Business Strategy and the Environment

WILEY

RESEARCH ARTICLE OPEN ACCESS

Modeling the Role of Big Data Analytics Capabilities in Impacting Corporate Environmental Performance: A Serial Mediation Analysis

Leul Girma Haylemariam[1] | Rana Muhammad Umar[2] | Stephen Oduro[3]

[1]Department of Management, Faculty of Economics, Sapienza University of Rome, Rome, Italy | [2]Department of Economics and Statistics, University of Udine, Udine, Italy | [3]Faculty of Economics and Management, Free University of Bozen-Bolzano, Bolzano, Italy

Correspondence: Stephen Oduro (stephen.oduro@unibz.it)

Received: 18 December 2024 | **Revised:** 26 March 2025 | **Accepted:** 19 May 2025

Keywords: ambidextrous green innovation | big data analytic capabilities | environmental performance | green competitive advantage

ABSTRACT

Big data analytical capabilities (BDAC) have emerged as a significant strategic tool for enhancing environmental performance in today's ever-growing green and digital economy. However, the serial process through which BDAC influences environmental performance remains understudied, particularly in multinational corporations (MNCs). Drawing on the dynamic capability view (DCV) and the natural resource-based view (NRBV), this study constructs a serial mediation model to explore the connection between BDAC, ambidextrous green innovation, green competitive advantage, and corporate environmental performance. A cross-sectional survey involving 244 MNCs in Germany was used for the analysis. The data were analyzed using partial least squares structural equation modeling (PLS-SEM). Our findings reveal that the impact of BDAC on environmental performance is sequential, occurring through ambidextrous green innovation and the development of green competitive advantage. Specifically, BDAC leads to ambidextrous green innovation, which in turn drives green competitive advantage and ultimately enhances the environmental performance of MNCs. The theoretical and managerial implications are drawn.

1 | Introduction

Did you know that multinational corporations (MNCs) contribute nearly 20% of the world's greenhouse or CO_2 emissions (Liao and Chen 2021; youmatter.world)? This alarming statistic underscores the urgent need for innovative solutions to enhance corporate environmental performance (CEP) among MNCs and highlights the importance of researching their green initiatives. Industry 4.0 (IR4.0) integrates advanced digital technologies, such as big data, AI, 3D printing, blockchain, closed-loop robotics, and IoT, into business operations, driving competitive advantage and economic growth. This transformation enables firms to rethink business models, organize operations, and enhance value generation. IR4.0 technologies also foster dynamic capabilities, such as innovation ambidexterity, which improves financial performance (FP) and non-FP (Oduro and De 2023; Mohapatra et al. 2024). Big data analytics is crucial for sustainability, enabling firms to enhance supply chain visibility, informed decision-making, and innovative strategies. This integration enhances resource management, reduces waste, and improves operational efficiency, thereby contributing to sustainability goals (Sahoo et al. 2023; Sharma et al. 2022; Laing et al. 2019).

Globally, environmental concerns are intensifying because of increasing business activities that contribute to biodiversity loss and ecological degradation. Research documents that many large MNCs produce and market unsustainable and unhealthy products, contributing to the greenhouse effect and global warming (Liao and Chen 2021). Against this backdrop, big data plays a significant role in impacting environmental sustainability, functioning as a comprehensive tool for detecting patterns in an extensive and intricate collection of environment-related data from sources such as process sensors, meteorological data, and agricultural activities (Sahoo et al. 2023). Our research aims to explore further and understand the role of big data analytics in promoting sustainable development. Beyond environmental management, big data analytic capabilities (BDAC) support sustainable development goals by promoting resource efficiency, reducing waste, and enhancing social and economic sustainability.

For instance, Walmart, a multinational company, employs big data to enhance its supply chain through an extensive tracking system, leading to a decrease of over 650,000 metric tons of CO_2 emissions and over 3 million metric tons of greenhouse gases in a matter of a year (https://vorecol.com). Likewise, Pirelli, the fifth largest tire producer globally, uses real-time big data for inventory management, helping the company to shirk landfill tire disposal and reduce greenhouse gas emissions proactively (TriplePundit Reports 2016; Le and Vu 2024). BDAC function as a firm's capability to acquire, organize, and assess extensive data from different sources to spot trends and patterns (Le and Vu 2024; Riggs et al. 2023), which, in turn, can be used strategically to enhance resource utilization and efficiency as well as sustainability issues like product recycling, material reuse, and waste management (Kristoffersen et al. 2021). BDAC not only enhance internal processes but also contribute significantly to global sustainability goals. By reducing carbon footprints and promoting circular economy practices, BDAC can help companies align their business strategies with broader environmental objectives (Mohapatra et al. 2024).

Besides, recent literature suggests that BDAC is connected to environmental performance, defined as the ability of a firm to minimize the negative impact of its operations on the environment (Oduro 2024), showing that BDAC enhances energy efficiency and supports organizational goals related to social and environmental sustainability (Mikalef et al. 2019; Song et al. 2017). From the theoretical fronts of the dynamic capability view (DCV), BDAC can enable firms to achieve CEP by examining extensive datasets to produce valuable insights in identifying potential risks and capitalizing on eco-friendly business opportunities (Waqas et al. 2021; Sahoo et al. 2023; Waqas and Tan 2023). BDAC can provide a competitive advantage by enabling companies to innovate and differentiate themselves through sustainable practices and strategies. This can include examples of companies that have successfully leveraged BDAC to gain a competitive edge (Sahoo et al. 2023).

In recent years, a growing body of literature has emerged on the relationship between BDAC and environmental performance. However, prevailing studies often examine the environmental impact of business processes based on general frameworks (Sharma et al. 2022), but they fall short of addressing the nuances of incorporating BDAC into actionable corporate environmental strategies of MNCs. Moreover, much of the literature is conceptual or qualitative in nature. For example, Wu et al. (2017) and Song et al. (2018) present conceptual studies. In contrast, Belhadi et al. (2020) and Cheng and Liu (2018) focus on qualitative aspects. Some research addresses definitions and measurements of various dimensions, examining their effects on organizational capabilities and economic performance. Notable contributions in this area include studies by Gupta and George (2016) and Côrte-Real et al. (2020). Additional significant works have been provided by Wamba et al. (2017), Ferraris et al. (2019), and Mikalef et al. (2020).

Additionally, empirical findings on the relationship between BDAC and CEP are mixed, revealing both positive and negative relations, as well as insignificant ones (Belhadi et al. 2020; Dubey, Gunasekaran, and Childe 2019; Dubey, Gunasekaran, Childe, Papadopoulos, et al. 2019; Bag et al. 2020). As well as that, most of the studies have concentrated on examining the direct relationship between BDAC and environmental performance (Le and Vu 2024), with limited attention to the causal relationship between BDAC and environmental performance (Dubey, Gunasekaran, and Childe 2019; Dubey, Gunasekaran, Childe, Papadopoulos, et al. 2019; Bag et al. 2020), mainly arising from the dependence on perceived benefits, which may not realistically reflect the real impact of BDAC strategies with MNCs (Waqas et al. 2021). Although these studies reveal that BDAC can predict environmental performance, the explanatory mechanisms underlying such ability have not been systematically and sequentially examined. Therefore, the extent to which BDAC is able to explain the environmental performance of firms and the pathway through which BDAC's effects are manifested are concerns of both theoretical and managerial significance.

Recent studies investigating the causal effects of BDAC focus on how it influences CEP through green innovation (Waqas et al. 2021) or dynamic capabilities (Calic and Ghasemaghaei 2021; Bag et al. 2020; Dubey, Gunasekaran, and Childe 2019; Dubey, Gunasekaran, Childe, Papadopoulos, et al. 2019). However, we are unaware of any study examining the serial mediating role of ambidextrous green innovation (AGI) and green competitive advantage (GCA), as per our review of the existing literature. AGI is a firm strategy that simultaneously pursues the exploitation and exploration of green innovation (Z. Wang et al. 2023; Nielsen et al. 2018). Exploitative green innovation involves leveraging existing environmental knowledge and skills to enhance current green products, processes, and services, whereas exploratory green innovation focuses on discovering and applying new environmental knowledge and skills to develop innovative green products, processes, and services that cater to emerging market demands and potential customer needs (J. Wang, Xue, Sun, et al. 2020; J. Wang, Xue, and Yang 2020; Raisch and Birkinshaw 2008; O'Reilly and Tushman 2008). According to the DCV, BDAC can help firms explore and exploit environmental knowledge to enhance GCA (Teece 2017) and CEP (J. Wang, Xue, and Yang 2020). The natural resource-based view (NRBV) also suggests that AGI can enhance CEP by promoting and strengthening GCA, which is defined as a successful ecological and sustainability strategy that competitors cannot replicate (Kuo et al. 2022).

Given the argument that the impact of BDAC on CEP may not be direct (Al-Khatib 2022; Dahiya et al. 2022), coupled with the limited understanding of the underlying mechanisms of the BDAC–CEP relationship, we attempt to close this research lacuna and add to the limited body of knowledge on BDAC by developing and testing a conceptual framework connecting BDAC to CEP, using AGI and GCA as intervening variables. We build on current advancements in the DCV and NRBV to investigate how BDAC, complemented by AGI and GCA, contributes to CEP.

Significantly, we do this while controlling for the sector, FP, and corporate environmental responsibility (CER) known to influence CEP among MNCs, which include companies that "engage in foreign direct investment (FDI) and own or control value-adding activities in more than one country" (Dunning 1992, 12). Because of their size and global reach, MNCs operate across international value chains, contributing nearly one-third of the world's gross domestic product (GDP) (Mudambi et al. 2018). Because of the critical role of MNCs in addressing global environmental issues, there is a pressing need for further research on how BDAC influences their green behavior and environmental performance (Zhou et al. 2024).

In the present study, we aim to close the above gaps by addressing the following research questions:

1. How does BDAC influence the CEP of MNCs?
2. What is the mediating role of AGI and GCA in the relationship between BDAC and CEP?

Followingly, our specific research objectives are as follows:

1. To investigate the extent to which BDAC impacts CEP in MNCs.
2. To explore the mediating role of AGI and GCA as serial mediators in the BDAC–CEP relationship.

Addressing these research questions and objectives, we propose a set of hypotheses based on DCV and NRBV theoretical frameworks (Teece 2017) and investigate them through a survey of 244 MNCs headquartered in Germany. We strongly believe that Germany is an appropriate context due to its status as a highly developed and industrialized nation with extensive experience in implementing Industry 4.0 technologies, such as big data (Veile et al. 2020). The country has comprehensive environmental regulations and hosts numerous MNCs, which further underscores its relevance for research of this nature (Feng et al. 2022).

Our study's contribution is three-strand. First, we provide relevant insights into how BDAC affects CEP in MNCs while controlling for the effects of sector, firm age, firm size (measured by the number of employees), CER, and FP on the focal relationship. This insight enables a more comprehensive understanding of CEP, as several key organizational factors are considered in conjunction with and in connection to CEP. Our conceptual and empirical framework for the study enhances understanding of the impact of BDAC on CEP in the context of MNCs, which are considered to have a substantial environmental impact, enabling more novel empirical validation and generalizations. Given the limited research on the phenomenon in the context of MNCs, providing a deeper understanding of the interrelationships among these variables is a crucial theoretical issue (Singhania and Saini 2021). Second, the explanatory mechanisms underlying the ability of BDAC to predict CEP have not been sequentially and systematically explored in MNCs. Therefore, unlike previous studies that focus on mediating factors in the BDAC–CEP relationship our study emerges as one of the pioneering studies to empirically investigate the serial mediating role of AGI and GCA, revealing the pathway through which BDAC impacts CEP. By empirically testing the relationship through serial mediation in MNCs, our study fills a crucial lacuna in understanding the mechanisms linking BDAC to environmental outcomes. Our finding that BDAC relates to CEP *only* serially through AGI and GCA adds novel insights to ongoing debates about the key strategic and organizational variables that shape the impacts of BDAC on CEP (Le and Vu 2024). Third, we demonstrate the managerial relevance of AGI and GCA in facilitating the impact of BDAC on CEP in MNCs. More specifically, we reveal that for MNCs to benefit from BDAC in their environmental goals, they must integrate it with AGI and GCA, as BDAC alone cannot produce superior CEP. Hence, practitioners need to focus on utilizing BDAC to develop AGI and GCA strategies, which, in turn, can enhance CEP.

The remainder of the paper is structured as follows: Section 2 introduces the theoretical framework, conceptualizes the key constructs, and develops hypotheses grounded in existing literature. Section 3 outlines the research methodology, emphasizing the study's data collection and analytical method, whereas Section 4 presents the study's findings. Finally, Section 5 presents the results, discusses their implications, draws conclusions, acknowledges limitations, and offers recommendations for future research.

2 | Theory and Hypothesis Development

Scholars suggest that resource-based theories, such as resource-based views or NRBV for their lack of adaptability (McDougall et al. 2016). Correspondingly, they are unable to address the need for rapid resource orchestration due to continuously changing market dynamics (Eisenhardt and Martin 2000). In response to the static nature of resource-based theories, Teece et al. (1997) proposed the DCV, which encourages the continuous development of firm resources and competencies. Teece suggested that the dynamic capabilities view provides an understanding of how natural resources evolve, are used, and are managed in a firm in dynamic market conditions. Hence, the dynamic capability view has received considerable attention in academia, particularly in addressing the limitations of the NRBV (Hart and Dowell 2011; McDougall et al. 2016).

Because the objective of our study is to examine how BDAC enhances CEP through appropriate orchestration of firm natural resources, we utilize the DCV and NRBV. The DCV and NRBV are interconnected in their emphasis on the strategic management of resources to achieve competitive advantage. Although DCV focuses on an organization's ability to adapt, integrate, and reconfigure internal and external competencies to address rapidly changing environments, NRBV extends this by prioritizing environmentally friendly practices and sustainable resource management. Together, they provide a comprehensive framework for understanding how organizations can leverage BDAC to enhance CEP. By employing AGI, firms can simultaneously explore new ecological opportunities and leverage existing resources, thereby achieving a GCA and improved environmental outcomes.

Dynamic capabilities allow organizations to modify, expand, or develop operational capabilities (Winter 2003). Organizational "dynamic" refers to a company's ability to adapt and enhance its skills and competencies in dynamic environments (Hart 1995), whereas "capabilities" involve identifying, seizing, and reconfiguring internal and external resources and skills (Teece 2017). Operations and dynamic capabilities must be distinguished because an organization must be stable enough to offer its value uniquely and adaptable enough to rearrange its value proposition (Mikalef et al. 2019). As organizations grow, digital skills become crucial for strategy formulation and execution. Based on the dynamic capabilities view, researchers claim that BDAC and ambidexterity enable firms to adapt to the environment by reorganizing resources and strategies (Stekelorum et al. 2021). Recent scholars have built upon the dynamic capabilities view, finding that BDAC results in favorable firm outcomes, including ambidexterity (Wamba et al. 2020), competitive advantage (Waqas et al. 2021), and CEP (Waqas et al. 2021).

A firm's competitive advantage depends on its ability to build a structural knowledge base that enables it to respond to environmental changes (Sahoo et al. 2023). To this end, the dynamic capabilities view highlights three core capabilities of firms, including sensing capabilities, seizing capabilities, and transforming capabilities (Teece et al. 1997), providing a robust framework for operating in a dynamic business environment (Dubey et al. 2023). In the context of the present study, BDAC can be characterized as a sensing capability since it detects environmental knowledge (Sahoo et al. 2023; Laing et al. 2019). Moreover, we characterize AGI as seizing capabilities, as Katila and Ahuja (2002) argue that firms' existing capabilities are required to explore new dynamic capabilities, and these new dynamic capabilities enhance firms' existing knowledge base through a dynamic path of absorptive capacity. Consistent with the prior literature, we refer to AGI as a firm's ability to balance explorative and exploitative innovations (J. Wang, Xue, Sun, et al. 2020; J. Wang, Xue, and Yang 2020). Ambidextrous firms simultaneously explore new opportunities, knowledge, and eco-friendly technologies while also continually improving existing products and processes (Martínez-Falcó et al. 2024). Because the dynamic capabilities of a firm require a blend of explorative and exploitative (Eisenhardt and Martin 2000), prior scholars considered it a multidimensional construct with a nonsubstitutable and interdependent combination of explorative and exploitative capacities of an organization (Gibson and Birkinshaw 2004) and found its positive influence on firm environmental performance (Baquero 2024).

In prior investigations, multiple researchers have explained that the DCV and the NRBV jointly help firms develop more effective corporate strategies to enhance ecological responsiveness (Hart 1995). The NRBV is an extended form of the resource-based view that incorporates environmental considerations such as pollution prevention, waste reduction, and environmentally friendly operational excellence (Akhtar et al. 2024). Accordingly, the NRBV posits that firms employ three interconnected environmental strategies—pollution reduction, product stewardship, and sustainable development—to enhance and harmonize their interactions with the natural environment (Hart 1995; Hart and Dowell 2011). Because dynamic capabilities represent explorative and exploitative behaviors (Teece et al. 1997), reorganizing a firm's resource base and giving it an advantage over its competitors (Jurksiene and Pundziene 2016), the NRBV can benefit from the contemporary literature on dynamic capabilities (Hart and Dowell 2011) and link enterprises' natural resources, competencies, and environmental performance (Hart 1995). It can be argued that NRBV may guide firms' transforming capabilities in the context of environmentally friendly operations. In summary, our study extends the DCV by incorporating AGI as a dual mechanism, enabling MNCs to dynamically adapt their environmental performance strategies. Unlike previous studies, which predominantly examine BDAC and green initiatives in isolation, this study integrates ambidextrous and GCAs to explain the pathway to achieving CEP. Including GCA as a mediating factor reflects the necessity of addressing firm-specific capabilities beyond conventional innovation metrics. Accordingly, our conceptual framework (Figure 1) comprises BDAC as an independent variable, CEP as a dependent variable, and AGI and GCA as serial mediators.

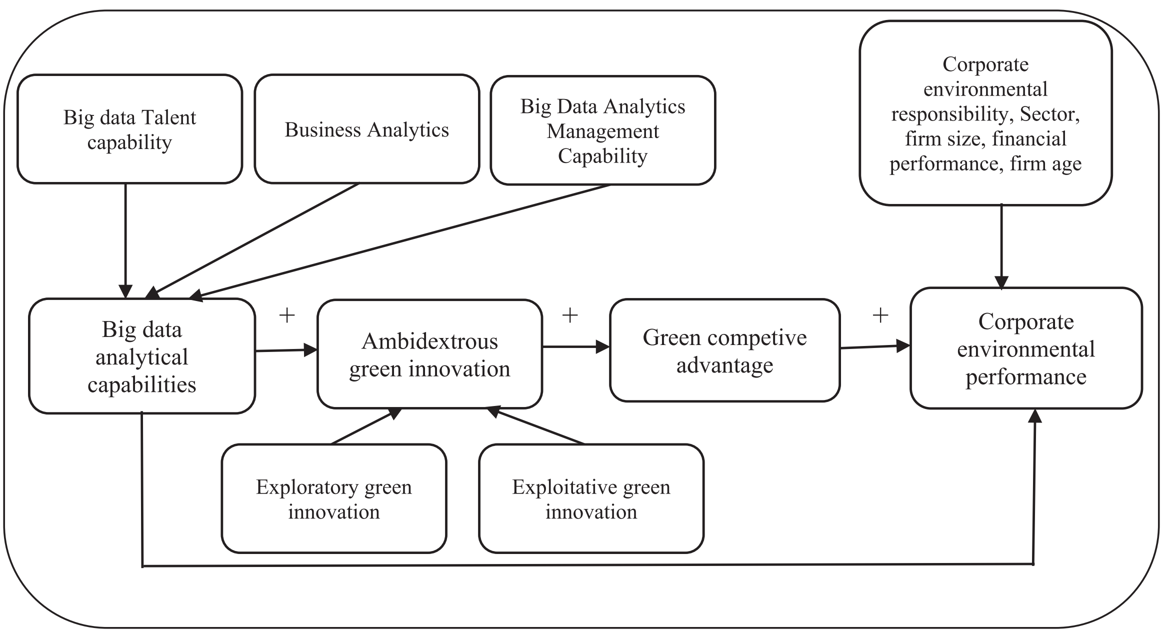

FIGURE 1 | Conceptual model.

2.1 | BDAC and CEP

BDAC is a firm's ability to collect, analyze, and apply data across processes, structures, and roles to gain actionable insights (Mikalef et al. 2019). These capabilities transform data into actionable insights by integrating all relevant resources from various organizations and applying them to both operational and strategic decision-making (Mikalef et al. 2019). They also assist organizations in detecting rapid external changes and developing business strategies for swift responses (Wamba et al. 2020), thereby increasing organizational ambidexterity and innovation (Muhammad et al. 2022). Researchers operationalize BDAC into three dimensions, such as (i) big data analytics talent capabilities, which relates to analytic specialists' expertise in big data contexts (Constantiou and Kallinikos 2015); (ii) big data analytics, which is the "comprehensive utilization of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to inform decisions and actions" (Davenport and Harris 2007, 42); and (iii) big data analytics capabilities management, which involves the components and procedures involved in establishing the capacity for analyzing big data (Mikalef et al. 2018). Building on DCV, Sahoo et al. (2023) argue that a firm's competitive edge depends on its ability to establish structural knowledge, which enables it to respond to dynamic environmental changes. Because the dynamic capabilities view classifies organizational dynamic capabilities into three categories—sensing capabilities, seizing capabilities, and transforming capabilities—Sahoo et al. (2023) characterized BDAC as sensing capabilities that enable firms to proactively detect changes in market trends, consumer needs, and technological advancements. Based upon the advanced detection of environmental changes, BDAC plays an instrumental role in fostering and reconfiguring business processes to get strategic, operational, and managerial benefits (Makhloufi et al. 2023). For instance, prior literature demonstrates that BDAC enables firms to establish valuable knowledge structures, fostering green innovation, competitive advantage, and improved environmental performance (Waqas et al. 2021). In this connection, several studies have empirically confirmed that a higher level of BDAC directly leads to a higher CEP (Ashikur Rahman et al. 2024; Sahoo et al. 2023). In light of this discussion, we hypothesize that

Hypothesis 1. *BDAC relates positively to the CEP of MNCs.*

2.2 | BDAC, AGI, and CEP

Building on dynamic capabilities theory, we contend that BDAC can be characterized as enterprises' sensing capabilities that illuminate the existing knowledge and strengthen management and operational skills, routines, know-how, new product development, processes, and individual practices (Hanifah et al. 2022; Lozada et al. 2023). Firms employ multiple strategies to develop these insights further and apply them across various aspects of the organization. For instance, by employing AGI, firms can mobilize strategic green knowledge resources to transfer them into corporate value (Asiaei et al. 2023). AGI is a corporate strategy that fosters a nuanced understanding of environmental changes (e.g., technological developments, competition, consumer behavior, and regulations) and enables an appropriate response to these opportunities and risks by reconfiguring company resources (Harreld et al. 2007). Thus, scholars divide AGI into two categories: exploitative green innovation, which uses existing information, abilities, and procedures to improve ecological response, and exploratory green innovation, which uses new environmental information and abilities (Nielsen et al. 2018; J. Wang, Xue, Sun, et al. 2020; J. Wang, Xue, and Yang 2020; Z. Wang et al. 2023). This ambidextrous approach helps organizations effectively manage, integrate, and exploit strategically essential information to produce distinctive ideas and boost competitiveness (J. Wang, Xue, and Yang 2020).

Prior research builds on the DCV to explain how BDAC translated into ambidexterity (Wamba et al. 2020) and eco-innovation (Ferraris et al. 2019). Bhatti et al. (2024) argue that organizations achieve innovative practices by overcoming challenges regarding ambidexterity. Bhatti et al. (2024) found that BDAC leads to organizational ambidextrous capabilities, resulting in innovations. In addition, increasing evidence suggests that adopting AGI strategies enhances an organization's ability to adapt to immediate and long-term changes and exploit ecological opportunities (Jansen et al. 2012; Lee et al. 2018; J. Wang, Xue, Sun, et al. 2020; J. Wang, Xue, and Yang 2020).

Hence, AGI can be a fundamental organizational capability that allows organizations to incorporate an environmentally friendly approach into their value creation activities (Albertini 2021) because it can effectively gather, extract, and evaluate the data produced during innovation activities and offers robust technological assistance for such operations (Tongtong and Xinhang 2022). Thus, AGI may help MNCs develop by leveraging existing expertise and discovering novel opportunities (Levinthal and March 1993; Jansen et al. 2006). Accordingly, the NRBV provides a sound theoretical lens through which to understand the relationship between AGI and GCA. For instance, given NRBV principles, firms can better leverage their natural resources to enhance their resource-based capabilities and translate them into GCA. Considering the DCV and NRBV, we argue that AGI, because of its simultaneous exploitation and exploration of green knowledge, can be significant resource-based dynamic capabilities that could help firms design strategies that are difficult to imitate, thus leading to GCA and enhanced CEP (Agyabeng-Mensah and Tang 2021). Hence, we hypothesize:

Hypothesis 2a. *BDAC is positively correlated with AGI of MNCs.*

Hypothesis 2b. *Through its impact on AGI, BDAC will positively relate to the CEP of MNCs.*

2.3 | BDAC, GCA, and CEP

Extant literature suggests that BDAC are firm dynamic capabilities that accumulate business knowledge to add value to businesses and provide a competitive advantage over their rivals in a dynamic market (Dubey et al. 2018; El-Kassar and Singh 2018). In the context of this study, GCA refers to firms' successful, rare, and hard-to-imitate ecological solutions (Zhang et al. 2022), which lead to long-term environmental sustainability and a green image (Chen and Chang 2013; Chen 2008). Thus, GCA is considered paramount in sustainable development (Kuo et al. 2022). Accordingly, organizations must maintain their environmentally friendly reputation, which distinguishes them from other companies and helps retain current customers (Widyastuti et al. 2019; Chen 2008). Therefore, MNCs engage in creative, innovative, and ecologically sustainable initiatives (Wysocki 2021). Subsequently, a GCA positions a firm as a market leader due to its ecological practices, which help attract more investors, encourage continued investment in emerging green technologies, and result in improved CEP. CEP refers to companies' obligation to safeguard the environment and exhibit quantifiable operational criteria within the specified boundaries of environmental management (Paillé et al. 2014). Scholars found that GCA positively correlates with CEP (Zameer et al. 2021). Baquero (2024) argues that the NRBV emphasizes considering environmental obligation and leveraging its unique resources to improve competitive positioning. The dynamic capabilities view posits that when firms develop new capabilities to respond to the requirements of internal and external stakeholders and address environmental challenges, they achieve improved CEP (Hart and Dowell 2011). Thus, building on the NBRV and the DCV, we can argue that BDAC identifies environmental opportunities that complement unique natural resources, enabling organizations to achieve a GCA and improve their CEP. Hence, we hypothesize:

Hypothesis 3a. *BDAC is positively correlated with the GCA of MNCs.*

Hypothesis 3b. *Through its impact on GCA, BDAC will positively relate to the CEP of MNCs.*

2.4 | BDAC, AGI, GCA, and CEP

Building on our preceding theoretical reasoning, we emphasize from the standpoint of dynamic capabilities that BDAC is a dynamic capability that enables enterprises to maintain their competitive advantage by reconfiguring their resources (Correggi et al. 2024). According to Wu et al. (2013), dynamic capabilities can enable MNCs to sense and seize opportunities, thereby achieving environmental, economic, and social benefits. Considering this notion, firms need to sense the opportunities and threats in their internal and external environments and determine what changes are required to address these opportunities and threats by developing AGI. A firm should implement these changes to enhance existing sustainable processes, products, and services or to orient itself toward new ones (Correggi et al. 2024). Thus, BDAC can facilitate a firm's ability to develop AGI, adapt to environmental changes, and reconfigure its strategies (Stekelorum et al. 2021). The NRBV view posits that a firm's competitive advantage, based on its natural environment and dynamic capabilities, is key to promoting environmentally sustainable economic activities (Hart 1995). Considering the dual nature of AGI, BDAC helps firms enhance their existing sustainable processes, products, and services while also exploring new ones. Similarly, AGI, because of its exploitative and exploratory, endeavors to develop and implement environmentally friendly practices in products, processes, and services (J. Wang, Xue, Sun, et al. 2020), is highly likely to be translated into the GCA of MNCs. Baquero (2024) suggests that AGI intervenes between a firm's intangible resources and its performance matrix. Similarly, a GCA can serve as a driver of CEP. Taken together, we argue from the dynamic capabilities view and the NRBV, considering how MNCs can develop their BDAC and AGI as enabling variables to align with the principles of the circular economy. We also examine how they reconfigure their resources and capabilities to achieve a GCA, ultimately improving CEP. Thus, we hypothesize:

Hypothesis 4. *The impact of BDAC on CEP will be serially mediated by AGI and GCA.*

3 | Methodology

3.1 | Research Approach and Philosophy

This study adopts a positivist research philosophy, emphasizing the use of objective, measurable evidence to examine the relationships among BDAC, AGI, GCA, and CEP. The positivist epistemological stance, which prioritizes quantifiable knowledge through systematic observation and statistical analysis (Creswell and Creswell 2017), is fundamental to our research. Ontologically, the study assumes that reality is objective and measurable through empirical data, as reflected in the use of multi-item scales. Methodologically, we employ a quantitative design, utilizing a cross-sectional survey and partial least squares structural equation modeling (PLS-SEM) to analyze data from MNCs in Germany. This approach is consistent with the positivist emphasis on objectivity and generalizability (Hair et al. 2017).

3.2 | Study Contexts and Sampling Procedures

Given the significant criticism of MNCs for being unsustainable (Burritt et al. 2020), various stakeholders, including the government, intergovernmental organizations, NGOs, and consumers, demand that MNCs redefine their efforts from short-term economic goals to long-term sustainable activity (Burritt et al. 2020). The present research considered MNCs operating in Germany as the context for the study. The relevance of Germany for this study is twofold. First, Germany has a unique legal and regulatory context where the rights and obligations of economic agents are carefully delineated. Specifically, environmental concerns are given significant importance in Germany (Cormier et al. 2004). Second, Germany is considered a developed, industrialized, and advanced country with experience implementing Industry 4.0 technologies (Veile et al. 2020). The environmental regulations in Germany cover a wide range of activities. For example, the German supply chain law passed on June 11, 2021, motivates German firms and firms operating in Germany to use digital technologies to trace their suppliers' social and environmental practices (Feng et al. 2022). Because the context of this study is to examine BDAC for CEP, Germany is considered an appropriate context for conducting this study. MNCs include companies that "engage in foreign direct investment (FDI) and own or control value-adding activities in more than one country" (Dunning 1992, 12).

Although the German context provides a robust framework for analyzing the relationship between BDAC and CEP, it is worth reflecting on how this relationship might play out in countries with weaker environmental regulations or less advanced technological infrastructure (Sahoo et al. 2023*)* In such contexts, firms may encounter significant challenges in implementing BDAC due to limited access to technology, fewer incentives for green innovation, or weaker institutional support for sustainability initiatives (AlNuaimi et al. 2021; Kamble et al. 2020). External pressures, such as stakeholder demands or international standards, might drive green innovation and sustainability practices even in less supportive environments (Wamba et al. 2017; Zhang and Zhu 2019). This reflection ensures that the study's insights are both relevant and applicable to developing economies and firms operating under diverse environmental conditions, where similar mechanisms may apply but with varying degrees of effectiveness.

The study used simple random and convenience sampling techniques to select the respondents, as these probability and nonprobability sampling methods offer participants an equal opportunity to participate in a study based on availability and willingness to participate (Oduro et al. 2023). Out of a total of 60,027 worldwide multinational firms, the present study considered 20,738 German multinational enterprises currently operating in Germany as the population of the study (https://www.destatis.de). Subsequently, we used several platforms, including Forbes Global 2000 Rankings 2023, EasyMarketing A2Z, and E-commerce Germany News, to identify our sample firms. We specifically focused on the firms engaged in FDI and that own or control value-adding activities in more than one country—automotive, healthcare, retail, and financial services.

3.3 | Data Collection

A self-administered online survey was conducted to gather data based on the theoretical framework and research objectives. The online questionnaire was created in English using Google Forms (Neeley 2012). Our sample comprises CEOs and general and operational managers from MNCs, who were selected based on specific criteria and received the questionnaire via email. Each questionnaire included a cover letter that described the study's background and provided all relevant information to enable respondents to decide whether to participate. From November 10 to December 22, 2023, 32 German MNCs participated in a pilot test to identify issues and opportunities for improvement. The scale's Cronbach alpha was 0.96 for BDAC, 0.95 for AGI, 0.91 for GCA, and 0.90 for CEP in the pilot trial, indicating reliability. Thus, we chose the survey form for final data collection. The data–gathering period was from January to April 2024. Upon selecting the sample firms, we extracted their email addresses from their websites. The questionnaire went to 550 German MNCs. After many automatic reminder emails every 2 weeks, 244 answers were obtained and utilized for the final analysis. Because the response rate was substantially above the organizational study average, a response rate of 44.36% was considered acceptable (Baruch and Holtom 2008). The authors compared answers from the first 2 weeks to those from the final week to investigate nonresponse bias. We found no significant differences between sample characteristics and latent variable means, as reported by Armstrong and Overton (1977).

3.4 | Measures

The present study adapted scales from previous literature. BDAC is operationalized with three low-order key dimensions: big data talent capability (BDA-TC), business analytics (BA), and big data analytics management capability (BDA-CM). First, we operationalized BDA-TC as the competence of an analytics expert to work in a big data environment effectively (Constantiou and Kallinikos 2015) and measured it with a nine-item scale adapted from (Akter et al. 2020). BA was operationalized as the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions (Davenport and Harris 2007) and measured with three items adapted from previous studies (Duan et al. 2020; Zameer et al. 2022). BDA-CM was operationalized as an organization's strategic capabilities for implementing big data analytic projects and measured with six items (Bag et al. 2020). Regarding our mediating variables, AGI was operationalized as the organizational ability to utilize existing environmental knowledge and skills to improve innovation and explore new environmental knowledge and skills to identify new products, processes, and markets. It was measured on an eight-item scale, with four items each for exploratory green innovation (J. Wang, Xue, and Yang 2020) and exploitative green innovation (J. Wang, Xue, Sun, et al. 2020). For instance, "Our firm actively adjusts current green products, processes, and services" is one of the items. Moreover, we operationalized GCA as a company's unique set of strategies that allow it to outcompete competitors on ecological management or sustainable innovation (Alam and Islam 2021), and it was measured with a four-item scale adapted from Lin and Chen (2017). CEP was operationalized as the firm's ability to minimize its negative environmental impact and was measured with five items (Singh et al. 2020). We measured CER for the control variables with five items adapted from Singh et al. (2020). The sector was operationalized as the industry of operation and measured as a dichotomous variable (1 = service, 2 = manufacturing). Firm size is measured by the number of employees. Lastly, we operationalize FP as the firm realizes its goals in the last 5 years (items included ROA, ROI, and profitability) (Oduro et al. 2023). These measures are summarized in Table 1, whereas the full-scale items are shown in Appendix 1.

3.5 | Data Analysis

The present study conducted a two-step analysis including confirmatory factor analysis (CFA) and PLS-SEM. Prior scholars suggest that structural equation modeling is a comprehensive technique for examining complex relationships between studied variables (Abbas 2024). In addition, our theoretical framework includes a higher order construct (HOC) of BDAC, two mediating variables, AGI, and GCA, CEP (dependent variable), and a set of control variables, namely, firm age, firm size, sector, CEP, and FP. Therefore, we considered PLS-SEM as an analytical approach for our analysis. Previous researchers recommend a sample size for PLS-SEM to be 5–10 cases per construct (Hair et al. 2018). Correspondingly, our observations per variable are about 30, higher than the minimum threshold (Oliveira et al. 2021). Similarly, PLS-SEM is appropriate for formative constructs, small sample sizes (Ramayah et al. 2018), and complex models (Hair et al. 2014). Our mediation analysis is a serial mediation, unlike

TABLE 1 | Measurement scales.

Construct	Definition	Source	Items	Measurement scale	Reliability	AVE
Big data analytics capabilities (BDAC)	A firm's ability to acquire, organize, and analyze extensive data from various sources	Akter et al. (2020); Bag et al. (2020)	9 Items for BDA-TC, 3 items for BA, 6 items for BDA-CM	7-Point Likert scale	0.787	0.554
Business analytics (BA)	The extensive use of data, statistical analysis, and predictive models to drive decisions	Duan et al. (2020); Zameer et al. (2022)	3 Items	7-Point Likert scale	0.783	0.655
Ambidextrous green innovation (AGI)	The ability to simultaneously pursue exploitative and exploratory green innovation	J. Wang, Xue, Sun, et al. (2020); J. Wang, Xue, and Yang (2020)	8 Items (4 for exploitative and 4 for exploratory)	7-Point Likert scale	0.76	0.518
Corporate environmental performance (CEP)	A firm's ability to minimize its negative environmental impact	Singh et al. (2020)	5 Items	7-Point Likert scale	0.77	0.535
Green competitive advantage (GCA)	A firm's unique ecological and sustainability strategies that competitors cannot replicate	Lin and Chen (2017)	4 Items	7-Point Likert scale	0.789	0.557
Corporate environmental responsibility (CER)	A firm's commitment to environmental sustainability	Singh et al. (2020)	5 Items	7-Point Likert scale	0.819	0.536
Financial performance (FP)	A firm's ability to achieve its financial goals over the past 5 years	Oduro et al. (2024)	4 Items (ROA, ROI, and profitability)	7-Point Likert scale	0.876	0.765

simple mediation, which involves one mediator explaining the relationship between an independent and a dependent variable. Serial mediation involves multiple mediators in a sequential manner, providing deeper insights into the pathways connecting the variables (Hair et al. 2017). We follow the well-established procedure outlined by Preacher and Hayes (2008) to test for complete mediation. According to this approach, complete mediation is confirmed when the direct effect of the independent variable (BDAC) on the dependent variable (CEP) becomes insignificant after the mediators (AGI and GCA) are included in the model. Partial, complementary mediation indicates that the direct path remains significant after the introduction of the mediating factor, which also exerts a positive mediating effect. In contrast, partial, negative mediation means that the direct path is significant, but the mediating effect is significant and negative. This method is widely used in management and sustainability research to ensure that the mediators fully explain the relationship between the independent and dependent variables (Hair et al. 2017; Nitzl 2016).

3.6 | Robustness Checks

To ensure the robustness of the findings, several checks were performed, including tests for multicollinearity (using variance inflation factor, VIF) and common method bias (using Harman's single factor test). Because we used a self-reported survey and relied on a single source of respondents, our survey study was prone to common method bias. Prior scholars suggest that common method bias may cause inflation or deflation in the relationships between variables (Jakobsen and Jensen 2015). Therefore, we considered several precautions during the survey design and the data collection stage. For instance, we considered the scales' proven reliability and validity (Fuller et al. 2016). Moreover, we disentangled the survey questions and provided anonymity to the respondents, such as "there is no wrong or right answer" (Podsakoff et al. 2003). Similarly, we used clearly defined survey questions and counterbalanced the dependent and independent variables. Because literature suggests that an educated sample is less likely to demonstrate common method bias (Rindfleisch et al. 2008), a higher percentage of our participants hold a college degree or above. Once data was collected, we used Haman's single factor test to assess common method bias, and we found that the present study did not report common method bias. In the first phase, the authors considered performing a pilot test to ensure the validity and reliability of the scales. Moreover, we included multiple control variables to mitigate model misspecification, which may arise from omitted variables, and guarantee that our empirical findings do not overestimate or inflate the effects of BDAC on the outcome variable. Accordingly, we included three context factors (firm age, size, and sector) and two organizational variables (CER and FP). Furthermore, because of the potential endogeneity problem in AGI, we used the Gaussian Cupolas test to investigate whether AGI is endogenous. Our result is shown in Table 1. First, when GCA is the dependent variable, the values are insignificant ($B=-0.210$, $t=0.636$, $p=0.525$); when corporate environmental performance is the dependent variable, the Cupolas values are insignificant ($B=0.254$, $t=1.02$, $p=0.308$); AGI is the dependent variable, and the values are likewise insignificant ($B=0.881$, $t=1.345$, $p=0.179$). Thus, we consider AGI and GCA as exogenous variables and incorporate them into the structural equation model, as the Gaussian Cupolas statistics are insignificant (see Appendix 2). We also tested multicollinearity using the VIF method. Given that the highest value is 1.717, below the threshold of 5 or less, we can conclude that our data has no multicollinearity issues (Hair et al. 2018) (see Appendix 3).

4 | Results

4.1 | Sample Characteristics and Descriptive Statistics

As shown in Table 2, most of the firms were manufacturing firms (55.73%), 36% had been in existence for more than 30 years, 35.7% had net capital between 100 million and 3 billion, and finally, about 33% of firms had a number of employees between 1001 and 5000.

Table 3 presents the descriptive statistics and correlations for the constructs, including the control variables. The correlation values are all at or below the threshold of 0.70, indicating minimal multicollinearity issues in the data (Cohen 2013). Furthermore, the standard deviations are lower than the means, suggesting no overdispersion of nonnegative integers (Wooldridge 2012).

TABLE 2 | Sample characteristics of sampled firms (244).

Sample characteristics	Number of samples	%
Sector		
Service	108	44.26
Manufacturing	136	55.73
Firm age		
≤ 5 years	14	5.7
6–10 years	43	17.6
11–20 years	23	9.4
21–30 years	76	31.1
> 30 years	88	36.06
Capital (NT €)		
< 50 million	28	11.5
50 million to 100 million	37	15.2
100 million to 3 billion	87	23.36
3 billion to 5 billion	41	16.8
> 5 billion	51	20.9
Employees size		
≤ 50 persons	07	2.8
51–100 persons	26	10.7
101–1000 persons	86	35.2
1001–2000 persons	45	18.4
2001–5000 persons	36	14.8
> 5000 persons	44	18.0

TABLE 3 | Descriptive statistics.

Items	Mean	Std.	BTC	BA	BCM	ECR	GCA	EP	FP	SS	FS	BDAC	AGI
BTC	3.05	0.64	1										
BA	3.06	0.85	0.61**	1									
BCM	3.05	0.75	0.64**	0.63**	1								
CER	3.35	0.81	0.03	0.06	0.03	1							
GCA	3.33	0.86	0.02	0.08	0.02	0.61**	1						
CEP	3.36	0.88	0.05	0.07	0.05	0.65**	0.68**	1					
FP	3.40	0.85	0.03	0.05	0.04	0.61**	0.65**	0.65**	1				
SS	3.20	1.26	0.39**	−0.24*	−0.34**	0.15*	0.18*	0.15*	0.13*	1			
FS	3.66	1.33	−0.10	−0.11	−0.10	−0.11	−0.10	−0.08	−0.08	0.29**	1		
BDAC	3.06	0.68	0.61**	0.60**	0.63**	0.05	0.05	0.06	0.04	−0.34**	−0.10	1	
AGI	3.32	0.75	0.06	0.07	0.05	0.69**	0.60**	0.69**	0.69**	0.16*	−0.10	0.064	1

Abbreviations: FS = firm size (no. of employees); SS = sector.
*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

TABLE 4 | Measurement models fit indices and quality criteria.

	$\chi 2$	df	CFI	GFI	AGFI	NFI	RMSEA
Full model	234	124	0.97	0.95	0.90	0.93	0.054
Partial model (direct)	202	103	0.93	0.91	0.89	0.92	0.063
			R^2				
			R^2			R^2 adjusted	
CEP			0.604			0.597	
AGI			0.034			0.030	
GCA			0.471			0.464	

Abbreviations: AGI = ambidextrous green innovation; CEP = corporate environmental performance; GCA = green competitive advantage.

4.2 | Measurement Model Assessment

We conducted a CFA to examine the validity of the study's constructs and to determine the psychometric properties, including discriminant and convergent validity, composite reliability, and the average variance explained (AVE), based on the procedures outlined by Hair et al. (2014). To achieve these thresholds, we removed some indicators whose loadings were lower than 0.70: BCM_2, BCM_4, BCM_7; BTC_3, BTC_9; CER_4, CER_5, CER_8; AGI 1, AGI_4; EP_1; and GCA_3; we deleted one indicator from the FP construct (FP_5) because the outer loading was lower than 0.7. After rerunning the analysis, we found that our indicators met the threshold of 0.7 or greater (Hair et al. 2014) (see Appendix 4 for full factor loadings). Concerning the measurement model shown in Table 4, the model fit indices demonstrated a better fit for the full model (CFI = 0.97, GFI = 0.95, AGFI = 0.93, NFI = 0.91, and RMSEA = 0.054) relative to the partial model (CFI = 0.93, GFI = 0.91, AGFI = 0.89, NFI = 0.92, and RMSEA = 0.063), showing the distinctiveness and reliability of the five factors examined in this study.

TABLE 5 | Reliability and validity for LOC.

Indicators	Composite reliability (alpha)	Average variance extracted (AVE)
BA	0.783	0.655
BCM	0.787	0.554
BTC	0.754	0.515
ECR	0.819	0.536
CEP	0.770	0.535
AGI	0.760	0.518
GCA	0.789	0.557
FP	0.867	0.765

Moreover, Table 5 shows the output of the AVE and reliability. The AVE and composite reliability values were equal to or greater than 0.5 and 0.70, respectively, thus satisfying the convergent validity threshold (Hair et al. 2014).

We assessed the discriminant validity using the Fornell and Larcker (1981) measure of AVE. We also present the results of the discriminant validity analysis. As a rule of thumb, the square root of AVE values is higher than the constructs' correlation values (Fornell and Larcker 1981). Thus, our model's validity is acceptable (see Appendix 5).

4.3 | Validating HOC

We considered BDAC as an HOC based on three lower order constructs (LOCs)—BTC, BA, and BCM. We examined and validated the LOC and HOC using the reflective–formative type based on the disjoint two-stage approach (Sarstedt et al. 2022). Table 6 sets out the outcome of the HOC analysis. We first assessed the measurement model of the LOCs, established the reliability and validity, and then used the latent scores of the LOCs to compute the values for the HOC (BDAC) (Hair et al. 2018). We validated the HOC using the indices of outer loadings, outer weights, *T* statistics, and VIF. When the outer weights are statistically significant, HOC is validated (Sarstedt et al. 2022). However, if some of the LOCs are not significant but the outer loadings are significant, HOCs could be validated (Sarstedt et al. 2022). Given this, because our analysis reveals that the outer loadings of each construct forming BDAC were significant, we can conclude that HOC is validated, although LOCs BA and BTC's outer weights are not statistically significant (Sarstedt et al. 2022). Lastly, our HOC reveals no multicollinearity issues since the VIF values are less than 5 (Sarstedt et al. 2022).

4.4 | Hypothesis Testing

We assessed the sequential structural model using beta coefficients, *t* values, *p* values, and the coefficient of determination (R^2). BDAC explains 3.4% of the variability in green ambidextrous innovation, indicating that other factors drive AGI beyond BDAC. Moreover, BDAC, AGI, and GCA explain 60.4% of the variability in CEP of MNCs (see Table 4), which shows that these factors are major drivers of CEP in MNCs, whereas BDAC and AGI explain 47.10% of the variability in GCA, which demonstrates that these factors are key drivers of GCA in MNCs.

First, we found that the direct effect of BDAC was not statistically significant ($B=0.207$, $p=0.000$). Thus, we cannot confirm Hypothesis 1 regarding the direct effect of BDAC on CEP, which indeed justifies our serial mediation analysis, as BDAC influences AGI, which in turn influences GCA, which ultimately influences CEP (see Table 7). Moreover, as expected, BDAC is significantly related to AGI ($B=0.186$; $p=0.005$), thus supporting Hypothesis 2a, which means that MNCs with BDAC will develop more investments in AGI. In turn, AGI is positively related

TABLE 6 | Higher order validations.

HOC	LOC	Outer weights	*T* values	*ps*	Outer loadings	*p* values	VIF
BDAC	BA	0.429	1.199	0.231	0.774	0.001	1.390
	BCM	0.761	2.15	0.032	0.931	0.000	1.717
	BTC	−0.071	0.175	0.861	0.572	0.042	0.620

TABLE 7 | Sequential mediation analysis (direct links).

	Original sample (*O*)	Sample mean (*M*)	Standard deviation (STDEV)	T statistics (|*O*/STDEV|)	*p* values
BDAC → AGI	0.186	0.204	0.066	2.812	0.005
AGI → CEP	0.116	0.118	0.059	1.973	0.049
AGI → GCA	0.264	0.266	0.007	3.793	0.000
GCA → CEP	0.449	0.449	0.067	6.661	0.000
BDAC → CEP	0.018	0.019	0.052	0.350	0.726
BDAC → GCA	−0.003	0.009	0.054	0.060	0.952
Control variables					
Sector → CEP	0.206	0.207	0.081	2.556	0.002
CER → CEP	0.315	0.311	0.07	4.497	0.000
Firm age → CEP	0.091	0.093	0.124	0.750	0.453
Firm size → CEP	0.123	0.103	0.098	1.256	0.786
FP → CEP	0.239	0.238	0.083	3.793	0.005

Abbreviations: AGI = ambidextrous green innovation; BDAC = big data analytic capabilities; CEP = corporate environmental performance; CER = corporate environmental responsibility; FP = financial performance; GCA = green competitive advantage.

to GCA ($B = 0.264$; $p < 0.000$). Similarly, we found that a GCA is positively associated with CEP ($B = 0.449$; $p < 0.001$), indicating that MNCs with a better GCA will enhance the firm's CEP, suggesting that a GCA is a potential driver of CEP. However, BDAC is not directly related to GCA ($B = -0.003$; $p = 0.952$), thus disconfirming Hypothesis 3a. For the control variables, we found that sector ($B = 0.207$, $p = 0.000$), CEP ($B = 0.315$, $p = 0.000$), and FP ($B = 0.239$, $p = 0.005$) all have a positive effect on CEP. However, firm size and firm age do not have a significant relationship with CEP. The next section, therefore, examines the serial mediation effects of these direct effects.

4.5 | Bootstrap Test of the Serial Mediation Model

To test the mediation effect of AGI and GCA on the BDAC–CEP relationships, we employed procedures (Preacher and Hayes 2008) with subsamples of 5000 bootstrapping, which yield t values and confidence intervals for the mediating hypothesis. Bootstrapping is a nonparametric method used to assess the statistical significance of various PLS-SEM outcomes, such as path coefficients, confidence intervals, and t values. For instance, original PLS-SEM results are deemed significant if the confidence intervals do not encompass 0, and the t values are at least 1.96 (Becker et al. 2023; Hair et al. 2022). The serial multiple mediator model includes BDAC as the independent variable (X), two mediators—AGI (M_1) and GCA (M_2)—and environmental performance (Y) as the outcome variable (plus numerous controls). Figure 2 shows the serial mediating relationships analyzed.

The model aims to illustrate both the direct influence of X (BDAC) on Y (environmental performance) and three potential indirect influences. These indirect effects are represented by various paths (Hayes 2013) as follows:

$$X \rightarrow M_1 \rightarrow Y = a_1 b_1$$

$$X \rightarrow M_2 \rightarrow Y = a_2 b_2$$

$$X \rightarrow M_1 \rightarrow M_2 \rightarrow Y = a_1 d_{21} b_2$$

Table 8 shows the results obtained from the bootstrapping analysis of the mediating effects. As observed, AGI does not play a

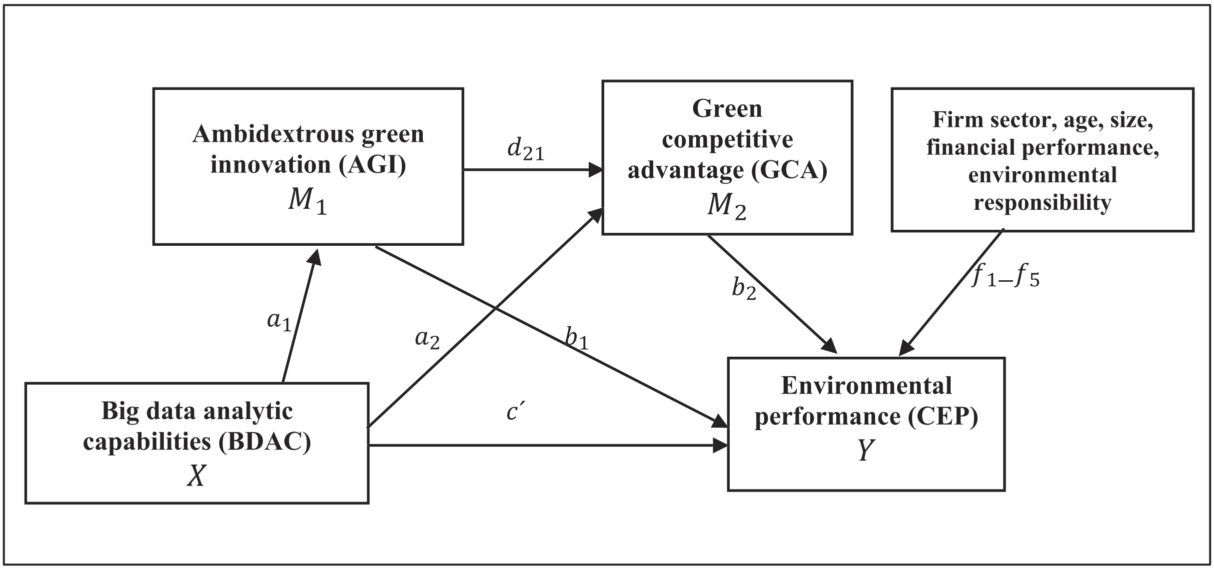

FIGURE 2 | Serial multiple mediator model analyzed. *Note:* a_1—the direct effect of BDAC on AGI; a_2—the direct effect of BDAC on GCA; b_1—the direct effect of AGI on EP; b_2—the direct effect of GCA on EP; c—the direct effect of BDAC on EP; d_{21}—the direct effect of AGI on GCA; and f_1–f_5 = the control effect of C-firm size, sector, age, corporate environmental responsibility, and financial performance on EP.

TABLE 8 | Total, direct, and indirect effects of BDAC on CEP via AGI and GCA.

Paths	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	*T* statistics (|O/STDEV|)	CI-2.5%	CI + 97.5%	P values
BDAC → AGI → CEP	0.024	0.025	0.016	1.441	−0.003	0.06	0.150
BDAC → GCA → CEP	−0.001	0.004	0.025	0.059	−0.047	0.05	0.953
BDAC → AGI → GCA → CEP	0.052	0.056	0.023	2.318	0.012	0.099	0.020
Direct effects	−0.008	−0.008	0.064	0.120	−0.138	0.114	0.905
Total indirect effects	0.075	0.045	0.036	2.083	0.011	0.181	0.034
Total effects	0.067	0.065	0.032	2.123	0.034	0.124	0.024

Abbreviations: AGI = ambidextrous green innovation; BDAC = big data analytic capabilities; CEP = corporate environmental performance; GCA = green competitive advantage.

significant positive mediating role in the relationship between BDAC and CEP ($X \rightarrow M_1 \rightarrow Y = a_1 b_1$), as the confidence intervals include 0 ($B = 0.024$, $t = 1.441$, CI = −0.003 to 0.06). Thus, we cannot support Hypothesis 2b.

Our Hypothesis 3b posited that BDAC would influence CEP through its influence on GCA ($X \rightarrow M_2 \rightarrow Y = a_2 b_2$). However, the mediating effect of GCA between BDAC and CEP is not significant ($B = -0.001$, $t = 0.059$, CI = −0.047 to 0.05), as the confidence interval includes 0. Thus, our findings do not support Hypothesis 3b either. Instead, our findings support Hypothesis 4, which posits that the impact of BDAC on CEP is serially or sequentially mediated by AGI and GCA ($X \rightarrow M_1 \rightarrow M_2 \rightarrow Y = a_1 d_{21} b_2$). As shown, the mediation effect of AGI and GCA in the relationship between BDAC and CEP was significant ($B = 0.052$, $t = 2.318$, $p = 0.020$), and the confidence intervals do not include 0 (CI = 0.012, 0.099). This suggests that BDAC fosters AGI, which in turn drives a GCA, ultimately influencing the CEP of MNCs. The overall indirect effect of BDAC on CEP, mediated by AGI and GCA, was significant ($B = 0.075$, CI = 0.011–0.118). This type of mediation is indirect only, as the direct effect was not significant ($B = -0.008$, $p = 0.995$) in the full model (Zhao et al. 2010). Therefore, AGI and GCA play a complementary and mediating role in the BDAC–CEP relationships (BDAC → AGI → GCA → CEP).

5 | Discussion

The present study proposes a theoretical framework of CEP and discusses its relationship with BDAC through AGI and GCA. Although several studies have examined the impact of BDAC on CEP, no study exists that investigates the serial path through which this focal relationship prevails, particularly in MNCs. Our study examines the serial mediating effects of AGI and GCA on the relationships between BDAC and CEP, yielding several interesting findings. For example, this study hypothesized a direct relationship between BDAC and CEP, whereas it highlights that BDAC has no direct significant impact on CEP.

This finding is inconsistent with the previous literature, which has suggested a direct relationship between BDAC and CEP (e.g., Rahman et al. 2024; Sahoo et al. 2023). One possible reason for this result is the lack of strategic alignment between BDAC initiatives and firm-level outcomes. When firms prioritize financial, operational, or manufacturing outcomes over big data analytics capabilities, their resource allocation is driven by these initiatives instead of environmental ones. This highlights that mediating factors, such as strategic environmental orientation and environmental management systems, indicating firms' priorities toward environmental protection, may help us understand this relationship. Similarly, several moderating factors, such as leadership commitment or stakeholder pressure, may have a potential impact on such results.

This study highlights that BDAC has a significant positive impact on AGI. These results align with the DCV, which suggests that BDAC enables a firm to develop ambidexterity capabilities by facilitating adaptation to the environment through reconfiguration of resources and strategies (Stekelorum et al. 2021). This finding aligns with the results of Waqas et al. (2021), who demonstrated that BDA-TC, BA, and BDA-CM have a positive impact on green innovation. Thus, these findings extend the DCV and NRBV that firms that efficiently develop BDAC capabilities can explore and exploit green innovation opportunities (Makhloufi et al. 2023), as AGI strategies enhance an organizational ability to adapt to immediate and long-term changes and exploit ecological opportunities (Jansen et al. 2012; Lee et al. 2018; J. Wang, Xue, Sun, et al. 2020; J. Wang, Xue, and Yang 2020). Therefore, the study contributes to the scholarly discussion that organizations with greater commitment toward BDAC can better formulate and implement AGI in today's green and digital economy.

Another important finding of this study is that AGI positively affects GCA. Theoretically, this finding not only supports previous studies that claimed green innovation has a significant and positive impact on competitive advantage (Waqas et al. 2021), but it also supports the classical view that competitive advantage is the result of firms' resources, which are called dynamic capabilities (Teece et al. 1997). Accordingly, our results extend the NRBV that AGI enables companies to utilize their dynamic capabilities better to be more competitive. In addition, this study proved that AGI has a significant positive impact on environmental performance. This finding lends support to the previous literature that when organizations are more committed to AGI and continuously improve their ecological products and processes, as a result, they easily modify the conventional modes of company operations and mitigate the impact of firm operations on the environment and exhibit an improved environmental performance by producing green innovative products and the improved process by environmental restoration, cleansing, and rehabilitation (Shehzad et al. 2022).

The present study found that a GCA has a significant impact on CEP. Therefore, our results align with the finding of Zameer et al. (2021) that a significant positive association exists between GCA and CEP. In terms of the mediating role of AGI between BDAC and GCA, this study found that AGI plays a significant mediating role in the relationship between BDAC and GCA. In other words, BDAC facilitates firms in exploitative green innovation by providing customized and appropriate information that helps them improve existing green products and processes. Regarding exploratory green innovation, BDAC enables firms to examine a large amount of environmental data, market trends, and consumer behavior, which helps them make informed decisions. Accordingly, companies can easily explore new sustainable technologies and optimize the use of natural resources. Our study concludes that AGI enables firms to achieve green competitiveness. This aligns with the findings in the literature, which indicate that big data analytics have a significantly positive impact on green innovation and competitive advantage (Mehmood et al. 2023; Zameer et al. 2020). Furthermore, the present study found that GCA mediates the relationship between AGI and CEP (Mehmood et al. 2024; Hayat and Qingyu 2024). Interestingly, however, we did not find support for the mediating effect of AGI between BDAC and CEP, which buttresses our argument that the impact of BDAC on CEP is serial through AGI and GCA. Therefore, we reveal that BDAC has a significant and positive impact on CEP through a serial mediation of AGI and GCA. This indicates that the management of big data capability talent and business analytics capabilities enhances AGI, leading to competitive advantage and subsequent improved CEP (Waqas et al. 2021). Converging evidence suggests that dynamic capabilities encompass both explorative and exploitative activities (Teece et al. 1997), enabling a firm to reconfigure its resource base and gain a competitive advantage (Jurksiene and Pundziene 2016). Accordingly, this study advances the DCV and NRBV that BDAC drives AGI, which propels GCA and, ultimately, CEP. These findings have numerous theoretical and managerial implications, which are discussed in the next section.

6 | Implications

6.1 | Theoretical Contributions

The study contributes to multiple dimensions of the digital economy, sustainability, and green economy literature. Our first theoretical contribution rests in reframing AGI within the DCV as an indispensable capability for leveraging BDAC to achieve sustainable outcomes. Our study introduces a nuanced serial mediation model, a first-of-its-kind, that details the interplay between BDAC, AGI, and GCA in environmental performance within MNCs. This addition advances the NRBV theory by empirically validating that environmental competitiveness is inseparable from dynamic operational capabilities. Second, whereas considerable efforts are focused on understanding the relationship between BDAC and environmental performance, empirical findings are mixed (Belhadi et al. 2020; Dubey, Gunasekaran, and Childe 2019; Dubey, Gunasekaran, Childe, Papadopoulos, et al. 2019; Bag et al. 2020). Our study reveals the causal relationship between BDAC and CEP in MNCs, clarifying previously anecdotal findings. Third, although some studies have examined mediating factors in the BDAC–CEP (Waqas et al. 2021), our research is pioneering to (a) explicate the sequential path through which BDAC impacts environmental performance, (b) to do so in the context of MNCs, and (c) explicitly take into account not only the influence of contextual variables (sector, size) but also other critical organizational variables, like sector, CER, and FP. More specifically, our empirical findings contribute to the digital economy and green economy literature by demonstrating that a serial mediation model incorporating AGI and GCA can explain how BDAC ultimately translates into environmental performance. In line with the DCV, we argue that BDAC is a key driver of AGI, helping the firm to enhance green dynamic capabilities by using existing knowledge to strengthen management and operational skills, routines, know-how, new product creation, processes, and individual practices while exploring for new environmental knowledge (Hanifah et al. 2022; Lozada et al. 2023). Therefore, we demonstrate that MNCs that develop BDAC are likely to develop AGI. Similarly, consistent with the NRBV, AGI leads to GCA, which, in turn, leads to environmental performance. Therefore, we contribute to the literature that implementing AGI through pollution prevention techniques, product stewardship, and sustainable development leads to GCA and CEP (Agyabeng-Mensah and Tang 2021), showing AGI and GCA as critical drivers of environmental performance. Furthermore, our inclusion of a multiple set of control variables contributes to mitigating model misspecification, which may arise from omitted variables, and guarantees that our empirical findings do not overestimate or inflate the effects of BDAC on the outcome variable. We specifically integrated our model with the firm sector, firm size, FP, and CEP because they have been revealed in previous studies to impact firm performance, including CEP (Oduro and De Nisco 2023; Oduro 2024). Our nuanced insight deepens our understanding of how MNCs and firms can effectively leverage BDAC to handle environmental menaces in an increasingly turbulent business environment. Lastly, the study's conceptual framework and its findings open avenues for future scholars to develop a serial mediation model to understand the impact of BDAC on firm performance.

6.2 | Managerial and Policy Implications

BDAC may influence AGI which can improve MNCs' GCA and CEP. Managers and practitioners must invest in modern data analytics tools and establish data-driven decision-making processes to drive innovation and utilize environmentally friendly technology. Prioritizing training and technological infrastructure to maximize BDAC may help MNCs enhance their ambidextrous approach to green innovation and CEP. When used appropriately, AGI may boost GCA and CEP. Managers of MNCs should develop a comprehensive innovation plan that incorporates green technology in all aspects of the business, from product development to operations. MNCs can satisfy environmental requirements and gain an economic advantage in sustainability-driven markets, thereby ensuring a better and more sustainable future. This connection enhances the MNC's market position by demonstrating its commitment to sustainability and appealing to investors and customers who value environmental concerns. In a general approach to sustainability, these results demonstrate that green efforts, new ideas driven by BDAC, and the effective use of financial resources all contribute to enhancing CEP. MNCs will be able to participate in markets that are becoming increasingly controlled by sustainability standards and customer demands if they combine data analytics with sustainability efforts and fulfill their financial and environmental responsibilities.

MNCs should prioritize the development of AGI, as BDAC impacts both GCA and environmental performance. In this regard, MNCs should enhance and refine their existing green products and processes; strengthen the current green market and technology through incremental innovations; adopt new green products, processes, and services; leverage them; discover new green markets; and acquire new green technology through market segmentation and dynamic market monitoring. Our findings also show that practitioners must adopt effective green management systems, offer higher quality green products, and invest more in environmental research, development, and green innovation than major competitors to achieve superior environmental performance. BDAC, AGI, and GCA enhance environmental performance, but the study's control factors offer valuable insights for MNC management. FP and CER directly influence CEP and resource and initiative management. The positive association between financial success and CEP suggests that resource allocation is crucial for improving environmental outcomes, as MNCs may allocate more resources to green technologies, resulting in higher profitability. Managers might be wise to allocate their profits to green projects for the sake of the environment. This approach immediately improves CEP and promotes sustainability. CER also makes a significant difference in how sound companies treat the environment, demonstrating that it should be a core part of business strategy rather than merely an added benefit. CER is beneficial for MNCs because it enhances CEP and the perception of the company among stakeholders. MNC managers should combine environmental responsibility actions with measurable environmental goals, such as lowering pollution and protecting resources.

Policymakers shape the regulatory and support environment for sustainable business. They may encourage MNCs to adopt BDAC and integrate it into their operations by granting tax exemptions, grants, or subsidies for sustainable business practices and technology, thereby improving environmental outcomes. Policymakers also may promote green innovation by encouraging government, academic, and MNC cooperation. They can speed up eco-friendly technology development by supporting collaborations and knowledge-sharing platforms that integrate MNCs' BDAC skills with public sector resources. R&D collaboration and data exchange can enhance green innovation, and a GCA drives environmental performance. To get MNCs to seek GCA, states and regulatory bodies should set standards for green approval and eco-labeling. Lastly, the government could help MNCs align their business plans with global and national sustainable development goals. It would promote more environmentally friendly business practices. Thus, governments should reconsider sustainability incentives by prioritizing observable sustainability outcomes through innovation and technology adoption.

7 | Limitations and Further Research

This study enhances our understanding of how BDAC drives AGI, GCA, and CEP in MNCs, but certain limitations highlight areas for further exploration. The cross-sectional design restricts insights into how these relationships evolve. Future longitudinal studies could provide a deeper understanding of BDAC's impact on AGI and CEP across various market and technological changes (Farrington and Hawkins 1991; Rindfleisch et al. 2008). While offering generalizability, the quantitative approach may not fully capture the mechanisms underlying the interactions between BDAC, AGI, and CEP. However, the potential of qualitative methods, such as case studies, to offer richer, context-specific insights into the dynamics that shape sustainable practices is exciting. Focusing solely on MNCs may limit applicability to other organizational types. Replicating this model in small- and medium-sized enterprises (SMEs), public sector organizations, or nonprofits could enhance generalizability. Conducted within a single-country setting, this research may not accurately reflect the global diversity of regulatory, cultural, or economic factors that affect BDAC's role in sustainability. Cross-national studies can provide broader insights, particularly in regions with diverse policy frameworks or varying market maturity. The model also fails to account for external stakeholders, such as suppliers and consumers, who may influence sustainability practices. Future studies could examine how BDAC aligns with consumer demands for sustainable practices or investor pressures, highlighting BDAC's role in responding to external expectations. Finally, with the rapid advancements in technologies like AI and IoT, future research should explore how these tools interact with BDAC to foster environmental innovation. These synergies may unlock more sophisticated, impactful sustainability initiatives.

Acknowledgments

Open access publishing facilitated by Libera Universita di Bolzano, as part of the Wiley - CRUI-CARE agreement.

References

Abbas, J. 2024. "Does the Nexus of Corporate Social Responsibility and Green Dynamic Capabilities Drive Firms Toward Green Technological Innovation? The Moderating Role of Green Transformational Leadership." *Technological Forecasting and Social Change* 208: 123698. https://doi.org/10.1016/j.techfore.2024.123698.

Agyabeng-Mensah, Y., and L. Tang. 2021. "The Relationship Among Green Human Capital, Green Logistics Practices, Green Competitiveness, Social Performance, and Financial Performance." *Journal of Manufacturing Technology Management* 32, no. 7: 1377–1398. https://doi.org/10.1108/JMTM-11-2020-0441.

Akhtar, S., C. Li, J. M. Sohu, Y. Rasool, M. I. U. Hassan, and M. Bilal. 2024. "Unlocking Green Innovation and Environmental Performance: The Mediated Moderation of Green Absorptive Capacity and Green Innovation Climate." *Environmental Science and Pollution Research* 31, no. 3: 4547–4562. https://doi.org/10.1007/s11356-023-31403-w.

Akter, S., A. Gunasekaran, S. F. Wamba, M. M. Babu, and U. Hani. 2020. "Reshaping Competitive Advantages With Analytics Capabilities in Service Systems." *Technological Forecasting and Social Change* 159: 120180. https://doi.org/10.1016/j.techfore.2020.120180.

Alam, S. S., and K. Z. Islam. 2021. "Examining the Role of Environmental Corporate Social Responsibility in Building Green Corporate Image and Green Competitive Advantage." *International Journal of Corporate Social Responsibility* 6, no. 1: 8. https://doi.org/10.1186/s40991-021-00062-w.

Albertini, E. 2021. "What Are the Environmental Capabilities, as Components of the Sustainable Intellectual Capital, That Matter to the CEOs of European Companies?" *Journal of Intellectual Capital* 22, no. 5: 918–937. https://doi.org/10.1108/JIC-06-2020-0215.

Al-Khatib, A. W. 2022. "Big Data Analytics Capabilities and Green Supply Chain Performance: Investigating the Moderated Mediation Model for Green Innovation and Technological Intensity." *Business Process Management Journal* 28, no. 5/6: 1446–1471. https://doi.org/10.1108/BPMJ-07-2022-0332.

AlNuaimi, B. K., M. Khan, and M. M. Ajmal. 2021. "The Role of Big Data Analytics Capabilities in Greening E-Procurement: A Higher Order PLS-SEM Analysis." *Technological Forecasting and Social Change* 169: 120808.

Armstrong, J. S., and T. S. Overton. 1977. "Estimating Nonresponse Bias in Mail Surveys." *Journal of Marketing Research* 14, no. 3: 396–402. https://doi.org/10.1177/002224377701400320.

Asiaei, K., N. G. O'Connor, O. Barani, and M. Joshi. 2023. "Green Intellectual Capital and Ambidextrous Green Innovation: The Impact on Environmental Performance." *Business Strategy and the Environment* 32, no. 1: 369–386. https://doi.org/10.1002/bse.3136.

Bag, S., L. C. Wood, L. Xu, P. Dhamija, and Y. Kayikci. 2020. "Big Data Analytics as an Operational Excellence Approach to Enhance Sustainable Supply Chain Performance." *Resources, Conservation and Recycling* 153: 104559. https://doi.org/10.1016/j.resconrec.2019.104559.

Baquero, A. 2024. "Linking Green Entrepreneurial Orientation and Ambidextrous Green Innovation to Stimulate Green Performance: A Moderated Mediation Approach." *Business Process Management Journal* 30, no. 8: 71–98. http://creativecommons.org/licences/by/4.0/legalcode, https://doi.org/10.1108/BPMJ-09-2023-0703.

Baruch, Y., and B. C. Holtom. 2008. "Survey Response Rate Levels and Trends in Organizational Research." *Human Relations* 61, no. 8: 1139–1160. https://doi.org/10.1177/001872670809486.

Becker, M., Brockmann, M., Niemietz, P., Trauth, D., Bergs, T., and C. Brecher. 2023. "The Internet of Production as the Foundation of Data Utilization in Production: Challenges and Solutions of Data-Driven Knowledge Gain." In *The Monetization of Technical Data: Innovations from Industry and Research*, 247–264. Springer.

Belhadi, A., S. S. Kamble, K. Zkik, A. Cherrafi, and F. E. Touriki. 2020. "The Integrated Effect of Big Data Analytics, Lean Six Sigma, and Green Manufacturing on the Environmental Performance of Manufacturing Companies: The Case of North Africa." *Journal of Cleaner Production* 252: 119903. https://doi.org/10.1016/j.jclepro.2019.119903.

Bhatti, S. H., W. M. H. W. Hussain, J. Khan, S. Sultan, and A. Ferraris. 2024. "Exploring Data-Driven Innovation: What's Missing in the Relationship Between Big Data Analytics Capabilities and Supply Chain Innovation?" *Annals of Operations Research* 333, no. 2: 799–824. https://doi.org/10.1007/s10479-022-047727.

Burritt, R. L., K. L. Christ, H. G. Rammal, and S. Schaltegger. 2020. "Multinational Enterprise Strategies for Addressing Sustainability: The Need for Consolidation." *Journal of Business Ethics* 164, no. 2: 389–410. https://doi.org/10.1007/s10551-018-4066-0.

Calic, G., and M. Ghasemaghaei. 2021. "Big Data for Social Benefits: Innovation as a Mediator of the Relationship Between Big Data and Corporate Social Performance." *Journal of Business Research* 131: 391–401. https://doi.org/10.1016/j.jbusres.2020.11.003.

Chen, Y. S. 2008. "The Driver of Green Innovation and Green Image–Green Core Competence." *Journal of Business Ethics* 81: 531–543. https://doi.org/10.1007/s10551-007-9522-1.

Chen, Y. S., and C. H. Chang. 2013. "The Determinants of Green Product Development Performance: Green Dynamic Capabilities, Green Transformational Leadership, and Green Creativity." *Journal of Business Ethics* 116: 107–119. https://doi.org/10.1007/s10551-012-1452-x.

Cheng, J., and Y. Liu. 2018. "The Effects of Public Attention on the Environmental Performance of High-Polluting Firms: Based on Big Data From Web Search in China." *Journal of Cleaner Production* 186: 335–341. https://doi.org/10.1016/j.jclepro.2018.03.146.

Chun, R. 2005. "Corporate Reputation: Meaning and Measurement." *International Journal of Management Reviews* 7, no. 2: 91–109.

Cohen, J. 2013. *Statistical Power Analysis for the Behavioral Sciences*. Routledge.

Constantiou, I. D., and J. Kallinikos. 2015. "New Games, New Rules: Big Data and the Changing Context of Strategy." *Journal of Information Technology* 30, no. 1: 44–57. https://doi.org/10.1057/jit.2014.17.

Cormier, D., I. M. Gordon, and M. Magnan. 2004. "Corporate Environmental Disclosure: Contrasting Management's Perceptions With Reality." *Journal of Business Ethics* 49: 143–165. https://doi.org/10.1023/B:BUSI.0000015844.86206.b9.

Correggi, C., P. Di Toma, and S. Ghinoi. 2024. "Rethinking Dynamic Capabilities in Light of Sustainability: A Bibliometric Analysis." *Business Strategy and the Environment* 33: 7990–8016. https://doi.org/10.1002/bse.3901.

Côrte-Real, N., P. Ruivo, and T. Oliveira. 2020. "Leveraging Internet of Things and Big Data Analytics Initiatives in European and American Firms: Is Data Quality a Way to Extract Business Value?" *Information & Management* 57, no. 1: 103141. https://doi.org/10.1016/j.im.2019.01.003.

Creswell, J. W., and J. D. Creswell. 2017. *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. Sage Publications.

Dahiya, R., S. Le, J. K. Ring, and K. Watson. 2022. "Big Data Analytics and Competitive Advantage: The Strategic Role of Firm-Specific Knowledge." *Journal of Strategy and Management* 15, no. 2: 175–193. https://doi.org/10.1108/JSMA-08-2020-0203.

Davenport, T. H., and J. G. Harris. 2007. *Competing on Analytics: The New Science of Winning*. Harvard Business Review Press.

Duan, Y., G. Cao, and J. S. Edwards. 2020. "Understanding the Impact of Business Analytics on Innovation." *European Journal of Operational Research* 281, no. 3: 673–686. https://doi.org/10.1016/j.ejor.2018.06.021.

Dubey, R., A. Gunasekaran, and S. J. Childe. 2019. "Big Data Analytics Capability in Supply Chain Agility: The Moderating Effect of Organizational Flexibility." *Management Decision* 57, no. 8: 2092–2112. https://doi.org/10.1108/MD-01-2018-0119.

Dubey, R., A. Gunasekaran, S. J. Childe, et al. 2019b. "Can Big Data and Predictive Analytics Improve Social and Environmental Sustainability?" *Technological Forecasting and Social Change* 144: 534–545. https://doi.org/10.1016/j.techfore.2017.06.020.

Dubey, R., D. J. Bryde, Y. K. Dwivedi, et al. 2023. "Dynamic Digital Capabilities and Supply Chain Resilience: The Role of Government Effectiveness." *International Journal of Production Economics* 258: 108790.

Dubey, R., N. Altay, A. Gunasekaran, et al. 2018. "Supply Chain Agility, Adaptability and Alignment: Empirical Evidence From the Indian Auto Components Industry." *International Journal of Operations & Production Management* 38, no. 1: 129–148.

Dunning, J. H. 1992. *Multinational Enterprises and the Global Economy*. Addison-Wesley.

Eisenhardt, K. M., and J. A. Martin. 2000. "Dynamic Capabilities: What Are They?" *Strategic Management Journal* 21, no. 10–11: 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11%3C1105::AID-SMJ133%3E3.0.CO;2-E.

El-Kassar, A. N., and S. K. Singh. 2018. "Green Innovation and Organizational Performance: The Influence of Big Data and the Moderating Role of Management Commitment and HR Practices." *Technological Forecasting and Social Change* 144: 483–498. https://doi.org/10.1016/j.techfore.2017.12.016.

Farrington, D. P., and J. D. Hawkins. 1991. "Predicting Participation, Early Onset and Later Persistence in Officially Recorded Offending." *Criminal Behaviour and Mental Health* 1, no. 1: 1–33. https://doi.org/10.1002/cbm.1991.1.1.1.

Feng, S., R. Zhang, and G. Li. 2022. "Environmental Decentralization, Digital Finance and Green Technology Innovation." *Structural Change and Economic Dynamics* 61: 70–83. https://doi.org/10.1016/j.strueco.2022.02.008.

Ferraris, A., A. Mazzoleni, A. Devalle, and J. Couturier. 2019. "Big Data Analytics Capabilities and Knowledge Management: Impact on Firm Performance." *Management Decision* 57, no. 8: 1923–1936. https://doi.org/10.1108/MD-07-2018-0825.

Fornell, C., and F. D. Larcker. 1981. "Evaluating Structural Equation Models With Unobservable Variables and Measurement Error." *Journal of Marketing Research* 18, no. 1: 170–1712.

Fuller, C. M., M. J. Simmering, G. Atinc, Y. Atinc, and B. J. Babin. 2016. "Common Methods Variance Detection in Business Research." *Journal of Business Research* 69, no. 8: 3192–3198. https://doi.org/10.1016/j.jbusres.2015.12.008.

Gibson, C. B., and J. Birkinshaw. 2004. "The Antecedents, Consequences, and Mediating Role of Organizational Ambidexterity." *Academy of Management Journal* 47, no. 2: 209–226. https://doi.org/10.5465/20159573.

Gupta, M., and J. F. George. 2016. "Toward the Development of a Big Data Analytics Capability." *Information & Management* 53, no. 8: 1049–1064. https://doi.org/10.1016/j.im.2016.07.004.

Hair, J. F., D. Harrison, and J. Risher. 2022. "Post-Pandemic Reflections on Challenges and Opportunities for Marketing Research in the 21st Century." *Journal of Sustainable Competitive Intelligence* 12, no. 1: e0411.

Hair, J. F., G. T. M. Hufit, C. M. Ringle, and M. Sarstedt. 2014. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage Publications. https://doi.org/10.1007/978-3-030-80519-7.

Hair, J. F. Jr., L. M. Matthews, R. L. Matthews, and M. Sarstedt. 2017. "PLS-SEM or CB-SEM: Updated Guidelines on Which Method to Use." *International Journal of Multivariate Data Analysis* 1, no. 2: 107–123.

Hair, J. F., M. Sarstedt, C. M. Ringle, and S. P. Gudergan. 2018. *Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage Publications. https://doi.org/10.1007/978-3-319-57413-4_15.

Hanifah, H., N. Abd Halim, A. Vafaei-Zadeh, and K. Nawaser. 2022. "Effect of Intellectual Capital and Entrepreneurial Orientation on Innovation Performance of Manufacturing SMEs: Mediating Role of Knowledge Sharing." *Journal of Intellectual Capital* 23, no. 6: 1175–1198. https://doi.org/10.1108/JIC-06-2020-0186.

Harreld, J. B., C. A. O'Reilly III, and M. L. Tushman. 2007. "Dynamic Capabilities at IBM: Driving Strategy Into Action." *California Management Review* 49, no. 4: 21–43. https://doi.org/10.2307/41166404.

Hart, S. L. 1995. "A Natural-Resource-Based View of the Firm." *Academy of Management Review* 20, no. 4: 986–1014. https://doi.org/10.5465/amr.1995.9512280033.

Hart, S. L., and G. Dowell. 2011. "Invited Editorial: A Natural-Resource-Based View of the Firm: Fifteen Years After." *Journal of Management* 37, no. 5: 1464–1479. https://doi.org/10.1177/0149206310390219.

Hayat, K., and Z. Qingyu. 2024. "The Synergistic Effects of Green Innovation Strategies on Sustainable Innovative Performance With the Mediation of Green Innovative Competitive Advantage." *Corporate Social Responsibility and Environmental Management* 31: 4172–4189. https://doi.org/10.1002/csr.2770.

Hayes, J. R. 2013. *The Complete Problem Solver*. Routledge.

Jakobsen, M., and R. Jensen. 2015. "Common Method Bias in Public Management Studies." *International Public Management Journal* 18, no. 1: 3–30. https://doi.org/10.1080/10967494.2014.997906.

Jansen, J. J., Z. Simsek, and Q. Cao. 2012. "Ambidexterity and Performance in Multiunit Contexts: Cross-Level Moderating Effects of Structural and Resource Attributes." *Strategic Management Journal* 33, no. 11: 1286–1303. https://doi.org/10.1002/smj.1977.

Jansen, J. J., F. A. Van Den Bosch, and H. W. Volberda. 2006. "Exploratory Innovation, Exploitative Innovation, and Performance: Effects of Organizational Antecedents and Environmental Moderators." *Management Science* 52, no. 11: 1661–1674. https://doi.org/10.1287/mnsc.1060.0576.

Jurksiene, L., and A. Pundziene. 2016. "The Relationship Between Dynamic Capabilities and Firm Competitive Advantage: The Mediating Role of Organizational Ambidexterity." *European Business Review* 28, no. 4: 431–448. https://doi.org/10.1108/EBR-09-2015-0088.

Kamble, S. S., A. Gunasekaran, and S. A. Gawankar. 2020. "Achieving Sustainable Performance in a Data-Driven Agriculture Supply Chain: A Review for Research and Applications." *International Journal of Production Economics* 219: 179–194.

Katila, R., and G. Ahuja. 2002. "Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction." *Academy of Management Journal* 45: 1183–1194. https://doi.org/10.5465/3069433.

Kristoffersen, E., P. Mikalef, F. Blomsma, and J. Li. 2021. "The Effects of Business Analytics Capability on Circular Economy Implementation, Resource Orchestration Capability, and Firm Performance." *International Journal of Production Economics* 239: 108205. https://doi.org/10.1016/j.ijpe.2021.108205.

Kuo, F. I., W. T. Fang, and B. A. LePage. 2022. "Proactive Environmental Strategies in the Hotel Industry: Eco-Innovation, Green Competitive Advantage, and Green Core Competence." *Journal of Sustainable Tourism* 30, no. 6: 1240–1261. https://doi.org/10.1080/09669582.2021.1931254.

Laing, T., A. Upadhyay, S. Mohan, and N. Subramanian. 2019. "Environmental Improvement Initiatives in the Coal Mining Industry: Maximisation of the Triple Bottom Line." *Production Planning & Control* 30, no. 5–6: 426–436.

Le, H., and K. C. Vu. 2024. "Big Data Analytics and Environmental Performance: The Moderating Role of Internationalization." *Finance Research Letters* 64: 105484. https://doi.org/10.1016/j.frl.2024.105484.

Lee, S. U., G. Park, and J. Kang. 2018. "The Double-Edged Effects of the Corporate Venture Capital Unit's Structural Autonomy on Corporate Investors' Explorative and Exploitative Innovation." *Journal of Business Research* 88: 141–149. https://doi.org/10.1016/j.jbusres.2018.01.049.

Levinthal, D. A., and J. G. March. 1993. "The Myopia of Learning." *Strategic Management Journal* 14, no. S2: 95–112. https://doi.org/10.1002/smj.4250141009.

Liao, J., and Q. Chen. 2021. "Biodegradable Plastics in the Air and Soil Environment: Low Degradation Rate and High Microplastics Formation." *Journal of Hazardous Materials* 418: 126329. https://doi.org/10.1016/j.jhazmat.2021.126329.

Lin, Y. H., and Y. S. Chen. 2017. "Determinants of Green Competitive Advantage: The Roles of Green Knowledge Sharing, Green Dynamic Capabilities, and Green Service Innovation." *Quality & Quantity* 51, no. 4: 1663–1685. https://doi.org/10.1007/s11135-016-0358-6.

Lozada, N., J. Arias-Pérez, and E. A. Henao-García. 2023. "Unveiling the Effects of Big Data Analytics Capability on Innovation Capability Through Absorptive Capacity: Why More and Better Insights Matter." *Journal of Enterprise Information Management* 36, no. 2: 680–701. https://doi.org/10.1108/JEIM-02-2021-0092.

Makhloufi, L., L. Vasa, J. Rosak-Szyrocka, and F. Djermani. 2023. "Understanding the Impact of Big Data Analytics and Knowledge Management on Green Innovation Practices and Organizational Performance: The Moderating Effect of Government Support." *Sustainability* 15, no. 11: 8456. https://doi.org/10.3390/su15118456.

Martínez-Falcó, J., E. Sánchez-García, B. Marco-Lajara, and K. Lee. 2024. "Green Supply Chain Management and Sustainable Performance: Exploring the Role of Green Ambidexterity Innovation and Top Management Environmental Awareness." *Business Process Management Journal* 30, no. 6: 1824–1847. https://doi.org/10.1108/BPMJ-12-2023-0981.

McDougall, N., B. Wagner, and J. MacBryde. 2016. "Exploring Dynamic Natural-Resource-Based Capabilities for Sustainable Agri-Food Chains." In *Sustainable Design and Manufacturing 2016. SDM 2016. Smart Innovation, Systems and Technologies*, edited by R. Setchi, R. Howlett, Y. Liu, and P. Theobald, vol. 52. Cham: Springer. https://doi.org/10.1007/978-3-319-32098-4_39.

Mehmood, K., F. Jabeen, M. Rashid, S. M. Alshibani, A. Lanteri, and G. Santoro. 2024. "Unraveling the Transformation: The Three-Wave Time-Lagged Study on Big Data Analytics, Green Innovation and Their Impact on Economic and Environmental Performance in Manufacturing SMEs." *European Journal of Innovation Management*, ahead of print. https://doi.org/10.1108/EJIM-10-2023-0903.

Mehmood, K., A. Kiani, and M. D. Rashid. 2023. "Is Data the Key to Sustainability? The Roles of Big Data Analytics, Green Innovation, and Organizational Identity in Gaining Green Competitive Advantage." *Technology Analysis & Strategic Management* 37, no. 5: 1–15. https://doi.org/10.1080/09537325.2023.2293867.

Mikalef, P., M. Boura, G. Lekakos, and J. Krogstie. 2019. "Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment." *British Journal of Management* 30, no. 2: 272–298. https://doi.org/10.1111/1467-8551.12343.

Mikalef, P., J. Krogstie, I. O. Pappas, and P. Pavlou. 2020. "Exploring the Relationship Between Big Data Analytics Capability and Competitive Performance: The Mediating Roles of Dynamic and Operational Capabilities." *Information & Management* 57, no. 2: 103169. https://doi.org/10.1016/j.im.2019.05.004.

Mikalef, P., I. O. Pappas, J. Krogstie, and M. Giannakos. 2018. "Big Data Analytics Capabilities: A Systematic Literature Review and Research Agenda." *Information Systems and e-Business Management* 16: 547–578. https://doi.org/10.1007/s10257-017-0362-y.

Mohapatra, S., S. Roy, A. Upadhyay, and A. Kumar. 2024. "Circular Value Creation Through Environmental Entrepreneurship Initiatives: A Case-Based Exploration." *Business Strategy and the Environment* 33, no. 5: 3811–3831. https://doi.org/10.1002/bse.3682.

Mudambi, R., L. Li, X. Ma, et al. 2018. "Zoom in, Zoom Out: Geographic Scale and Multinational Activity." *Journal of International Business Studies* 49: 929–941.

Muhammad, A., C. K. Yu, A. Qadir, W. Ahmed, Z. Yousuf, and G. Fan. 2022. "Big Data Analytics Capability as a Major Antecedent of Firm Innovation Performance." *International Journal of Entrepreneurship and Innovation* 23, no. 4: 268–279. https://doi.org/10.1177/14657503211050809.

Neeley, T. 2012. "Global Business Speaks English: Why You Need a Language Strategy Now." *Harvard Business Review* 90, no. 5: 116–124.

Nielsen, J. A., L. Mathiassen, and A. M. Hansen. 2018. "Exploration and Exploitation in Organizational Learning: A Critical Application of the 4I Model." *British Journal of Management* 29, no. 4: 835–850. https://doi.org/10.1111/14678551.12324.

Nitzl, C. 2016. "The Use of Partial Least Squares Structural Equation Modelling (PLS-SEM) in Management Accounting Research: Directions for Future Theory Development." *Journal of Accounting Literature* 37, no. 1: 19–35.

Oduro, S. 2024. "Eco-Innovation and SMEs' Sustainable Performance: A Meta-Analysis." *European Journal of Innovation Management* 27, no. 9: 248–279. https://doi.org/10.1108/EJIM-11-2023-0961.

Oduro, S., and A. De Nisco. 2023. "From Industry 4.0 Adoption to Innovation Ambidexterity to Firm Performance: A MASEM Analysis." *European Journal of Innovation Management* 27, no. 8: 3060–3082. https://doi.org/10.1108/EJIM-02-2023-0106.

Oduro, S., A. De Nisco, and G. Mainolfi. 2023. "Do Digital Technologies Pay Off? A Meta-Analytic Review of the Digital Technologies/Firm Performance Nexus." *Technovation* 128: 102836.

Oduro, S., L. G. Haylemariam, and R. M. Umar. 2024. "Influence of Corporate Digital Responsibility on Financial Performance: The Mediating Role of Firm Reputation." *Business Ethics, the Environment & Responsibility*.

Oliveira, A. S. d., G. Q. Souki, R. M. Gandia, and L. H. d. B. Vilas Boas. 2021. "Coffee in Capsules Consumers' Behaviour: A Quantitative Study on Attributes, Consequences and Values." *British Food Journal* 123, no. 1: 191–208. https://doi.org/10.1108/BFJ-02-2020-0116.

O'Reilly, C. A., III, and M. L. Tushman. 2008. "Ambidexterity as a Dynamic Capability: Resolving the Innovator's Dilemma." *Research in Organizational Behavior* 28: 185–206. https://doi.org/10.1016/j.riob.2008.06.002.

Paillé, P., Y. Chen, O. Boiral, and J. Jin. 2014. "The Impact of Human Resource Management on Environmental Performance: An Employee-Level Study." *Journal of Business Ethics* 121: 451–466. https://doi.org/10.1007/s10551-013-1732-0.

Podsakoff, P. M., S. B. MacKenzie, J. Y. Lee, and N. P. Podsakoff. 2003. "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies." *Journal of Applied Psychology* 88, no. 5: 879–903. https://doi.org/10.1037/0021-9010.88.5.879.

Preacher, K. J., and A. F. Hayes. 2008. "Asymptotic and Resampling Strategies for Assessing and Comparing Indirect Effects in Multiple Mediator Models." *Behavior Research Methods* 40, no. 3: 879–891. https://doi.org/10.3758/BRM.40.3.879.

Rahman, M. A., P. Saha, H. M. Belal, S. Hasan Ratul, and G. Graham. 2024. "Big Data Analytics Capability and Supply Chain Sustainability: Analyzing the Moderating Role of Green Supply Chain Management Practices." *Benchmarking: An International Journal*, ahead of print. https://doi.org/10.1108/BIJ-10-2024-0852.

Raisch, S., and J. Birkinshaw. 2008. "Organizational Ambidexterity: Antecedents, Outcomes, and Moderators." *Journal of Management* 34, no. 3: 375–409. https://doi.org/10.1177/0149206308316058.

Ramayah, T., J. Cheah, F. Chuah, H. Ting, and M. A. Memon. 2018. *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using SmartPLS 3.0: An Updated Guide and Practical Guide to Statistical Analysis*. Pearson.

Riggs, R., J. L. Roldán, J. C. Real, and C. M. Felipe. 2023. "Opening the Black Box of Big Data Sustainable Value Creation: The Mediating Role of Supply Chain Management Capabilities and Circular Economy Practices." *International Journal of Physical Distribution and Logistics Management* 53, no. 7/8: 762–788. https://doi.org/10.1108/IJPDLM-03-2022-0098.

Rindfleisch, A., A. J. Malter, S. Ganesan, and C. Moorman. 2008. "Cross-Sectional Versus Longitudinal Survey Research: Concepts, Findings, and Guidelines." *Journal of Marketing Research* 45, no. 3: 261–279. https://doi.org/10.1509/jmkr.45.3.261.

Sahoo, S., A. Upadhyay, and A. Kumar. 2023. "Circular Economy Practices and Environmental Performance: Analysing the Role of Big Data Analytics Capability and Responsible Research and Innovation." *Business Strategy and the Environment* 32, no. 8: 6029–6046. https://doi.org/10.1002/bse.3471.

Sarstedt, M., J. F. Hair, M. Pick, B. D. Liengaard, L. Radomir, and C. M. Ringle. 2022. "Progress in Partial Least Squares Structural Equation Modeling Use in Marketing Research in the Last Decade." *Psychology & Marketing* 39, no. 5: 1035–1064. https://doi.org/10.1002/mar.21640.

Sharma, M., A. Kumar, S. Luthra, S. Joshi, and A. Upadhyay. 2022. "The Impact of Environmental Dynamism on Low-Carbon Practices and Digital Supply Chain Networks to Enhance Sustainable Performance: An Empirical Analysis." *Business Strategy and the Environment* 31, no. 4: 1776–1788. https://doi.org/10.1002/bse.2983.

Shehzad, K., U. Zaman, M. Ahmad, and X. Liu. 2022. "Asymmetric Impact of Information and Communication Technologies on Environmental Quality: Analyzing the Role of Financial Development and Energy Consumption." *Environment, Development and Sustainability* 24, no. 2: 1761–1780. https://doi.org/10.1007/s10668-021-01506-w.

Singh, S. K., M. Del Giudice, R. Chierici, and D. Graziano. 2020. "Green Innovation and Environmental Performance: The Role of Green Transformational Leadership and Green Human Resource Management." *Technological Forecasting and Social Change* 150: 119762. https://doi.org/10.1016/j.techfore.2019.119762.

Singhania, M., and N. Saini. 2021. "Demystifying Pollution Haven Hypothesis: Role of FDI." *Journal of Business Research* 123: 516–528. https://doi.org/10.1016/j.jbusres.2020.10.007.

Song, B., G. Zeng, J. Gong, et al. 2017. "Evaluation Methods for Assessing Effectiveness of In Situ Remediation of Soil and Sediment Contaminated With Organic Pollutants and Heavy Metals." *Environment International* 105: 43–55. https://doi.org/10.1016/j.envint.2017.05.001.

Song, M. L., R. Fisher, J. L. Wang, and L. B. Cui. 2018. "Environmental Performance Evaluation With Big Data: Theories and Methods." *Annals of Operations Research* 270: 459–472.

Stekelorum, R., I. Laguir, K. H. Lai, S. Gupta, and A. Kumar. 2021. "Responsible Governance Mechanisms and the Role of Suppliers' Ambidexterity and Big Data Predictive Analytics Capabilities in Circular Economy Practices Improvements." *Transportation Research Part E: Logistics and Transportation Review* 155: 102510. https://doi.org/10.1016/j.tre.2021.102510.

Teece, D. J. 2017. "Dynamic Capabilities and (Digital) Platform Lifecycles." In *Entrepreneurship, Innovation, and Platforms*, vol. 37, 211–225. Emerald Publishing Limited. https://doi.org/10.1108/S0742-332220170000037008.

Teece, D. J., G. Pisano, and A. Shuen. 1997. "Dynamic Capabilities and Strategic Management." *Strategic Management Journal* 18, no. 7: 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z.

Tongtong, S., and C. Xinhang. 2022. "Research on the Impact of Enterprise Big Data Analytics Capability on Ambidextrous Innovation Capability—The Mediating Effect of Agility." *Technology Analysis & Strategic Management* 36, no. 9: 2242–2256. https://doi.org/10.1080/09537325.2022.2132140.

TriplePundit Reports. 2016. "A Year in CSR: The Top 10 Trends of 2016." https://www.triplepundit.com/story/2016/year-csr-top-10-trends-2016/20756.

Veile, J. W., D. Kiel, J. M. Müller, and K. I. Voigt. 2020. "Lessons Learned From Industry 4.0 Implementation in the German Manufacturing Industry." *Journal of Manufacturing Technology Management* 31, no. 5: 977–997. https://doi.org/10.1108/JMTM-08-2018-0270.

Wamba, S. F., R. Dubey, A. Gunasekaran, and S. Akter. 2020. "The Performance Effects of Big Data Analytics and Supply Chain Ambidexterity: The Moderating Effect of Environmental Dynamism." *International Journal of Production Economics* 222: 107498. https://doi.org/10.1016/j.ijpe.2019.09.019.

Wamba, S. F., A. Gunasekaran, S. Akter, S. J. F. Ren, R. Dubey, and S. J. Childe. 2017. "Big Data Analytics and Firm Performance: Effects of Dynamic Capabilities." *Journal of Business Research* 70: 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009.

Wang, J., Y. Xue, X. Sun, and J. Yang. 2020. "Green Learning Orientation, Green Knowledge Acquisition and Ambidextrous Green Innovation." *Journal of Cleaner Production* 250: 119475. https://doi.org/10.1016/j.jclepro.2019.119475.

Wang, J., Y. Xue, and J. Yang. 2020. "Boundary-Spanning Search and Firms' Green Innovation: The Moderating Role of Resource Orchestration Capability." *Business Strategy and the Environment* 29, no. 2: 361–374. https://doi.org/10.1002/bse.2369.

Wang, Z., H. Sun, C. Ding, L. Xin, X. Xia, and Y. Gong. 2023. "Do Technology Alliance Network Characteristics Promote Ambidextrous Green Innovation? A Perspective From Internal and External Pressures of Firms in China." *Sustainability* 15, no. 4: 3658. https://doi.org/10.3390/su15043658.

Waqas, M., X. Honggang, N. Ahmad, S. A. R. Khan, and M. Iqbal. 2021. "Big Data Analytics as a Roadmap Towards Green Innovation, Competitive Advantage and Environmental Performance." *Journal of Cleaner Production* 323: 128998. https://doi.org/10.1016/j.jclepro.2021.128998.

Waqas, M., and L. Tan. 2023. "Big Data Analytics Capabilities for Reinforcing Green Production and Sustainable Firm Performance: The Moderating Role of Corporate Reputation and Supply Chain Innovativeness." *Environmental Science and Pollution Research* 30, no. 6: 14318–14336. https://doi.org/10.1007/s11356-022-23082-w.

Widyastuti, S., M. Said, S. Siswono, & D. A. Firmansyah. 2019. Customer Trust Through Green Corporate Image, Green Marketing Strategy, and Social Responsibility: A Case Study. University of Malta Open Access Repository. https://www.um.edu.mt/library/oar/handle/123456789/43004.

Winter, S. G. 2003. "Understanding Dynamic Capabilities." *Strategic Management Journal* 24: 991–995. https://doi.org/10.1002/smj.318.

Wooldridge, M. 2012. "Does Game Theory Work?" *IEEE Intelligent Systems* 27, no. 6: 76–80.

Wu, K. J., C. J. Liao, M. L. Tseng, M. K. Lim, J. Hu, and K. Tan. 2017. "Toward Sustainability: Using Big Data to Explore the Decisive Attributes of Supply Chain Risks and Uncertainties." *Journal of Cleaner Production* 142: 663–676. https://doi.org/10.1016/j.jclepro.2016.04.040.

Wu, X., X. Zhu, G. Q. Wu, and W. Ding. 2013. "Data Mining With Big Data." *IEEE Transactions on Knowledge and Data Engineering* 26, no. 1: 97–107.

Wysocki, J. 2021. "Innovative Green Initiatives in the Manufacturing SME Sector in Poland." *Sustainability* 13, no. 4: 2386. https://doi.org/10.3390/su13042386.

Zameer, H., Y. Wang, D. G. Vasbieva, and Q. Abbas. 2021. "Exploring a Pathway to Carbon Neutrality via Reinforcing Environmental Performance Through Green Process Innovation, Environmental Orientation and Green Competitive Advantage." *Journal of Environmental Management* 296: 113383. https://doi.org/10.1016/j.jenvman.2021.113383.

Zameer, H., Y. Wang, H. Yasmeen, and S. Mubarak. 2022. "Green Innovation as a Mediator in the Impact of Business Analytics and Environmental Orientation on Green Competitive Advantage." *Management Decision* 60, no. 2: 488–507. https://doi.org/10.1108/MD-01-2020-0065.

Zameer, H., H. Yasmeen, R. Wang, et al. 2020. "An Empirical Investigation of the Coordinated Development of Natural Resources, Financial Development and Ecological Efficiency in China." *Resources Policy* 65: 101580.

Zhang, X., and Q. Zhu. 2019. "Information-Centric Virtualization for Software-Defined Statistical QoS Provisioning Over 5G Multimedia Big Data Wireless Networks." *IEEE Journal on Selected Areas in Communications* 37, no. 8: 1721–1738.

Zhang, Z., Y. Shang, L. Cheng, and A. Hu. 2022. "Big Data Capability and Sustainable Competitive Advantage: The Mediating Role of Ambidextrous Innovation Strategy." *Sustainability* 14, no. 14: 8249. https://doi.org/10.3390/su14148249.

Zhao, X., J. G. Lynch Jr., and Q. Chen. 2010. "Reconsidering Baron and Kenny: Myths and Truths About Mediation Analysis." *Journal of Consumer Research* 37, no. 2: 197–206.

Zhou, X., S. X. Ying, J. You, and H. Wu. 2024. "Like Parent, Like Child: MNCs' CSR and Their Foreign Subsidiaries' Environmental Footprint." *Journal of Business Research* 172: 114413. https://doi.org/10.1016/j.jbusres.2023.114413.

Appendix A

Questionnaire

To which extent do you agree or disagree with the following statements? These questions measure your firm's big talent capability in terms of big talent capability, business analytics, big data analytical capability management, green ambidextrous innovation, environmental corporate social responsibility, green competitive advantage, environmental performance, and financial performance.

1. Big talent capability (BTC)
(Numbers close to 7 stand for a strong agreement while numbers close to 1 stand for a strong disagreement. Please, choose one number on the scale from 1 to 7, which best reflects your opinion about Big Talent Capability)

Our analytics personnel are very capable in terms of programming skills.	1 2 3 4 5 6 7
Our analytics personnel are very capable in terms of managing project lifecycles.	1 2 3 4 5 6 7
Our analytics personnel are very capable in the areas of data and network management and maintenance.	1 2 3 4 5 6 7
Our analytics personnel show superior understanding of technological trends.	1 2 3 4 5 6 7
Our analytics personnel are very knowledgeable about the critical factors for the success of our organization	1 2 3 4 5 6 7
Our analytics personnel understand our organization's policies and plans at a very high level.	1 2 3 4 5 6 7
Our analytics personnel are very knowledgeable about the business environment.	1 2 3 4 5 6 7
Our analytics personnel work closely with suppliers to provide key inputs useful for developing innovative green products.	1 2 3 4 5 6 7
Our analytics personnel work closely with customers and maintain productive user/client relationships.	1 2 3 4 5 6 7

Source: Akter et al. (2020).

2. Business analytics (BA)
(Numbers close to 7 stand for a strong agreement while numbers close to 1 stand for a strong disagreement. Please, choose one number on the scale from 1 to 7, which best reflects your opinion about Business Analytics)

We use business intelligence and data mining to provide the context of and trending information on past or current events.	1 2 3 4 5 6 7
We use statistical models and forecasts to provide an accurate projection of future happenings and the reasoning as to why.	1 2 3 4 5 6 7
We use optimization and simulation to recommend one or more courses of action and show the likely outcome of each decision.	1 2 3 4 5 6 7

Source: Duan et al. (2020); Zameer et al. (2022).

3. Big data analytical capability management (BCM)
(Numbers close to 7 stand for a strong agreement while numbers close to 1 stand for a strong disagreement. Please, choose one number on the scale from 1 to 7, which best reflects your opinion about big data analytical capability management)

We continuously examine the innovative green opportunities for the strategic use of Big Data Analytical.	1 2 3 4 5 6 7
We enforce adequate plans for the introduction and utilization of Big Data Analytical.	1 2 3 4 5 6 7
We perform Big Data Analytical planning processes in systematic and formalized ways.	1 2 3 4 5 6 7
We frequently adjust Big Data Analytical plans to better adapt to changing environmental conditions.	1 2 3 4 5 6 7
In our organization, business analysts and design people meet frequently to discuss important issues both formally and informally.	1 2 3 4 5 6 7

In our organization, information is widely shared between business analysts and line people so that those who make decisions or perform jobs have access to all available know-how.	1 2 3 4 5 6 7

Source: Bag et al. (2020).

4. Ambidextrous green innovation (AGI) (Numbers close to 7 stand for a strong agreement while numbers close to 1 stand for a strong disagreement. Please, choose one number on the scale from 1 to 7, which best reflects your opinion about Green Ambidextrous Innovation)	
Our firm actively improves current green products and processes.	1 2 3 4 5 6 7
Our firm actively adjusts current green products, processes, and services.	1 2 3 4 5 6 7
Our firm actively strengthens the current green market.	1 2 3 4 5 6 7
Our firm actively strengthens current green technology.	1 2 3 4 5 6 7
Our firm actively adopts new green products, processes, and services.	1 2 3 4 5 6 7
Our firm actively exploits new green products, processes, and services.	1 2 3 4 5 6 7
Our firm actively discovers new green market.	1 2 3 4 5 6 7
Our firm actively enters new green technology.	1 2 3 4 5 6 7

Source: J. Wang, Xue, Sun, et al. (2020); J. Wang, Xue, and Yang (2020).

5. Corporate environmental responsibility (CER) (Numbers close to 7 stand for a strong agreement while numbers close to 1 stand for a strong disagreement. Please, choose one number on the scale from 1 to 7, which best reflects your opinion about environmental corporate social responsibility)	
The firm contributes to the projects promoting the well-being of the society.	1 2 3 4 5 6 7
The firm invests in projects for future generations.	1 2 3 4 5 6 7
The firm contributes to support other nongovernmental agencies working in troublesome areas.	1 2 3 4 5 6 7
The firm takes part in the initiatives for promoting and improving the natural environment.	1 2 3 4 5 6 7
The firm aims at sustainable growth of the society for future generations.	1 2 3 4 5 6 7
The firm inspires employees to participate in societal activities voluntarily.	1 2 3 4 5 6 7
The firm operationalizes distinct schemes for mitigating the negative effects on ecology.	1 2 3 4 5 6 7
The firm shows respect for the rights of customers and legal aspects.	1 2 3 4 5 6 7
The firm discloses complete and precise information regarding products for the customers.	1 2 3 4 5 6 7

Source: Alam and Islam (2021).

6. Green competitive advantage (GCA) (Numbers close to 7 stand for a strong agreement while numbers close to 1 stand for a strong disagreement. Please, choose one number on the scale from 1 to 7, which best reflects your opinion about green competitive advantage)	
The firm has a high-cost competitive advantage regarding green management in comparison with major competitors.	1 2 3 4 5 6 7
The firm offers better quality green products in comparison with major competitors.	1 2 3 4 5 6 7
The firm invests more money in environmental research and development and green innovation than its competitors.	1 2 3 4 5 6 7
The firm has greater capability than competitors regarding green management.	1 2 3 4 5 6 7

Source: Lin and Chen (2017).

7. Corporate environmental performance (CEP)	
(Numbers close to 7 stand for a strong agreement while numbers close to 1 stand for a strong disagreement. Please, choose one number on the scale from 1 to 7, which best reflects your opinion about environmental performance)	
In our enterprise, environmental activities have reduced overall costs. Reduced overall costs.	1 2 3 4 5 6 7
In our enterprise, environmental activities have reduced the lead times.	1 2 3 4 5 6 7
In our enterprise, environmental activities have improved product/ process quality.	1 2 3 4 5 6 7
The environmental activities have improved the reputation of my company.	1 2 3 4 5 6 7
In our enterprise, environmental activities have reduced waste within the entire value chain process.	1 2 3 4 5 6 7

Source: Singh et al. (2020).

8. Financial performance (FP)	
(Numbers close to 7 stand for a strong agreement while numbers close to 1 stand for a strong disagreement. Please, choose one number on the scale from 1 to 7, which best reflects your opinion about financial performance)	
Market share growth relevant to competition	1 2 3 4 5 6 7
Sales growth from enterprise customers (ROS)	1 2 3 4 5 6 7
Business unit profitability	1 2 3 4 5 6 7
Return on investment (ROI)	1 2 3 4 5 6 7
Return on equity (ROI)	1 2 3 4 5 6 7

Source: Chun (2005).

9. Sample information	
Gender	Female Male Not to mention
Education	○ Elementary school (8 grades) ○ High school (4 stages) ○ College (3 years) ○ University (4 years or more)
Age	○ 18 to 24 years ○ 25 to 34 years ○ 35 to 44 years ○ 45 to 54 years ○ 55 to 64 years ○ 65 years or older
Annual income	○ Less than 30,000 € ○ €31,000–€50,000 ○ €50,001–€80,000 ○ €80,001–€120,000 ○ €120,001–€200,000 ○ €200,001–€500,000 ○ Above €500,000
Number of employees	• Less than 50 • 51–100 • 101–1000 • 1001–2000 • 2001–5000 • Above 5000

Appendix B

Bootstrapping Test for Endogeneity

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	*T* statistics (|O/STDEV|)	*ps*
GC (BDAC) → AGI	0.881	0.512	0.655	1.345	0.179
GC (AGI) → CEP	0.254	0.177	0.249	1.02	0.308
GC (AGI) → GCA	−0.21	−0.19	0.33	0.636	0.525

Appendix C

Factor Loadings

	BA	BCM	BTC	ECR	EP	GAI	GCA	FP
BA-1	0.966							
BA_2	0.876							
BA-3	0.891							
BCM_1		0.738						
BCM_3		0.828						
BCM_4		0.786						
BCM-5		0.902						
BCM-6		0.867						
BCM-9		0.789						
BTC_1			0.732					
BTC-2			0.786					
BTC-4			0.904					
BTC-5			0.705					
BTC_6			0.802					
BTC-7			0.767					
BTC_8			0.764					
CER_1				0.789				
CER_2				0.743				
CER-4				0.898				
CER-6				0.786				
CER_7				0.763				
CER-9				0.870				
CEP-2					0.877			
CEP_3					0.876			
CEP_4					0.895			
CEP_5					0.711			
AGI_1						0.723		
AGI_2						0.801		
AGI_3						0.771		
AGI_5						0.796		
AGI_7						0.789		
AGI_8						0.897		

	BA	BCM	BTC	ECR	EP	GAI	GCA	FP
GCA_1							0.786	
GCA_2							0.715	
GCA_4							0.830	
FP-1								0.897
FP-2								0.776
FP-3								0.809
FP-4								0.786

Appendix D

Multicollinearity Checks

Indicator variables	VIF
BA_1	1.178
BA_2	1.178
BA-3	1.107
BCM_1	1.260
BCM_3	1.103
BCM_4	1.231
BCM_5	1.155
BCM-6	1.123
BCM-9	1.103
BTC_1	1.108
BTC_2	1.109
BTC-4	1.078
BTC_5	1.093
BTC_6	1.240
BTC_7	1.234
BTC_8	1.250
CER_1	1.534
CER_2	1.254
CER-4	1.078
CER_6	1.327
CER_7	1.717
CER_9	1.658
CEP_2	1.247
CEP-3	1.087
CEP_4	1.199
CEP_5	1.166
AGI_1	1.261
AGI_2	1.089
AGI_3	1.155
AGI_5	1.165
AGI_7	1.136

Indicator variables	VIF
AGI_8	1.451
GCA_1	1.206
GCA_2	1.166
GCA_4	1.317
FP_1	1.232
FP_2	1.304
FP_3	1.206
FP_4	1.087

Appendix E

Discriminant Validity

	BA	BCM	BTC	ECR	CEP	AGI	GCA	FP	FS	Age	Sector
BA	0.809										
BCM	0.494	0.744									
BTC	0.446	0.593	0.718								
CER	0.102	0.092	0.125	0.732							
CEP	0.109	0.082	0.158	0.608	0.731						
AGI	0.157	0.185	0.114	0.592	0.52	0.720					
GCA	0.136	0.072	0.084	0.638	0.672	0.556	0.746				
FP	0.089	0.167	0.123	0.201	0.214	0.128	0.189	0.756			
FS	−0.09	−0.08	−0.10	0.076	0.054	0.012	0.101	0.023	0.665		
Firm age	0.081	0.012	0.078	0.056	0.065	0.123	0.078	0.065	0.034	0.679	
Sector	0.078	0.076	0.054	0.001	0.067	0.126	0.065	0.096	0.042	0.023	0.702