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Big Data Analytics and Green Core Competencies: Important Role of Data-Driven Decision-Making Culture and Leader Conscientiousness

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Abstract

Given the growing emphasis on business sustainability and environmental management aimed at protecting the natural environment, this study, drawing insights from organizational information processing theory, investigates the direct association of artificial intelligence-supported big data analytics (AI-BDA) with organizations' green core competencies as well as the indirect association through green data-driven decision-making culture (GDDC). Additionally, the role of leader conscientiousness as an important boundary condition is examined. Data collected from 339 managers is analyzed using structural equation modeling in Mplus (8.8). Our findings indicate that AI-BDA has both direct and indirect positive relationships with green core competencies. Moreover, leader conscientiousness moderated the direct impact of AI-BDA on GDDC. Supplementary semi-structured interviews with 12 senior managers provide contextual validation and illustrate how AI-BDA, green data-driven culture, and leader conscientiousness jointly shape green core competencies in practice. Our research provides actionable insights that empower organizations to develop green core competencies, thereby enhancing their impact on initiatives aimed at preserving the natural environment. By integrating technological capabilities with leadership traits, this study highlights a pathway for organizations to align digital transformation with environmental sustainability goals, thereby advancing their corporate responses to environmental challenges.

Keywords. AI-supported big data analytics, green data-driven decision-making culture, green core competencies, leader conscientiousness

Managerial Relevance Statement

This paper offers valuable insights for engineering managers seeking to enhance their organization's green core competencies through digital advancements and effective leadership. Our findings showed that AI-BDA has a positive association with green core competencies both directly and indirectly through GDDC. AI-BDA enables organizations to achieve real-time environmental monitoring and data-driven decision-making, supporting positive environmental performance and green innovations. Positive impacts of AI-BDA are best realized when there is a GDDC, a culture where gathering, analyzing, and using green data are critical components of decision-making processes and operations. Moreover, our findings indicate that the positive impact of AI-BDA on GDDC is more pronounced when leaders are conscientious. Leaders who are more responsible, organized, detail-oriented, and diligent are more likely to integrate sustainability into their decision-making and motivate people to innovate through data-driven approaches. Therefore, organizations should develop training sessions that focus on conscientiousness, such as paying attention to detail and promoting greater ethical, self-discipline, and accountability.

1. Introduction

There is a growing emphasis on business sustainability and environmental management, as well as the role of emerging technologies in shaping sustainable business practices, reflecting a global shift toward practices aimed at protecting the natural environment [10], [25], [60]. Big data encompasses heterogeneous formats and is distinguished by velocity, volume, veracity, and variety [55]. This combination empowers organizations to leverage advanced algorithms and machine learning models for real-time analysis, uncovering hidden patterns and making data-driven decisions [13], [52], [38]. In this context, artificial intelligence-based big data analytics (AI-BDA) may play a pivotal role. AI-BDA reflects a transformative approach, integrating artificial intelligence techniques with big data analytics processes to derive valuable insights, patterns, and trends from large and complex datasets [21], [27], [42], [52]. Previous studies (see

Appendix A) suggest that AI-BDA improves organizations' market performance [48], fosters green supply chain performance [10], [25], increases organizations' environmental performance [39], and leads to green supply chain integration and green innovation [5], [16], [60].

Despite growing interest in AI-BDA and its potential benefits, existing research has paid little attention to how it contributes to the development of green core competencies. While studies have acknowledged the importance of green core competencies for outcomes such as green innovation, green absorptive capacity, green image, and green innovation performance [2], [15], [47], limited empirical work has examined their technological antecedents. Recent literature reviews (e.g., [2], [47]) specifically call for further research on what enables such competencies to emerge. Therefore, this study responds to that call by investigating AI-BDA as a structural capability that may directly and indirectly improve green core competencies, thereby addressing a critical and underexplored link in the sustainability literature. To support this argument, we draw on organizational information processing theory (OIPT) [29], [56] to propose AI-BDA as an organizational structural capability that leads to green core competencies. OIPT emphasizes the structures and mechanisms within organizations that enable the flow of information and effective decision-making processes [10]. The theory posits that organizations with strong capabilities in processing and utilizing data are better equipped to address external uncertainties and demands. In this context, adopting new-generation technologies such as AI-BDA is seen as a means to bolster information processing capabilities [37], [10]. These technologies enable organizations to utilize advanced tools for handling vast amounts of diverse data and processing it quickly, thereby enhancing their analytical capabilities [41]. As such, we contend that by facilitating the effective processing and utilization of big data, AI-BDA enables organizations to integrate environmental data and insights into their strategies and operations, helping them develop green core competencies.

Furthermore, to illustrate how AI-BDA enhances green core competencies, we propose that a green data-driven decision-making culture (GDCC) serves as a mediator in the established relationship. Drawing on previous studies (e.g., [6], [63].), we define GDCC as an organizational culture where collecting, analyzing, and utilizing environmentally relevant data are integral to decision-making processes and

operations. We consider GDDC because it emphasizes leveraging data-driven insights to guide environmental management practices and sustainability initiatives, thereby reducing ecological footprints and mitigating environmental issues. This culture fosters a proactive approach to sustainability by promoting the use of data to inform and drive green initiatives across all levels of the organization [31], [40]. Thus, we contend that by cultivating a strong GDDC, organizations can leverage data-driven decision-making to drive environmental sustainability initiatives within the organization and develop green core competencies. Davenport and Bean [18] report that 99% of their study respondents indicated their businesses were striving to transition to a data-driven decision-making culture. However, only one-third of the organizations had successfully achieved this goal. Despite this gap being consistently identified in annual surveys, there has been little improvement in companies' success rates in achieving a data-driven decision-making culture. Furthermore, previous studies suggest that there is a scarcity of research on how and when AI-BDA contributes to environmentally sustainable initiatives [39]. To address these gaps, we argue that studying the role of GDDC can bring to the fore its value for developing core competencies that may encourage organizations to adopt such a culture.

The current study further argues that the influence of AI-BDA on GDDC may differ across organizations. We propose that leader conscientiousness can explain these differentiated effects. One of the five personality traits in the Five-Factor Model of Personality, conscientiousness, is a concept that describes an “individual who is generally ambitious, responsible, and abides by ethical principles, and considers the consequences of his/her behavior before acting” [12, p. 92]. Leaders’ personality plays a vital role in interpreting the effect of organizations’ initiatives related to big data analytics on organizational outcomes [9]. Leaders high on conscientiousness are expected to pay more attention to AI-BDA because, compared to others, they show higher degrees of obligation toward their organizations. Leaders who are high on conscientiousness are more mindful and cognizant of environmental challenges, fulfill environmental obligations, and alleviate environmental issues [10]. As such, we contend that leaders’ conscientiousness can substantially affect the role of AI-BDA in cultivating GDDC, which, in turn, may augment organizational green core competencies. The proposed model is depicted in Figure 1.

Insert Figure 1 about here

The current research adds to the following important streams of literature. First, our study addresses the calls for further research on business sustainability and environmental management, which aim to protect the natural environment [2], [15], [47], as well as the role of digital technologies in environmental management [8], [12]. Existing studies have found a positive impact of big data analytics on various outcomes, including firm performance [48], user satisfaction [34], sustainable performance [35], and green supply chain performance [51]. This research contributes to the existing literature by highlighting the significant yet underappreciated role of AI-BDA in enabling organizations to develop green core competencies. Second, by illustrating AI-based BDA and GDDC as the antecedents of green core competencies, the present research contributes to the limited research on the antecedents of green core competencies [2], [15], [47]. Third, existing studies on data-driven decision-making culture demonstrate that it enhances firms' competitive advantage [57], sustainability performance [14], and environmental performance [58]. By suggesting the crucial role of GDDC as a mediator in the connection between AI-BDA and green core competencies, this study contributes to the existing literature on the determinants and outcomes of a green data-driven culture. Finally, the present study adds to the literature on leader conscientiousness (e.g., [8], [12]). By analyzing the hypothesized links, the current research answers the recent calls for further research on how organizations can reduce their carbon emissions through various environmentally sustainable initiatives and competencies [2], [47] and the role of AI-BDA in developing organizations' pro-environmental capabilities [25], [39].

2. Theoretical background

2.1. Organizational information processing theory

Organizations are operating in a dynamic, complex, and turbulent environment that creates uncertainty for managers while identifying the opportunities and threats in the marketplace, trying to adapt

to the relevant changes within organizations, and deciding to make organization-wide decisions, such as changing the core strategies [26], [33]. Managers must consider many factors that require allocation with different weights in the decision-making process [24], [44]. Organizations face a range of uncertainties (e.g., shifts in customer preferences, rapid technological advancements, and changes in regulations and laws) that can significantly impact their decision-making effectiveness. In situations of high uncertainty, the capabilities of organizations to process, analyze, and utilize information about the events in their environment become crucial for an effective decision-making process [28], [45].

Previous studies mostly use resource-based view theory [65], [66], organizational learning theory [67], and complexity theory [68] to examine the relationship between big data analytics and firm performance. Unlike these studies, we build on OIPT to hypothesize the relationships examined in the research model. Organizational learning theory and resource-based view focus on an organization's internal resources or knowledge acquisition. Specifically, the resource-based view emphasizes firm-specific tangible and intangible resources that are valuable, rare, inimitable, and non-substitutable [79]. In contrast, organizational learning theory highlights how firms systematically pursue, acquire, and apply information to improve their capacity to adapt and innovate in processes, products, and services [80]. Complexity theory, on the other hand, views organizations as complex adaptive systems that evolve through self-organization and multiple interacting elements [81]. Rather than assuming a single linear path to performance outcomes, complexity theory emphasizes that different combinations of conditions may lead to similar results, acknowledges the existence of contrarian cases, and highlights causal asymmetry in organizational phenomena [82]. Unlike these perspectives, OIPT provides a direct explanation of how organizations respond to environmental uncertainty by enhancing their information processing capacity. Since our study investigates AI-BDA and GDDC as mechanisms through which firms gather, analyze, and utilize environmental data to build green core competencies, OIPT offers a more suitable theoretical lens than RBV, organizational learning theory, or complexity theory.

OIPT addresses the need for organizations to manage uncertainties and process information efficiently in dynamic contexts. OIPT posits that organizations need more information while making

decisions in uncertain external conditions to make effective decisions and sustain the desired level of performance [28], [53]. In other words, information is considered a key organizational resource that is pivotal in determining an organization's competitiveness in the dynamic business environment. Accordingly, in this study, which is theoretically grounded in OIPT, we investigate how organizations can enhance their green core competencies by adopting AI-based BDA directly and through GDDC.

3. Hypotheses Development

3.1. AI-BDA and Green Core Competencies

Core competencies enable organizations to adapt to a changing environment and are considered a pivotal source of competitive advantage [15]. Core competencies enable organizations to explore and capitalize on new opportunities, thereby differentiating themselves from competitors [46]. Considering the current environmental regulations and stakeholders' increasing awareness of environmental issues, organizations feel severe pressure on themselves to comply with environmental sustainability practices [47]. Building on the concept of core competence by [46] and existing literature on green core competence [2], [15], [47], we define green core competencies as the collective learning and capabilities concerning environmental management and technologies that are rare, less imitable by competitors, and less likely to be substituted. Developing green core competencies serves as a strong indicator of an organization's commitment to environmental responsibility [15].

Organizations can gain valuable insights from AI-BDA, including forecasting energy demand, formulating more effective plans to minimize waste, and optimizing energy usage during manufacturing processes [4], [27]. AI-BDA may help organizations improve the processes to mitigate resource consumption and reduce environmental impact. For instance, a recent study [36] highlighted the significant impact of AI-BDA on forecasting water availability, optimizing resource allocation, and enhancing infrastructure maintenance in a multifaceted manner. By leveraging AI-BDA, organizations can identify patterns and trends in environmental data that may not be readily apparent through traditional methods. Consequently, organizations may develop a deeper understanding of environmental challenges and

opportunities for improvement that can form the foundation for green core competencies. Furthermore, as organizations continually gather and analyze environmental data, they accumulate knowledge and capabilities and adopt technological advancements that are rare and less imitable by competitors. The sophistication and complexity of AI algorithms and data processing techniques are likely to contribute to the uniqueness of these competencies, making them difficult for competitors to replicate or substitute.

OIPT suggests that organizations with strong capabilities in processing and utilizing data are better equipped to deal with uncertain external environmental conditions, making effective decisions and developing capabilities that help them gain a foothold in the market [28]. OIPT also suggests that “employing computers” and “various machine mechanisms” are critical factors in effective decision-making, as they enhance organizational information processing capabilities [15, p. 17]. Therefore, investment in information technology is considered a crucial aspect of enhancing the flow of information, improving effective decision-making capability, and reducing uncertainties [15]. Researchers highlight the role of employing new-generation technologies, such as artificial intelligence and big data analytics, for enhancing an organization's information processing capabilities [37], [10]. These technologies have democratized access to tools capable of handling extensive data volumes, which are diverse in nature, and processing them at high velocities, empowering organizations with unprecedented analytical capabilities [41]. As such, drawing on OIPT, we contend that by leveraging the distinct advantages of AI-BDA in acquiring, processing, and utilizing vast amounts of environmental data, organizations can develop green competencies that are rare and less likely to be imitable. Based on the above arguments, we propose the following hypothesis.

H₁: AI-BDA is positively associated with organizational green core competencies.

3.2. AI-BDA and GDDC

AI-BDA represents a cutting-edge set of technologies and infrastructures tailored to efficiently extract value from vast volumes of diverse data [16]. AI-BDA empowers organizations to promptly capture, discover, and analyze data, facilitating the generation of valuable insights and effective decision

making [30]. Big data analyzed using AI methods can help organizations gain insights from a larger dataset by identifying patterns and trends, thereby steering them toward more effective and environmentally conscious operational strategies [27]. We argue that AI-BDA may serve as a catalyst for cultivating GDDC within organizations. OIPT suggests that organizations with robust IT systems (e.g., AI-BDA) can more effectively gather, interpret, and act upon environmental data [28]. Studies suggest that the availability of big data tools fosters data literacy across the organization as employees become more proficient in interpreting and leveraging data to inform their actions [16], [60]. Decision-making using AI-BDA by top management encourages managers at different levels and employees to engage with data in their decision-making processes [9]. Furthermore, AI-BDA facilitates evidence-based decision-making by enabling organizations to derive insights from empirical evidence, rather than relying solely on intuition or anecdotal evidence [40]. Consistent use of data-driven insights enhances the accuracy and effectiveness of decisions, encouraging a culture of using data insights to inform decisions [9]. Overall, we contend that AI-BDA plays a pivotal role in instilling a culture where data is valued as a strategic asset and utilized to drive organizational success.

Additionally, a culture of using accurate and comprehensive information related to trends and projections, encompassing sustainability, customer expectations, and the availability of raw materials, is crucial for organizations to identify and implement eco-friendly practices within their production and operational processes [40]. In GDDC, managers prioritize using data over intuition and integrating environmental considerations into their decision-making processes [40]. GDDC is a fundamental requirement for continuously improving manufacturing processes to achieve low energy consumption, utilize recycled and reused materials, and employ cleaner technology to prevent pollution [61], [7]. GDDC fosters a proactive approach toward leveraging product development opportunities [20] and supports firms in achieving ambidextrous innovation and enhancing business sustainability [35], [1]. Furthermore, GDDC helps organizations navigate uncertainty by enhancing their data scanning capabilities and enabling them to respond promptly to market dynamics and changing customer needs [6], [63]. GDDC enhances the awareness and attitudes of the organization's members toward sustainable practices, leading them to

reconsider their manufacturing processes in order to reduce waste and the use of raw materials [32], [43]. In green culture, environmental considerations are embedded in organizations' strategy, operations, and decision-making processes [32]. Therefore, a green culture based on data insights can cultivate a heightened awareness of sustainability issues and opportunities. This heightened awareness may prompt the organization to invest in developing capabilities related to environmental management, technologies, and innovation that can nurture green core competencies. For example, an electronics manufacturer may use AI-BDA to analyze product lifecycle data. When these insights are regularly used to guide design and supply chain decisions, it reflects a GDDC. Over time, this leads to the development of green capabilities, including green innovation and a green image. This example illustrates how GDDC mediates the relationship between AI-BDA and green core competencies. Consistent with OIPT, AI-BDA acts as a structural mechanism that enhances the organization's capacity to collect, interpret, and use environmental information. This technological capability precedes and shapes the development of GDDC, which reflects the cultural manifestation of these enhanced information-processing capacities. Thus, GDDC serves as the pathway through which AI-BDA's technological potential is transformed into organizational green competencies. Together, based on the above arguments, we hypothesize the following.

H₂: GDDC mediates the relationship between AI-BDA and green core competencies.

3.3. Leader conscientiousness as a moderator

Organizations today face considerable complexity and uncertainty in the context of environmental sustainability due to external factors largely beyond their control, including new regulations, shifting customer expectations, and natural disasters. In these conditions, OIPT suggests that organizations with enhanced abilities to gather, process, and utilize information are better equipped to adapt to their environments, make informed decisions, and ultimately achieve higher levels of effectiveness and success. A key premise of OIPT is that enhanced information processing capability leads to improved organizational performance [28]. Building on this premise of OIPT, we propose that leader conscientiousness strengthens the direct link between AI-BDA and GDDC and the indirect link between

AI-BDA and green core competencies. Conscientiousness is a concept based on the Big Five personality model. The concept of responsibility is a very important factor in shaping the attitudes and behaviors of leaders. Conscientiousness represents the tendency to be goal-oriented, responsible, and organized [17]. Leader conscientiousness is a fundamental attribute affecting various organizational dynamics [11], [49]. The effectiveness of an organization's environmental sensitivity and the formulation of environmentally conscious policies and strategies largely hinges on the moral integrity of its leaders. Conscientious leaders are characterized by their awareness, perseverance, determination, and ability to complete tasks [8]. Conscientiousness involves ambition and a conscientious attitude toward others in the immediate environment [3], [8]. Individuals with a high level of conscientiousness are relatively better positioned to focus on ongoing events [23].

Leaders high in conscientiousness proactively motivate employees to engage in eco-friendly behaviors and prioritize sustainability within the work environment [3]. Therefore, they are likely to encourage and direct organizational members to use environmental data in their decision-making. Through their systematic and disciplined approach, conscientious leaders may ensure that the organization effectively utilizes big data insights to drive environmentally conscious behaviors and practices across all levels. By setting clear objectives and establishing robust processes, they may create an environment where integrating big data capability with green initiatives becomes feasible and ingrained in the organizational ethos. As a result, leader conscientiousness acts as a catalyst, reinforcing the link between big data capability and the cultivation of GDDC, ultimately facilitating sustainable green core competencies. Within the framework of these arguments, our hypotheses are formulated as follows:

H₃: Leader conscientiousness moderates the association of AI-BDA with GDDC, such that the association is stronger when leader conscientiousness is high (vs. low).

4. Methodology

4.1. Sample and procedure

Data were collected using a time-lagged design, with three phases separated by two-week intervals.

The target population comprised senior managers working in manufacturing firms across China, specifically in industries such as leather, textiles, and ceramics. We focused on these industries due to their significant environmental impact and ongoing adoption of AI-BDA and green practices. Participants were recruited from a pool of 700 alumni of a large public university in China. These alumni held senior managerial positions and were actively involved in strategic or operational decision-making processes within their organizations. Each potential participant received an invitation via email, which explained the purpose of the study, the voluntary nature of participation, the assurance of confidentiality, and the anonymity of responses. Out of 700, a total of 482 managers agreed to participate in the study.

In phase 1, we distributed the first wave of the questionnaire to these 482 consenting participants, focusing on demographic and organizational variables (e.g., firm age and size), AI-BDA, and leader conscientiousness. A total of 445 valid responses were returned within the specified time frame. Two weeks later, in phase 2, the same participants were contacted again to provide data on GDDC. We received 376 complete responses in this round. In phase 3, conducted two weeks after Phase 2, the third and final survey was distributed to collect data on green core competencies. This round yielded 346 responses. To ensure accuracy and consistency, each participant was assigned a unique code, which allowed us to match responses across all three phases. After eliminating responses with missing or unmatched data, the final sample consisted of 339 complete and usable responses. The data were analyzed using structural equation modeling (SEM) in Mplus (8.8). Firms' average age was 34.15 years.

4.2. Common method bias and response bias

A time-lagged design was employed to address the issues related to common method bias. We also tested the data for sampling bias. We also employed Harman's single-factor method. To do so, all the items were constrained to load on a single factor. This single factor explained 31.39% of the variance, which is well below the 50% cut-off.

We also tested the data for response bias. No demographic differences were found between the final sample (n = 339) at Time 3 and the initial sample (n = 445) at Time 1. Furthermore, to assess whether

subject attrition from Time 1 to Time 3 led to non-random sampling, we tested whether the probability of remaining in the final sample ($n = 339$) could be predicted by demographics and the variables measured at Time 1 (AI-BDA). We employed the criteria suggested by [78]. We used logistic regression analysis to assess the presence of non-random sampling. Overall, results indicated that respondents' attrition in the sample was mainly random

4.3. Measures and variables

The details regarding the measurement of the constructs used in the current research are as follows. We assessed AI-BDA by adopting a four-item scale ($\alpha = .88$) [4]. "We use advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision-making" was a sample item. GDDC was assessed by adopting a five-item scale ($\alpha = .88$) [63]. "We continuously coach our employees to make decisions based on data" was a sample item. Green core competencies were measured by adapting a five-item scale ($\alpha = .87$) from [15]. "The environmental capabilities, technologies, or know-how of the firm are rare in the marketplace" was a sample item. Conscientiousness was measured by adopting a four-item scale ($\alpha = .83$) [19]. The items were assessed on a 5-point scale (1 = strongly disagree and 5 = strongly agree), with greater scores showing greater conscientiousness. Sample item: "I get chores done right away."

4.4. Control variables

Extant studies show that firm age and size may confound the results [10], [63] and were consequently considered control variables. Furthermore, green knowledge-sharing culture (GKSC) can confound the results. GKSC creates a foundation for informed decision-making and can enhance green competencies [27], [40]. Thus, we controlled for GKSC. To measure GKSC, we adapted a 5-item scale ($\alpha = .85$) from [76]. Sample items include: "*In our organization, employees share environmentally-friendly knowledge with other organizational members.*"

4.5. Supplementary Qualitative Phase

To enhance methodological rigor and provide deeper contextual insights, we supplemented the quantitative survey with a sequential explanatory qualitative phase [83]. After completing the survey analysis, we conducted 12 semi-structured interviews with senior managers from Chinese manufacturing firms across various sectors, including leather, textiles, and ceramics. Participants were purposively selected from the same alumni network used for the survey to ensure comparability. Interviews lasted 45-50 minutes and were conducted via WeChat, audio-recorded, and transcribed verbatim.

The initial set of questions (Appendix A) consisted of eight open-ended questions. The questions probed actual practices corresponding to the scale items used in the survey. Data were analyzed using thematic analysis [84]. Themes are presented in (Appendix B). Coding was performed by the first author and cross-checked by the second author; disagreements were resolved through discussion. Theoretical saturation was reached after the 12th interview. This qualitative phase triangulates and illustrates the quantitative findings, offering concrete examples of how AI-BDA, GDDC, leader conscientiousness, and green core competencies interact in practice.

5. Results

5.1. Means and correlations

Means and correlations are presented in Table 1. All the correlations among the main variables were significant and largely in the expected direction.

Insert Table 1 about here

5.2. Measurement model

Confirmatory factor analysis was employed to assess the measurement model, which comprised AI-BDA, GDDC, green core competencies, leader conscientiousness, and GKSC. All items demonstrated statistically significant loadings ($p < .01$). The results of the confirmatory factor analysis indicated a

satisfactory model fit: $\chi^2(220) = 522.325$, $\chi^2/df = 2.38$, IFI = .93, TLI = .92, SRMR = .07, and RMSEA = .06. These fit indices confirm that the measurement model aligns well with the observed data. Additionally, the average variance extracted (AVE) for each construct exceeded the recommended threshold of 0.50 (see Table 2), indicating support for convergent validity. Discriminant validity was also established, as the square roots of AVEs for all constructs were higher than their respective inter-construct correlations. Moreover, both the average shared variance (ASV) and the maximum shared variance (MSV) for each construct were lower than their AVE values. Collectively, these results confirm that the measurement model demonstrates strong validity in terms of both convergent and discriminant validity.

Insert Table 2 about here

5.3. Hypotheses testing

The results with controls are presented in Table 3. Overall, the results supported our hypotheses despite the presence of controls. The results (Table 3) confirmed a significant positive association between AI-BDA and green core competencies ($B = .23$, $SE .05$, $p < .01$). Thus, hypothesis 1 was supported. We also found a significant indirect positive relationship between AI-BDA and green core competencies via GDDC ($B = .09$, $SE = .03$, $p < .01$). Thus, hypothesis 2 was supported.

Finally, to test the moderation effects, we included the interaction terms of AI-BDA and leader conscientiousness in the mediation model. The moderation analysis showed that the interaction between AI-BDA and leader conscientiousness was positively related to GDDC ($B = .09$, $SE = .04$, $p < .05$). The interactions plotted at +1/-1 SD (Figure 2) from the mean of leader conscientiousness shows that the positive influence of AI-BDA on GDDC was stronger when leader conscientiousness was high ($B = .35$, $SE = .07$, $p < .01$) compared to when leader conscientiousness was low ($B = .13$, $SE = .06$, $p < .05$). Thus, hypothesis 3 was supported.

Insert Table 3 and Figure 2 about here

5.4. Qualitative Findings

Thematic analysis of the 12 semi-structured interviews provided rich, convergent evidence to support the quantitative model, while adding contextual depth to the mechanisms. The interviewees confirmed that AI-BDA is actively used for environmental decision-making. Typical applications included real-time monitoring of energy, water, and emissions. One textile plant manager explained:

“Our AI system analyses dyeing machine data every minute and automatically adjusts temperature and chemical dosage. Last year, we were able to reduce water consumption by 22% and dye chemicals by 18% without sacrificing quality.”

GDDC emerged as the critical bridge between technology and green outcomes. Ten respondents emphasized that identical AI tools produced dramatically different results depending on cultural acceptance. A leather company operations director stated:

“Only the plants where the factory head starts every morning meeting with ‘Show me the data’ actually improved. In the others, people still decide by experience.”

Leader conscientiousness was the most frequently mentioned boundary condition (11 of 12 interviews). Respondents consistently contrasted high- and low-conscientious leaders. The sustainability director of a large leather group stated:

“Our group president is detail-oriented and disciplined. Every month, he would personally review the ESG dashboard with each factory head and ask for evidence-based explanations. He is like that; the entire organization has become data-driven on green issues.”

Interviewees repeatedly linked the rarity and inimitability of green core competencies to long-term, closed-loop integration of AI-BDA with proprietary historical data, and highlighted some barriers, such as middle-management resistance and talent shortages. Taken together, the interviews provide vivid, real-world

validation of the entire mediated moderation model.

6. Discussion

This study aimed to explore the mechanisms and boundary conditions through which AI-BDA influences firms' green core competencies. Drawing on OIPT, we proposed and tested a conceptual framework outlining both the direct and indirect effects of AI-BDA on green core competencies, with GDDC serving as the mediating variable. Additionally, we examined the moderating influence of leader conscientiousness on the relationship between AI-BDA and GDDC. Using a survey methodology and collecting data employing a time-lagged design, we empirically validated the model. The findings confirmed a significant positive direct relationship between AI-BDA and green core competencies. Moreover, the analysis demonstrated that GDDC plays a mediating role in this relationship. The results also showed that leader conscientiousness moderates the impact of AI-BDA on GDDC, indicating that the effect of AI-BDA is stronger when leaders exhibit higher levels of conscientiousness.

According to the findings of the study, GDDC mediates the relationship between AI-BDA and the ability to develop green core competencies. This finding is consistent with earlier studies that demonstrate the transformation of organizational culture and technology capabilities into benefits [75]. It is through a green, data-driven decision-making culture that businesses can exploit the opportunities provided by AI-BDA to create competitive advantages through competence development. This culture helps ensure that environmentally friendly decisions, based on data, are made to the maximum possible extent, thereby enhancing the organization's ability to meet its sustainability objectives [69]. Consequently, the mediating role of GDDC confirms that technology alone is insufficient to develop green competencies—an enabling organizational culture is imperative. While a prior study [50] on engineering management literature highlighted the benefits of big data analytics capability on firm performance via dynamic capabilities, our study extends that without a strong internal culture that institutionalizes data-informed green decision-making, AI-BDA alone may not be sufficient to develop green core competencies.

Furthermore, the analysis suggests that leader conscientiousness is a crucial factor in enhancing the influence of AI-BDA on becoming a green, data-driven decision-making organization. Such findings

generally support earlier literature, which highlights that leadership characteristics influence the pattern of organization management and processes [74]. Such leaders emphasize the importance of detail, obligation, and endurance, which form a foundation for establishing practices that inform decisions based on data, ultimately promoting the sustainability of organizations. It is likely that leaders who score higher on these levels of conscientiousness are better positioned to facilitate and integrate green data-oriented mechanisms within organizations, ensuring the effective support of AI-BDA initiatives with the firm's green agenda. It lends weight to the idea that leadership traits are essential in guiding the use of available technology toward practical implementation within an organization [70].

Furthermore, leadership conscientiousness was also found to serve as a moderator to the extent of this indirect relationship between AI-BDA and firms' green core competencies through GDDC. Compared to prior studies on AI-enabled business model innovation and the role of leaders [73], we shift the companies' focus from business model change to green core competencies. We also extend their results by providing empirical support for the role of conscientious leadership, an overlooked personality trait in the AI-environmental management nexus. Our findings indicate that the ability of AI-BDA to transform core competencies into greener ones relies not only on the existence of a favorable decision-making culture but also on the level of responsibility demonstrated by the leaders in charge of such initiatives. They evaluate practices such as AI-BDA, which would further enable GDDC to achieve a higher level of organizational sustainability commitment by supporting green strategic goals guided by a conscientious effort [71]. This evidence highlights the importance of aligning leadership, culture, and technology in achieving sustainable business outcomes. Therefore, companies seeking to adopt AI-BDA to achieve sustainability targets should focus not only on instilling a green data culture but also on ensuring leadership with prudent traits that support such a culture. While a recent study [22] explored how the interaction of green digital learning orientation and big data analytics fosters the link between green innovation and sustainable performance, our study differs in that it provides a broader capability-building perspective, offering a more systemic framework for engineering managers to understand performance-based models.

The qualitative post-analysis strongly corroborates the quantitative findings and adds explanatory

depth. The 12 interviews vividly illustrated how AI-BDA delivers real-time environmental insights (e.g., predictive water and emission management) and confirmed that a green, data-driven decision-making culture is the pivotal mechanism that translates technological capability into green core competencies. Most importantly, respondents repeatedly emphasized that highly conscientious leaders, described as detail-oriented, persistent, and accountability-focused, were the key differentiator in whether AI-BDA initiatives succeeded or failed.

These insights extend organizational information processing theory by showing that, in high-uncertainty sustainability contexts, information processing capacity (AI-BDA) is necessary but insufficient without a supporting data culture and conscientious leadership to enforce disciplined, evidence-based environmental decision-making. The interviews also revealed that the rarity and inimitability of green core competencies arise from long-term accumulation of proprietary data loops, reinforcing the resource-based logic underlying our definition of green core competencies.

7. Contributions

There is a growing emphasis on business sustainability and environmental management, reflecting a global shift toward practices that aim to protect the natural environment. Therefore, there are several calls for further research on the role of digital technologies in business sustainability and environmental management [2], [15], [47]. Our study responds to such calls for further research on business sustainability and environmental management aimed at protecting the natural environment [2], [15], [47] and the role of digital technologies in environmental management [8], [12]. By integrating AI-BDA, organizations can leverage data-driven insights not only to track and improve their environmental footprint but also to innovate their business processes and product offerings. This integration provides a more comprehensive approach to sustainability, encompassing economic, social, and environmental dimensions, thereby promoting a more resilient and adaptable business model. In doing so, our study extends the following literature streams.

By providing valuable insights into the intersection of AI-BDA and the development of green core

competencies within organizations, we contribute to the literature on the outcomes of AI-BDA. Previous research has demonstrated the positive impact of AI-BDA on various organizational outcomes, including firm performance [48], user satisfaction [34], sustainable performance [35], and green supply chain performance [51]. In addition, the formation of green core competencies relies on enterprises responding to environmental changes and achieving sustainable competitive advantages. Big data tools and AI processes for strategic decision-making can be seen as dynamic competencies [72]. In this regard, we demonstrate that AI-BDA can enhance organizations' environmental sustainability-oriented capabilities. Therefore, this study extends the body of literature by highlighting the overlooked yet crucial role of AI-BDA in facilitating the development of green core competencies. Moreover, by emphasizing the significant relationship between AI-BDA and GDDC as antecedents of green core competencies, this research contributes to the limited understanding of the factors influencing the development of such competencies. While previous studies have explored various antecedents of green core competencies [2], [15], [47], the specific role of AI-BDA and GDDC in this context remains underexplored. This study fills this gap by elucidating how organizations can harness AI-BDA capabilities and foster a GDDC to enhance their green core competencies, thus advancing our understanding of the mechanisms driving sustainable organizational performance and innovation.

Additionally, GDDC is critical in enhancing information processing capabilities by prioritizing data-driven decision-making [40]. This approach aligns with the principles of green core competencies, focusing on developing rare environmental management capabilities to enhance energy savings, pollution prevention, and waste recycling [62]. Through AI-BDA, organizations gain access to vast datasets related to sustainability trends and resource availability [27]. When integrated into a GDDC framework, these insights enable organizations to optimize resource allocation and implement eco-friendly practices [32], [59]. Ultimately, this cultural shift towards sustainability, supported by data-driven evidence, drives continuous improvement in manufacturing processes and fosters green core competencies.

Furthermore, leader conscientiousness moderates the indirect effect of GDDC on the relationship between AI-BDA and green core competencies. Conscientious leaders foster a culture of data-driven

decision-making, focusing on environmental sustainability, which aligns with the green core competencies' goals [15]. The responsible and goal-oriented approach ensures that data-driven strategies prioritize green initiatives, enhancing innovation and environmental performance [54], [64]. Conscientious leaders' advocacy for green initiatives within GDDC promotes sustainable practices and mitigates environmental issues [6]. This moderation by leader conscientiousness strengthens the influence of AI-BDA on GDDC and green core competencies within an OIPT framework.

Finally, we extended the scope of OIPT by demonstrating its applicability to modern, AI-driven environmental contexts. OIPT emphasizes the importance of organizations' ability to collect, analyze, and effectively utilize information [28]. Our study demonstrates how organizations enhance their environmental information processing capacity by effectively acquiring sustainability-related data through AI-BDA technologies, and how GDDC serves as a key underlying mechanism that transforms this capacity into green actions. Furthermore, we extend OIPT by examining leader conscientiousness as a moderator influencing how effectively organizations process and act upon environmental information. By jointly considering AI-BDA, GDDC, and leader conscientiousness, our study broadens the theoretical scope of OIPT and highlights its applicability in guiding organizations to proactively respond to and align with environmental demands from stakeholder groups.

7.1. Implications

Our research findings hold significant practical implications across various domains. First, AI-BDA offers significant practical implications for organizations seeking to develop green core competencies and enhance overall sustainability. By harnessing advanced algorithms and computational techniques, AI analytics enables organizations to process and analyze vast volumes of data swiftly, extracting valuable insights and patterns crucial for optimizing resource allocation and enhancing operational efficiency. This capability enables organizations to identify inefficiencies, reduce energy consumption, minimize waste production, and streamline production processes, ultimately leading to cost savings and enhanced sustainability performance. Additionally, AI-BDA empowers data-driven decision-

making by analyzing consumer preferences, market trends, and environmental regulations, guiding strategic initiatives toward core competencies that can enable eco-friendly products, services, and processes. Furthermore, AI algorithms facilitate predictive modeling and scenario analysis, enabling organizations to anticipate and mitigate environmental risks, adapt to changing conditions, and ensure business continuity while contributing to broader sustainability goals. Overall, AI-BDA serves as a catalyst for developing green core competencies that can reduce organizations' carbon footprint.

To practically implement AI-BDA, organizations should start by investing in robust AI-BDA infrastructure, including advanced data storage and analytical tools that can handle large-scale environmental data. AI-BDA infrastructure must be integrated into core decision-making systems across the organization, ensuring that environmental data informs strategies related to operations, supply chain, and product development. Additionally, managers, particularly decision-makers, should be trained to utilize and interpret AI-BDA insights in alignment with sustainability goals. Creating cross-functional green data teams can enhance collaboration between IT, sustainability experts, and operations leaders, ensuring that AI-driven insights are consistently applied across departments. Organizations should also establish data-driven key performance indicators (KPIs) tied to sustainability objectives, regularly monitoring progress using AI-BDA tools.

Second, fostering GDDC within organizations enables informed and strategic decision-making by leveraging data insights to identify environmental trends, assess risks, and implement targeted initiatives for sustainability. A data-driven culture promotes transparency, accountability, and stakeholder collaboration, thereby enhancing employee engagement and fostering a shared responsibility towards sustainability goals. GDDC facilitates continuous improvement and innovation in sustainable practices by analyzing environmental data, identifying areas for improvement, and innovating new solutions. Moreover, it may build trust and credibility among stakeholders, attracting environmentally conscious customers and investors while complying with regulatory requirements. Our findings indicate that AI-BDA enables firms to gather and analyze complex environmental data. However, it is the GDDC that ensures these data insights are consistently integrated into decision-making processes. A strong GDDC

can foster an organizational environment where data-driven insights are not only valued but also regularly applied to enhance sustainability practices. Consequently, it leads to the development of green core competencies. Without GDDC, the potential of AI-BDA may not be fully realized, as data insights may be underutilized or inconsistently applied across the organization.

Moreover, leaders with high levels of conscientiousness tend to exhibit strong organizational commitment, diligence, and responsibility toward environmental issues. They are more likely to prioritize sustainability initiatives, drive environmentally friendly practices, and advocate for green strategies within the organization. As a result, it strengthens the impact of AI-BDA on a culture that values environmental responsibility, promotes eco-friendly behaviors among employees, and integrates sustainability into core business practices. Conscientious leaders effectively foster a data-driven culture where decisions are grounded in evidence and insights from big data analytics. By leveraging data-driven decision-making, leaders can identify opportunities for green process innovation, optimize resource allocation, and reduce environmental impact across various operational areas. Conscientious leaders are crucial in promoting collaboration, communication, and knowledge sharing related to sustainability initiatives. They encourage cross-functional teams to work together towards environmental goals, facilitate learning and skill development on sustainability practices, and promote innovation through continuous improvement. To enhance leaders' conscientiousness, organizations can implement tailored training programs focusing on conscientious behaviors, such as attention to detail, accountability, and ethical decision-making. These programs should emphasize the importance of integrating sustainability into decision-making and highlight how conscientious leadership can enhance the effectiveness of AI-BDA in achieving green goals. Organizations can also introduce performance evaluation metrics that assess leaders based on their conscientiousness in decision-making, particularly regarding adopting data-driven, eco-friendly practices. Linking these behaviors to incentives, such as rewards for sustainability leadership or performance bonuses, encourages leaders to consider how they can best utilize AI-BDA in shaping GDDC to enhance organizations' green core competencies ultimately.

Our findings suggest that organizations can focus on three main factors to enhance their green core

competencies: AI-BDA, GDDC, and leader conscientiousness. AI-BDA enables organizations to process vast amounts of data precisely, facilitating informed decisions supporting green initiatives. As such, organizations should invest in AI-BDA to collect, analyze, and interpret large-scale environmental data. By enhancing their AI-BDA capabilities, firms can gain deep insights into sustainability challenges, track environmental performance in real-time, and identify opportunities for eco-innovation. Further, we suggest that AI-BDA alone is insufficient without a strong organizational culture that prioritizes data-driven decisions. To enhance green core competencies, organizations must foster a GDDC where environmental data and analytics are consistently used to guide strategic choices. GDDC would ensure that data insights from AI-BDA are applied systematically across the organization to drive sustainable practices in areas like resource efficiency, waste reduction, and environmental innovation. Additionally, leadership plays a crucial role in ensuring that AI-BDA and GDDC work effectively together to enhance organizations' core competencies. Organizations can enhance leader conscientiousness by promoting leaders who are diligent, responsible, and detail-oriented, particularly when it comes to integrating AI-BDA into green decision-making. Conscientious leaders are more likely to ensure that environmental data is used rigorously and consistently, holding their teams accountable for implementing sustainable practices based on data insights.

7.2. Limitations and future studies

The limitations of this study are important to acknowledge. First, while the use of a three-wave data collection method is a key strength that reduces the risk of common method bias, the study's cross-sectional design limits the ability to make causal inferences. Furthermore, while the supplementary qualitative phase of 12 in-depth interviews considerably strengthens interpretive depth and contextual confidence beyond what single-method survey studies typically offer, this qualitative component is modest in scale and confined to Chinese manufacturing firms in pollution-intensive industries. To address this, future research should consider employing longitudinal designs to establish more reliable causal relationships. Second, the data were collected from organizations in China, a country that is rapidly

adopting emerging technologies. As a result, generalizing the findings to developing countries, which may lag behind in technology adoption, should be done with caution. This opens up an avenue for future research to explore these dynamics in different geographical and technological contexts. Further, we relied on managers' data to reach our conclusions. Although collecting data from 339 managers across various organizations provided valuable insights, collecting data from other key stakeholders, such as employees, customers, or environmental experts, could provide a more holistic understanding of how AI-BDA influences green core competencies, as these groups may engage with sustainability initiatives in different ways.

Third, the study highlights the importance of leader conscientiousness in enhancing the impact of AI-BDA on GDDC and green core competencies. However, future research should explore the role of other leadership traits and compare their influence on AI-BDA's impact on green core competencies. Moreover, future studies could also examine GDDC as a potential moderating variable, rather than only a mediating one, to understand whether and how a strong data-driven culture may amplify or attenuate the impact of AI-BDA on green core competencies. Finally, while the study demonstrated strong relationships between AI-BDA, GDDC, and green core competencies, alternative mechanisms or explanations could exist. For example, AI-BDA may also influence green competencies through other factors, such as innovation capacity, organizational support, and green knowledge-sharing culture. In turn, these constructs may positively affect green core competencies. Including these variables in future research would offer a more nuanced understanding of how AI-BDA fosters green competencies.

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Table 1. Means and correlations

Construct	Mean	SD	1	2	3	4	5	6	7
1. AI-BDA	3.37	1.27							
2. GDDC	3.15	1.17	.26**						
3. Green core competencies	3.19	1.14	.25**	.43**					
4. Leader conscientiousness	3.38	1.19	.23**	.13*	.02				
5 Green knowledge-sharing	2.76	1.07	.14**	.22**	.33**	.04			
6. Firm age	34.15	8.20	.04	.11*	-.01	.01	-.06		
7. Firm size			.12*	-.05	.08	.00	-.03	-.08	

Notes. $N = 339$. * $p < .05$. ** $p < .01$ level (2-tailed). SD = standard deviation AI-BDA = AI-supported big data analytics capabilities. GDDC = Green data-driven decision-making culture.

Table 2. Discriminant validity and convergent validity

Construct	1	2	3	4	5	AVE	MSV	ASV
1. AI-BDA	.80					.64	.09	.08
2. GDDC	.30	.77				.59	.25	.12
3. Green core competencies	.29	.50	.75			.57	.25	.11
4. Leader conscientiousness	.26	.16	.03	.79		.63	.07	.03
5 Green knowledge sharing culture	.15	.20	.37	.01	.73	.54	.14	

Notes. $N = 339$. AVE = average variance extracted. MSV = maximum variance shared. ASV = average variance shared. Bolded values on the diagonals of columns 2 to 5 are the square root values of AVE. AI-BDA = AI-supported big data analytics capabilities. GDDC = Green data-driven decision-making culture.

Table 3. Hypotheses results

Variables	GDDC			GCC		
	B (SE)	P-value	CI (95%)	B (SE)	P-value	CI (95%)
AI-BDA	.22(.05)	.00	.13, .32	.23(.05)	.00	.11, .31
GDDC				.40(.05)	.00	.30, .50
Leader conscientiousness	.08(.05)	.15	-.03, .18	-.03(.05)	.53	-.13, .07
Green knowledge-sharing culture	.20(.06)	.00	.09, .32	.25(.05)	.00	.15, .35
Firm age	.01(.003)	.08	-.001, .01	-.001(.003)	.73	-.01, .005
Firm size	-.08(.05)	.15	-.18, .03	.04(.05)	.42	-.06, .15
Interaction	.09(.04)	.01	.02, .17			
				B (SE)	P-value	CI (95%)
Indirect effect of AI-BDA on GCC via GDDC				.09(.03)	.02	.05, .15
Conditional effects						
Conditional direct effect of AI-BDA on GDDC (on low leader conscientiousness)				.13(.06)	.04	.01, .25
Conditional direct effect of AI-BDA on GDDC (on high leader conscientiousness)				.35(.07)	.00	.21, .49

Notes: *p < .05. **p < .01. Sample size (N) = 339. AI-BDA = AI-supported big data analytics capabilities. GDDC = Green data-driven decision-making culture. GCC = Green core competencies. B = Unstandardized coefficient, SE = standard error, CI = Confidence interval. Bootstrapping was specified at 5000 with 95% confidence interval

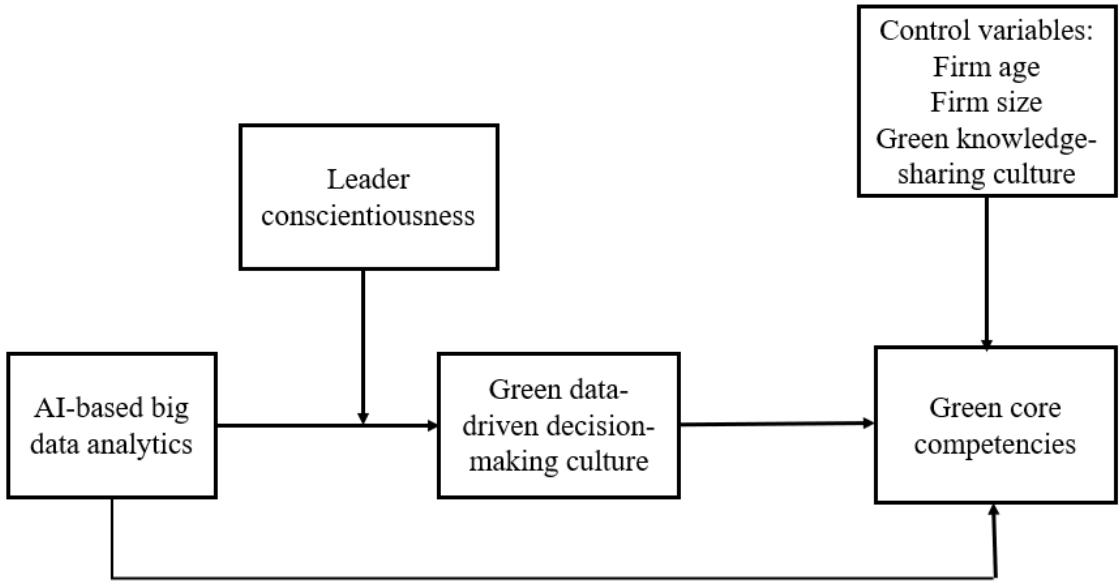


Figure 1. The proposed model

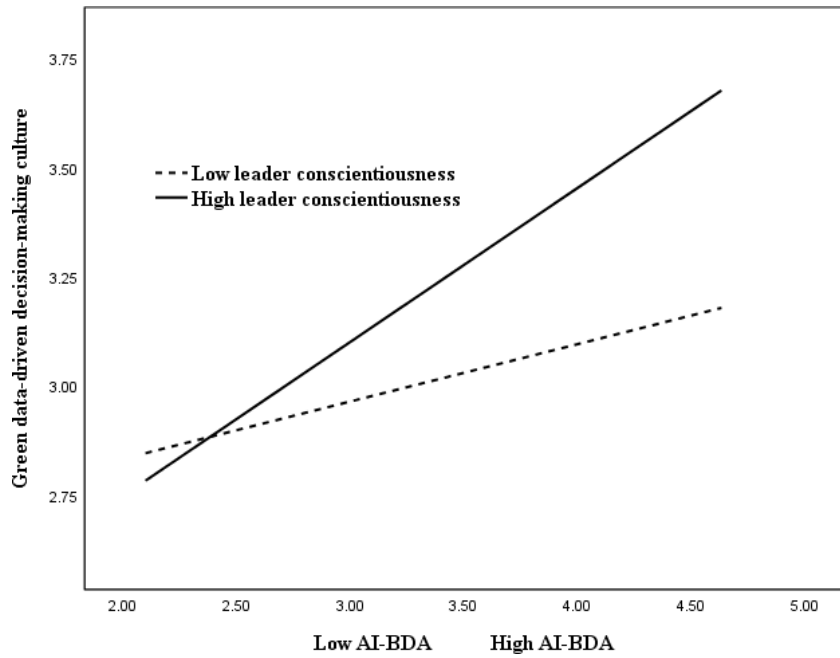


Figure 2. Leader conscientiousness as a moderator of the AI-BDA on GDDC

Appendix A: Semi-Structured Interview Protocol

1. Can you walk me through a recent example of how your company uses AI or big data analytics tools for environmental or sustainability decisions?
2. In daily operations, how commonly are environmental decisions made based on data analysis rather than experience or intuition?
3. What specific practices does your organization use to encourage employees to base green decisions on data (e.g., training, KPIs)?
4. To what extent do you believe your firm's environmental technologies, processes, or know-how are difficult for competitors to copy? Please give an example.
5. Thinking of the senior leaders you work with most closely, how would you describe their style regarding planning, follow-through, and attention to detail?
6. Do more conscientious/diligent leaders behave differently when rolling out AI-based big data analytics for sustainability initiatives? How?
7. What have been the biggest enablers and barriers in turning AI-based big data analytics insights into actual green competitive advantages?
8. Is there anything else you would like to add about the role of data analytics and leadership in building green capabilities?

Appendix C: Summary of qualitative themes

Theme	Description & Illustrative Quotations	Link to Model
1. AI-BDA as an enabler of real-time green insight	“Our AI system analyses dyeing machine data every minute and automatically adjusts temperature and chemical dosage. Last year, we were able to reduce water by 22% and chemicals 18%.” (Plant Manager of a textile company)	Direct effect (H1)
2. GDDC as the cultural bridge	“Only the plants where the factory head starts every morning meeting with ‘Show me the data’ actually improved. In the others, people still decide by experience.” (Operations Director of a leather company)	Mediation via GDDC (H2)
3. Conscientious leaders drive adoption and accountability	“Our group president is detail-oriented and disciplined. Every month, he would personally review the ESG dashboard with each factory head and ask for evidence-based explanations. He is like that; the entire organization has become data-driven on green issues.” (Sustainability Director of a large leather group)	Moderation (H3)
4. Rarity stems from proprietary data loops	“Competitors can buy the same software tomorrow, but they cannot buy our eight years of historical sensor data tied to every recipe.” (R&D head of ceramics company)	Explains GCC rarity/inimitability
5. Barriers	Middle-management resistance, data silos, shortage of dual-competence (Digital Operations Manager of a textile company)	