05$). The impact of green DCs on GPCI was positively significant in model 8b ($\beta = 0.51$, $p < 0.001$). After being added, ET had a positive and significant impact on GPCI in model 9b ($\beta = 0.21$, $p < 0.01$). In model 10b, the interaction terms between ET and green DCs were positive and significant ($\beta = 0.16$, $p < 0.01$). This finding provides support for H4c.

In the present study, the main model fit, standardized root mean square residual (SRMR), except for the regression model of the control variable on the dependent variable, was below 0.08, which proves that our model had an excellent fitting effect. The results of the structural equation model are summarized in Figure 2. This figure shows the estimates of the path between BDMCs, green DCs, GPDI, GPCI, and ET. The path coefficient (β) values, computed t-values, and p-values were evaluated, as well as the relationship between exogenous constructs and endogenous constructs. Moreover, we employed the Aiken and West [93] method to compute the slope of one standard deviation above and below the average value of ET. The interaction pattern is illustrated in Figure 3, confirming our hypotheses H4a, H4b, and H4c. When the level of ET was high, we observed a robust positive correlation between BDMCs and green DCs, between green DCs and GPDI, and between green DCs and GPCI. Table 5 provides a comprehensive summary of our hypotheses.

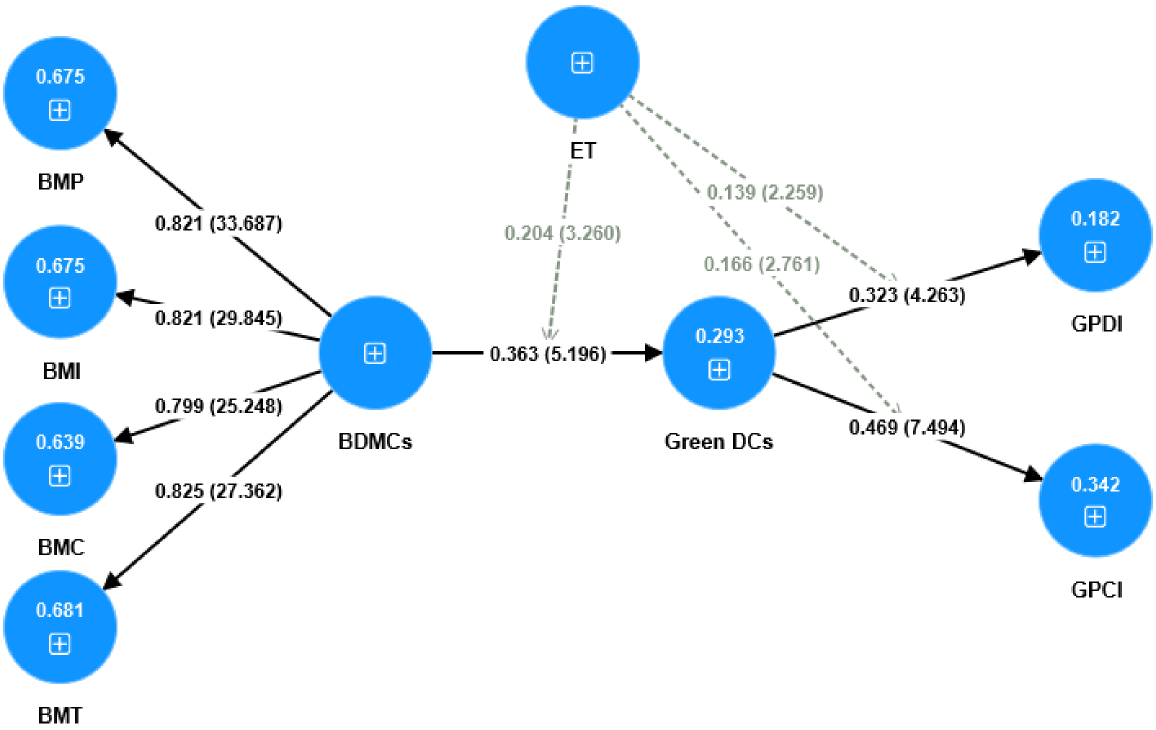
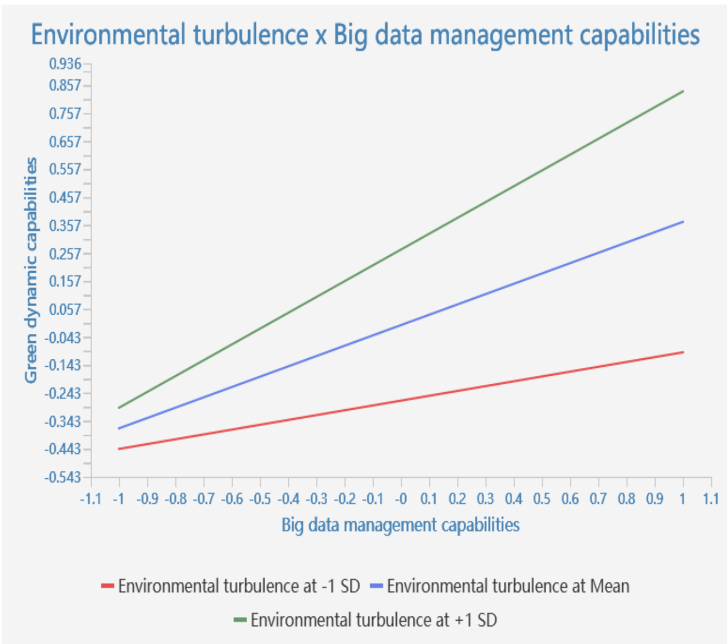
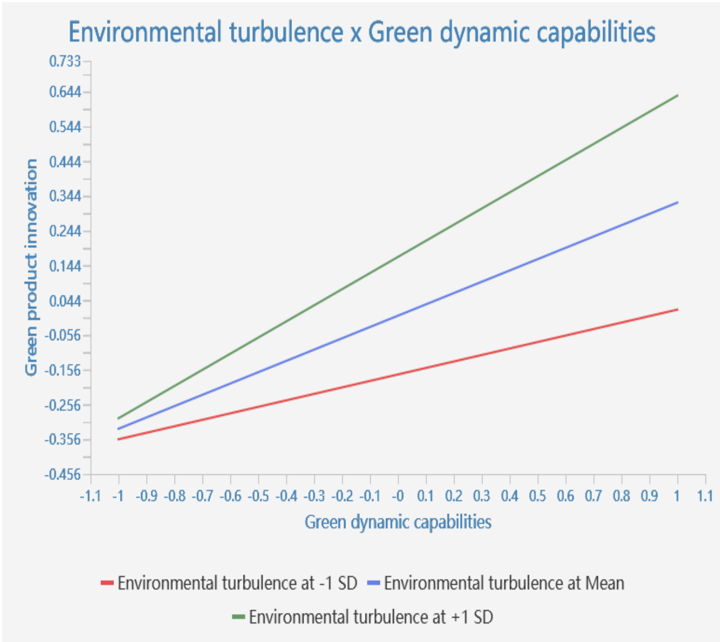


Figure 2. Structural equation modeling for the study model.

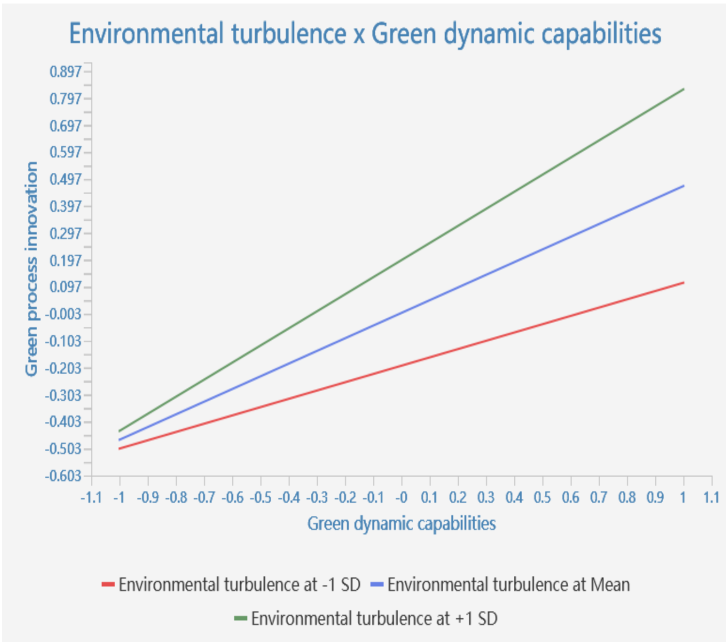


(**a**)

Figure 3. *Cont.*



(**b**)



(**c**)

Figure 3. Three interaction effects. (**a**) Interactions between BDMCs and green DCs. (**b**) Interactions between green DCs and GPDI. (**c**) Interactions between green DCs and GPCI.

Table 5. Results of hypotheses' testing.

Hypothesis	Results
H1: BDMCs have a significant positive impact on green DCs	Supported
H2a: Green DCs have a significant positive impact on GPDI	Supported
H2b: Green DCs have a significant positive impact on GPCI	Supported
H3a: Green DCs mediate the relationship between BDMCs and GPDI	Supported
H3b: Green DCs mediate the relationship between BDMCs and GPCI	Supported
H4a: ET positively moderates the relationship between BDMCs and green DCs	Supported
H4b: ET positively moderates the relationship between green DCs and GPDI	Supported
H4c: ET positively moderates the relationship between green DCs and GPCI	Supported

5. Discussion and Implication

5.1. Discussion

Through our empirical results, we obtained three main findings. Firstly, we found that BDMCs have emerged as a promising technology, fundamentally altering the way businesses innovate and create value, particularly in the context of increasing demand for green manufacturing. Our research demonstrates that leveraging big data resources enables manufacturing firms to enhance their GPDI/GPCI. This is because the capacity for handling vast amounts of data can help businesses identify new opportunities and points of innovation. By analyzing consumer behavior, market trends, and competitor activities, companies can uncover avenues for green innovation and drive innovation in green products and processes. This data-driven innovation approach allows businesses to target green innovation more effectively, ultimately enhancing their success rate. These findings are supported by Bag, Wood, Xu, Dhamija, and Kayikci [45] and Tian, Li, and Zhang [48].

Secondly, our study reveals that green DCs play a mediating role in the process of leveraging BDMCs for green transformation. Dynamic capabilities theory underscores the necessity for businesses to effectively adapt to evolving environments through organizational learning and adaptive adjustments. Expanding upon the RBV, green DCs posit that a firm's resources and capabilities form the bedrock of its competitive advantage. It is noteworthy that some enterprises undergo strategic transformations when employing big data analysis and management to support green innovation, aligning themselves more effectively with a constantly changing environment. Such strategic transformations encompass adjustments to organizational structure, process redesign, and resource reallocation—manifestations of green DCs. In this process, the integration of diverse resources and capabilities provides a foundational support for the realization of green DCs.

Lastly, our findings indicate that enterprises equipped with BDMCs are more likely to harness existing resources for adapting green DCs, especially in high ET scenarios, thereby facilitating capability transformation. This insight extends existing theories to some extent, suggesting a potentially positive influence of big data management capabilities on capability transformation in the face of environmental uncertainty. Dynamic capabilities theory maintains that adaptation to environmental changes and innovation through organizational learning and adjustments is paramount. The resource-based view underscores the significance of a firm's resources and capabilities as sources of competitive advantage, rendering capability transformation and innovation reasonable in uncertain environments. Furthermore, the study suggests that a high ET can compel enterprises to venture beyond their comfort zones, engaging in capability transformation, process optimization, and product innovation. This aligns with prior research, such as Mikalef, Boura, Lekakos, and Krogstie [7] and Waqas, Honggang, Ahmad, Khan, and Iqbal [6], indicating that environmental turbulence drives proactive change measures to adapt to shifting circumstances.

5.2. Implications

Our study significantly advances the existing literature by seamlessly integrating RBV and DC theory frameworks into the context of BDMCs and green innovation. Building upon the foundation laid by Yousaf [11], our research introduces and emphasizes a different facet of the green innovation discourse. By exploring the unique interplay between BDMCs, green DCs, and green innovation, our study enriches the current understanding in the domain of DCs theory. We contend that BDMCs represent a pivotal resource for organizations seeking to drive green innovation in intricate and evolving environments. The empirical insights garnered from our analysis underscore the profound influence of BDMCs in fostering and optimizing green DCs within organizations. This finding accentuates the positive impact of BDMCs on innovation, in alignment with the work of Mikalef, Boura, Lekakos, and Krogstie [7]. Consequently, our research extends the current body of knowledge on information technology and sustainable development by elucidating the intricate interplay between BDMCs, green DCs, and green innovation. These interconnected elements contribute synergistically to the long-term sustainability of businesses. Our proposed model presents an innovative avenue for refining the implementation mechanisms of GPDI and GPCI, offering a comprehensive framework to expedite sustainable innovation efforts. This pivotal role of BDMCs echoes prior research highlighting the significance of big data in driving innovation within manufacturing companies [7,49]. Our study underscores BDMCs as a key enabler, empowering organizations to harness the potential of big data for steering green innovation and steering enterprises towards lasting sustainability.

Furthermore, our research offers valuable insights into the practical realm, shedding light on the mediating effects of green DCs in the relationship between BDMCs and green innovation. By bridging DC theory with the RBV, we unveil a powerful mechanism for propelling green innovation through the conduit of BDMCs. While prior research has predominantly examined determinants of green innovation through various lenses, such as intention, capital efficiency, labor allocation, and R&D investment [48,50,51], our study underscores the pivotal role of dynamic capabilities in driving sustainable development. Empirical evidence underscores that green DCs play a more potent role in propelling GPCI than in enhancing GPDI within manufacturing enterprises adopting big data technology. As such, enterprises prioritizing GPCI in their sustainable initiatives should strategically invest in the development of dynamic capabilities, enhancing their capacity to adapt, learn, and innovate in response to the ever-changing environmental dynamics.

In addition, our study offers a comprehensive exploration of the moderating influence of ET, unveiling a new avenue of research. Through meticulous examination, we reveal that the impact of BDMCs on green DCs is significantly amplified under conditions of heightened ET. This novel insight highlights the instrumental role of BDMCs in facilitating organizational capability transformation and innovation amidst environmental uncertainty. Our findings illuminate the fact that turbulent environments compel enterprises to transcend their comfort zones, driving not only capability transformation but also process optimization and product innovation. These findings resonate with prior research by Mikalef, Boura, Lekakos, and Krogstie [7] and Waqas, Honggang, Ahmad, Khan, and Iqbal [6], reinforcing the idea that environmental turbulence acts as a catalyst for proactive organizational change, fostering adaptability in the face of evolving circumstances.

Our study makes significant contributions both theoretically and practically, highlighting the profound impact of BDMCs on driving green innovation through the intermediary role of green DCs, while the moderating effect of ET adds further depth to our insights. Collectively, these findings enhance our understanding of the complex dynamics underlying sustainable innovation in the realm of modern manufacturing enterprises, guiding more informed strategic choices and transformative initiatives. The implications of our research hold valuable lessons for corporate leaders. Firstly, our findings emphasize the pivotal importance of investing in BDMCs to achieve green innovation within the organization. This underscores the need for executives to prioritize the development of BDMCs, ensuring the ongoing sustainability of profitability. Secondly, while possessing a green DC is a crucial step towards fostering green innovation, it alone is insufficient. Companies must effectively manage and adapt their green DCs to evolving needs, maximizing their benefits. This entails not only hiring proficient BDMC experts but also strategically deploying BDMCs to enhance or attain green DC objectives. Lastly, our results underscore the substantial role played by ET in shaping a company's capacity for sustainable innovation. Although ET may lie beyond a firm's control, it is crucial for managers to comprehensively comprehend and manage its influence on BDMC investment decisions. The outcomes of our study suggest that enterprises operating in highly turbulent environments should prioritize BDMC development to effectively achieve a certain level of green innovation.

6. Limitations and Future Research

The current study has significantly contributed to our understanding of the impacts of BDMCs on green innovation. However, our research has some limitations that may be addressed in future studies. First, our sample consisted only of manufacturing enterprises. Therefore, our findings may not be generalizable to other sectors, such as services and retail. Future research should consider extending the current framework to nonmanufacturing sectors to gain further insight into the impacts of market environments on sustainable development. Second, we did not consider the particular market circumstances and conditions, even though the impacts of BDMCs on various kinds of green innovation were investigated. In certain situations, guiding the value of BDMCs may be more beneficial than developing green innovation strategies, such as dual and supply chain innovation. Further exploration into this domain is warranted for future investigations. Third, BDMCs are necessary for achieving green innovation; however, they still depend on several internal and external factors. Investigating how BDMCs evolve in different industries, the mechanisms that foster green innovation, and the methods for achieving such innovation is essential to gain insights into how firms can achieve sustainable development and positively impact the environment. Fourth, this study is based on the analysis of survey results rather than the analysis of quantitative indicators of enterprise activity. Analyzing quantitative indicators of enterprise activity within the framework of this research topic could be one of the potential areas for future research. Hence, future research should focus on exploring these aspects in greater depth.

7. Conclusions

The primary objective of our study was to investigate whether manufacturing enterprises in turbulent environments can achieve green sustainable development through their big data capability. This study effectively clarifies how BDMCs facilitate green innovation within companies. In particular, our findings reveal that green DCs serve as a mediator for the impacts of BDMCs on green innovation. This discovery not only contributes to the theoretical comprehension of the direct and indirect influences of BDMCs on green innovation but also furnishes empirical proof for their implications. Additionally, the moderating influence of ET on the correlation between BDMCs and green innovation is scrutinized in this study. Our outcomes demonstrate that the effects of BDMCs on green DCs are amplified when ET is high. This finding suggests that in turbulent environments, manufacturing enterprises can rapidly adapt and dynamically reallocate their capabilities and resources to achieve higher levels of GPDI and GPCI, thus facilitating green sustainable development. Our research contributes to the literature on BDMCs, green DCs, and green innovation by emphasizing the significance of developing BDMCs and green DCs as a means of achieving green development and innovative practices.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Sample Characteristics

Characteristics	Observations	Percentage
Ownership		
State-owned or -controlled	86	32.33%
Private	130	48.87%
Sino-foreign joint	13	4.89%
Wholly foreign-owned	12	4.51%
Others	25	9.40%
Organizational age		
≤5	102	38.35%
6–20	115	43.23%
21–50	39	14.66%
>50	10	3.76%
Number of employees		
≤50	38	14.28%
51–200	44	16.54%
201–500	54	20.30%
500–3000	55	20.68%
>3000	75	28.20%
Market share		
≤10%	115	43.23%
10–20%	89	33.46%
20–50%	52	19.55%
>50%	10	3.76%

Appendix B. Constructs and Measures

Constructs	Item	Measurement	Reference
Big Data Management Capabilities (BDMCs)			
BDMC planning (BMP)	BMP1	We continuously examine the innovative opportunities for the strategic use of big data analytics.	Akter, Wamba, Gunasekaran, Dubey and Childe [36], Behl, et al. [94]
	BMP2	We enforce adequate plans for the introduction and utilization of big data analytics.	
	BMP3	We perform big data analytics planning processes in systematic and formalized ways.	
	BMP4	We frequently adjust big data analytics plans to better adapt to changing conditions.	
BDMC investment (BMI)	BMI1	When we make big data analytics investment decisions, we think about and estimate the effect they will have on the productivity of employees' work.	
	BMI2	When we make big data analytics investment decisions, we consider and project about how much these options will help end users make quicker decisions.	
	BMI3	When we make big data analytics investment decisions, we think about and estimate the cost of training that end users will need.	
	BMI4	When we make big data analytics investment decisions, we consider and estimate the time managers will need to spend overseeing the change.	
BDMC coordination (BMC)	BMC1	In our organization, business analysts and line people meet frequently to discuss important issues both formally and informally.	
	BMC2	In our organization, business analysts and line people from various departments frequently attend cross-functional meetings.	
	BMC3	In our organization, business analysts and line people coordinate their efforts harmoniously.	
	BMC4	In our organization, information is widely shared between business analysts and line people; thus, those who make decisions or perform jobs can acquire all available know-how.	
BDMC control (BMT)	BMT1	In our organization, the responsibility for big data analytics development is clear.	
	BMT2	We are confident that big data analytics project proposals are properly appraised.	
	BMT3	We constantly monitor the performance of the big data analytics function.	
	BMT4	Our analytics department is clear about its performance criteria.	
Green dynamic capabilities (DCs)	DC1	The company has the ability to quickly monitor the environment to identify new green opportunities.	Chen and Chang [12], Yousaf [11]
	DC2	The company has effective routines to identify and develop new green knowledge.	
	DC3	The company has the ability to develop green technology.	
	DC4	The company has the ability to assimilate, learn, generate, combine, share, transform, and apply new green knowledge.	
	DC5	The company has the ability to successfully integrate and manage specialized green knowledge within the company.	
	DC6	The company has the ability to successfully coordinate employees to develop green technology.	
	DC7	The company has the ability to successfully allocate resources to develop green innovation.	
Green product innovation (GPDI)	GPDI1	The company chooses the materials of the product that produce the least amount of pollution to conduct the product development or design.	Chen and Chang [85], Yuan and Cao [28]
	GPDI2	The company chooses the materials of the product that consume the least amount of energy and resources to conduct the product development or design.	
	GPDI3	The company uses product materials that require the lowest amount when conducting product development or design.	
	GPDI4	The company would circumspectly deliberate whether the product is easy to recycle, reuse, and decompose when conducting the product development or design.	
Green process innovation (GPCI)	GPCI1	The manufacturing process of the company effectively reduces the emission of hazardous substances or waste.	
	GPCI2	The manufacturing process of the company recycles waste and emissions that can be treated and re-used.	
	GPCI3	The manufacturing process of the company reduces the consumption of water, electricity, coal, or oil.	
	GPCI4	The manufacturing process of the company reduces the use of raw materials.	
Environment turbulence (ET)	ET1	The modes of production/service change often and in a major way.	Schilke [71], Zhang, Teng, Le and Li [72]
	ET2	The environmental demands on us are constantly changing.	
	ET3	Marketing practices in our industry are constantly changing.	
	ET4	Environmental changes in our industry are unpredictable.	
	ET5	In our environment, new business models evolve frequently.	

Appendix C. Variable Definitions and Explanation

Construct	Definition	Reference
BDMCs (Big data management capabilities)	Critical organizational capabilities that enable firms to restructure, converge, and plan their big data resources	Akter, Wamba, Gunasekaran, Dubey and Childe [36], Behl, Gaur, Pereira, Yadav and Laker [94]
Green DCs (Green dynamic capabilities)	The ability of an enterprise to use existing resources and knowledge for updating and developing green organizational capabilities and managing random market changes	Chen and Chang [12], Yousaf [11]
GPDI (Green product innovation)	Focuses on improving product design by developing environmentally friendly products using low-carbon technology or recyclable materials to address environmental protection	Chen and Chang [85], Yuan and Cao [28]
GPCI (Green process innovation)	Manufacturing enterprises utilize novel ideas, techniques, and methods at every stage of the product lifecycle, from design and production to sales and disposal, to achieve minimal energy consumption and waste emission in response to sustainable development policies	
ET (Environment turbulence)	The volatility and unpredictability of environmental factors	Schilke [71], Zhang, Teng, Le and Li [72]

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