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Do Big Data Analytics and Artificial Intelligence Enhance Corporate Sustainability? The Moderating Roles of Regulation and Management Support

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ABSTRACT

We examine the effects of big data analytics (BDA) and artificial intelligence (AI) on corporate sustainability performance, specifically investigating the influence of regulatory pressure and top management support. Utilizing hierarchical regression analysis on questionnaire data from 220 Chinese manufacturing firms, we find that both BDA and AI positively and significantly impact the corporate sustainability of manufacturing firms. Furthermore, regulatory pressure and top management support (TMS) significantly moderate the relationship between AI and BDA and firms' corporate sustainability performance. Our results also highlight heterogeneity and sector differences: the electronics, chemical, and automotive sectors exhibited significant positive effects of BDA and AI on sustainability performance dimensions, with the electronics sector demonstrating the strongest and most consistent results. Interestingly, the moderation analyses show that the interaction of BDA and regulatory pressure improved environmental performance; AI combined with regulatory pressure enhanced economic outcomes. Additionally, when supported by top management, BDA boosted social performance; AI strongly influenced economic performance. Importantly, the study also identifies potential risks: BDA implementation without adequate contextual support can negatively affect social and economic performance. While TMS is a significant moderator, its effectiveness is contingent on alignment with clear technological strategies. Without this alignment, TMS may lead to overconfidence, strategic misdirection, or resource misallocation. Our study emphasize that BDA and AI can improve sustainability in manufacturing, with effects varying by size, industry, and region, and reliant on supportive internal and external conditions.

1 | Introduction

Digital technologies like big data analytics (BDA) and artificial intelligence (AI) are essential for fostering sustainable transformation. BDA enhances resource efficiency and supply chain transparency, whereas AI facilitates predictive modeling, real-time decisions, and the automation of sustainable operations (Cheng et al. 2023; Gupta et al. 2021; Lopes de Sousa Jabbour et al. 2025; Wamba et al. 2017). To date, most studies emphasize the operational benefits of BDA and AI, such as efficiency, automation, and faster decision-making (Ertz et al. 2025; Mikalef, Boura, et al. 2020; Mikalef, Krogstie, et al. 2020). Despite increasing interest in digital technologies and strategic priority of corporate sustainability (Geissdoerfer et al. 2017; Lozano 2015; Lozano et al. 2015), empirical evidence on the effect BDA and AI on corporate sustainability performance is still limited and unclear (Dubey et al. 2019; Toorajipour et al. 2021; Rashid et al. 2025). Specifically, limited research has focused on the impact of AI on corporate sustainability, primarily investigating its effects on firm performance (Ertz et al. 2025; Lopes de Sousa Jabbour et al. 2025). Moreover, research indicates the necessity of empirical studies to investigate how AI can improve corporate sustainability performance (Asokan et al. 2022; Dauvergne 2022; Khakurel et al. 2018). In the digital era, BDA and AI are essential strategic resources for businesses, helping them manage environmental data, anticipate sustainability risks, optimize resource usage, and create eco-efficient operations (Wamba et al. 2017; Dubey et al. 2019). This is especially relevant in emerging markets, where firms contend with significant institutional uncertainty and inconsistent enforcement of environmental and social regulations (He et al. 2024; Qin et al. 2022; Wan et al. 2024). Yet, limited studies have focused on how digital technologies like BDA and AI interact with institutional factors like regulatory pressure and top management support (TMS) to influence corporate sustainability in emerging economies. Current literature calls scholars to examine whether, how, and under what conditions digital technologies enable sustainable business transformation (Asokan et al. 2022; Dauvergne 2022; Khakurel et al. 2018). This study extends digital technologies and sustainability literature by exploring the impact of BDA and AI on sustainability performance through regulatory pressure and TMS. In this study, we investigate the following central research questions: (1) To what extent do AI and BDA enhance the environmental, social and economic (ESE) sustainability performance? (2) Does regulatory pressure moderate the relationship between AI/BDA and sustainability outcomes? (3) To what extent does TMS moderate AI and BDA effects on sustainability outcomes?

Our investigation is guided by an integrative theoretical framework combining the resource-based view (RBV), dynamic capabilities view (DCV), and institutional theory (IT). The RBV (Barney 1991) conceptualizes BDA and AI as valuable, rare, and hard-to-imitate resources that provide firms with a competitive edge by enabling more efficient and sustainable operations. However, possession of such resources is not sufficient. The DCV (Teece 2007) extends the RBV by emphasizing firms' ability to sense, seize, and transform resources to adapt to changing environments, highlighting BDA and AI as dynamic capabilities necessary for responding proactively to sustainability challenges. IT (DiMaggio and Powell 1983) adds an essential contextual lens, suggesting that external institutional forces, such as regulatory pressure, and internal organizational norms, such as leadership commitment, shape the strategic use and impact of these technologies. Collectively, these three perspectives inform our conceptual model and hypotheses, providing a comprehensive understanding of how digital capabilities interact with institutional and organizational contexts to influence sustainability outcomes.

Empirical evidence suggests that regulatory pressures prompt companies to develop advanced BDA-AI capabilities, promoting sustainable operations, process efficiency, and circular economy practices (Bag et al. 2021; Awan et al. 2021; Madanaguli et al. 2024; Chin-Tsu Chen et al. 2024). In addition, decision-making is often shaped by hierarchical structures and risk-averse cultures, making the role of top management critical in interpreting regulatory signals and championing technology adoption (Sharma et al. 2023; Wang et al. 2023; Delmas and Toffel 2008; Li et al. 2025; Wu et al. 2024; Tang et al. 2015). The strategic orientation and commitment of top management significantly influence resource allocation and the interpretation of digital technologies for sustainability (Sharma et al. 2023; Wang et al. 2023). However, research on BDA-AI and sustainability often overlooks how technology interacts with institutional and organizational contexts (George et al. 2021; Hartmann et al. 2023). To date, the effects of regulatory pressure and TMS as moderators in the relationship between digital technologies and sustainability outcomes remain largely unexamined (Jin et al. 2024; Liao 2018), particularly in emerging economies where regulatory and organizational conditions differ significantly from developed contexts.

China presents a compelling empirical context, with the country under intensifying pressure to reduce industrial emissions and improve social responsibility, driven by both internal mandates such as the "dual carbon" goals and the Environmental Protection Law and external stakeholder scrutiny (Chen et al. 2024; Li 2018; Zhou et al. 2021). The Chinese regulatory environment creates significant regional variation in enforcement and interpretation (Wang et al. 2024; Yan et al. 2024), which could enhance or hinder the impact of digital technologies on sustainability goals (He et al. 2024; Qin et al. 2022; Wan et al. 2024). By investigating these dynamics in a complex institutional setting, our study aims to provide fresh insights into the BDA-AI and sustainability nexus, aligning with a growing body of research advocating for a contextualized understanding.

To empirically test our framework, we collected questionnaire data from 220 Chinese manufacturing firms from November 2024 to April 2025. Utilizing hierarchical regression analysis, we find that both BDA and AI significantly enhance the ESE performance of Chinese manufacturing firms. Moreover, these effects are positively and significantly moderated by RP and TMS. We show that BDA and AI enhance sustainability, with heterogeneity and sector differences varying by firm size, industry, region, and enhanced by RP and TMS: (1) the electronics, chemical and automotive sectors showed positive and significant effects of BDA and AI on all sustainability performance dimensions, with the electronics sector showing the strongest and most consistent effects; (2) the impact of BDA and AI on sustainability performance varied among firms, with smaller firms showing weak effects, medium-sized firms showing moderate effects, and large firms consistently showing strong effects; (3) the interaction of BDA and RP improved environmental performance, AI affected by RP enhanced economic outcomes, BDA with TMS boosted social performance, and AI with TMS strongly impacted economic performance; (4) our regional differences show that firms in Shanghai showed the strongest and most consistent positive effects, with significant coefficients across sustainability dimensions compared to Zhejiang and Jiangsu. Interestingly, our analysis uncovered some unexpected patterns. In the absence of regulatory alignment or managerial support, BDA showed a negative impact on social and economic performance. This suggests that digital tools may be insufficient and potentially counterproductive due to their lack of support for institutional and organizational conditions. Similarly, excessive or misaligned involvement from top management without clear digital strategies can lead to overconfidence, misallocation of resources, and ineffective implementation.

Our research contributes to the existing literature. First, while literature has extensively examined BDA effects on firm performance and sustainability (Ertz et al. 2025; Lopes de Sousa Jabbour et al. 2025), there is limited empirical evidence on the effects of BDA on corporate sustainability in manufacturing firms. Therefore, we address this gap, confirming that BDA capabilities and resources in Chinese manufacturing firms enhance sustainability outcomes by optimizing efficiency and supporting ESE goals. Second, we explore the influence of AI on sustainability performance in Chinese manufacturing firms, contrasting previous research on AI impact on sustainability performance (Chen et al. 2025; Lopes de Sousa Jabbour et al. 2025; Shan et al. 2025). We highlight the positive impact of AI on the sustainability performance of Chinese manufacturing firms, demonstrating its transformative potential in emerging economies. Third, while previous studies have explored the influence of institutional and regulatory pressure on sustainability and innovation (Jin et al. 2024), current literature lacks understanding of how RP and TMS influence the relationship between BDA-AI and sustainability outcomes, particularly in China. Our study provides new empirical evidence demonstrating the importance of RP and TMS in maximizing the sustainability benefits of AI and BDA. Finally, we provide empirical support for an integrative theoretical model that combines RBV, DCV, and IT indicating how internal capabilities and external pressures jointly influence sustainable digital transformation. Our findings offer practical insights for managers and policymakers: Effective sustainability outcomes require not only digital investment but also strategic alignment with institutional regulations and executive leadership.

We used Section 2 to present a theoretical foundation, hypothesis development, and conceptual framework. The data and methods are summarized in Section 3, while Section 4 presents results, robustness, and additional test analysis. Section 5 presents the primary findings, outlining their theoretical, practical, and social implications, and concludes by highlighting limitations for future research.

2 | Theoretical Foundation, Hypothesis, and Conceptual Framework

2.1 | Theoretical Underpinning

In this paper, we integrate the RBV, DCV, and IT to explain how advanced digital capabilities like BDA and AI influence corporate sustainability performance. To date, the impact of digital capabilities on manufacturing sustainability performance dimensions is limited, and the relationship between internal and external factors is not well understood. We propose an integrated model that synthesizes IT (capturing regulatory pressure and TMS), RBV (explaining the strategic value of BDA and AI as firm-specific resources), and DCV (highlighting the adaptive capabilities required for digital and sustainability transformation).

The RBV posits that firms gain a competitive advantage through the possession and strategic deployment of valuable, rare, inimitable, and non-substitutable resources (Barney and Clark 2007). The capabilities of firms are enhanced by both tangible resources, such as data infrastructure, and intangible resources like employee skills in data analytics, algorithm design, and machine learning (Dubey et al. 2019; Hart 1995; Soriano 2012). Building on this, the DCV highlights a firm's ability to adapt to dynamic environments by integrating, building, and reconfiguring internal and external competencies, expanding the RBV concept of resource possession (Teece 2007). BDA and AI are revolutionizing businesses by enabling them to adapt to environmental changes, capitalize on eco-innovation opportunities, and enhance operational efficiency, ultimately transforming their business models and production processes (Ertz et al. 2025; Makhloufi 2024). DCV is especially relevant in volatile institutional settings like China, where firms must swiftly adapt to strict environmental regulations and competitive pressures.

IT suggests that organizational behavior is influenced by both coercive (formal regulations) and normative (cultural and managerial expectations) pressures within a broader socio-political system (Powell and Colyvas 2008; Scott 2005). Powell and Colyvas (2008) further explore the micro-foundations of IT, highlighting how managerial actions and beliefs influence organizational responses to institutional pressures. Widely applied in various organizational contexts, IT has been used to investigate diversity, multinational corporations, green supply chain practices (Kondra and Hinings 1998; Zhu et al. 2013), digital transformation, and sustainability when adopting big data technologies (Dubey et al. 2019).

The integration of RBV, DCV, and IT provides a comprehensive perspective on how companies utilize AI and BDA for improving corporate sustainability. IT evaluates external pressures and influences on strategic decision making, while the RBV highlights internal resources, and the DCV emphasizes adaptability and reconfiguration of these resources in changing contexts. Collectively, these theories highlight that the adoption of sustainability-oriented AI and BDA is affected by resource availability, a firm's responsiveness to institutional factors, and its capacity for change over time. We used the following sections to develop hypotheses within an enhanced theory framework by extending IT, RBV, and DCV in institutional contexts, and inform strategic investments in BDA-AI and sustainability.

2.2 | BDA and Corporate Sustainability

BDA is a cutting-edge technology that enables businesses to rapidly acquire, process, and analyze large volumes of structured and unstructured data in real-time (Bonsu 2024; Ertz et al. 2025). While sustainability is a strategic priority and regulatory requirement, BDA enhances operational optimization, resource allocation, waste minimization, and environmental monitoring in high-pollution industries (Wamba et al. 2017; Yoshikuni et al. 2025). Empirical studies affirm that BDA enhances the firm's ESE performance (Jeble et al. 2018; Raffoni et al. 2018) and improves corporate decision-making by analyzing sustainability indicators in manufacturing processes, increasing residual product value and environmental impact estimation, and supporting responsible digitalization (Rusch et al. 2023).

BDA, as a responsible digital adoption strategy where companies use digital technologies for economic and societal benefits, demonstrates a commitment to environmental sustainability. RBV identifies BDA as a valuable, rare, and non-substitutable strategic intangible asset that firms can invest in to generate actionable insights for the triple bottom line. BDA systems collect detailed product-level data on raw materials, production inputs, equipment, usage patterns, and waste outputs, enhancing transparency, traceability, and sustainable production and consumption practices (Mastos et al. 2021). From a DCV perspective, BDA enhances sustainability challenges, strategic initiatives, and operational adjustments, enhancing agility and resilience in dynamic regulatory and environmental contexts, particularly in emerging markets like China (Teece 2007). Recent research shows positive correlations between BDA and firm environmental and financial performance (Ertz et al. 2025; Chatterjee et al. 2023; Vitari and Raguseo 2020; Le and Vu 2024), but its strategic role in promoting integrated corporate sustainability, especially in Chinese manufacturing firms, is still underexplored. In this context, we argue that firms that incorporate BDA into their sustainability strategies are more likely to achieve superior performance on the triple bottom line as hypothesized below:

H1. *BDA positively influence (a) environmental performance, (b) social performance, and (c) economic performance.*

2.3 | AI and Corporate Sustainability

AI utilizes machine learning, natural language processing, and computer vision to automate decision-making, predict equipment failures, optimize logistics, and monitor environmental standards, leading to improved sustainability (Dubey et al. 2022). RBV views AI as a strategic, valuable, rare, and inimitable intangible resource that augments operational foresight, personalized customer engagement, and agile market adaptation for firms (Ghura and Harraf 2021; Helfat et al. 2023). Additionally, AI-enhanced decision-support systems are vital for sustainable value creation due to the growing relevance of BDA and AI. The DCV suggests that AI enhances a firm's adaptive capacity by facilitating continuous learning, intelligent decision-making, and process reconfiguration in response to evolving environmental and institutional demands (Teece 2007). For instance, AI enhances corporate sustainability by improving environmental efficiency, social accountability, economic value, energy use optimisation, supply chain transparency, and productivity through automation and innovation (Chidepatil et al. 2020; Dauvergne 2020; Iftikhar et al. 2020; Khakurel et al. 2018). While research suggests AI's potential for corporate sustainability (Goralski and Tan 2020; Vinuesa et al. 2020), the relationship between AI and ESE performance has not been extensively studied (Asokan et al. 2022; Kopka and Grashof 2022). The limitation presents an opportunity to explore AI's transformative potential through a more comprehensive and integrated framework. Therefore, we develop the following hypothesis on AI's impact on firms' sustainability:

H2. *AI positively influences (a) environmental performance, (b) social performance, and (c) economic performance of manufacturing firms.*

2.4 | Moderating Role of Regulatory Pressure

Both BDA and AI are anticipated to improve sustainability performance, but their actual impact appears to depend on contextual and institutional factors. For instance, BDA requires strong technical infrastructure, alignment with national and sectoral strategies and skilled personnel to convert data into actionable insights. Similarly, AI offers advantages such as automation, predictive intelligence, and process optimization, provided that regulatory compliance is maintained. Notably, regulatory requirements for AI include environmental compliance, ethical guidelines, algorithmic transparency, data protection laws, and explainability standards (Chazette et al. 2021). These requirements mandate risk assessments, fairness audits, and restrictions on automated decision-making in sensitive areas, influencing the development and deployment of AI tools. In China's manufacturing context, regulations such as the Personal Information Protection Law and draft guidelines on AI governance are prompting companies to adopt more responsible, transparent, and auditable AI practices (Cui and Qi 2021; Ye et al. 2024). Accordingly, regulatory frameworks significantly influence the technological and organizational strategies that allow AI to effectively support corporate sustainability.

Firms may face challenges in utilizing technologies and may experience negative outcomes from misaligned digital initiatives when external conditions are lacking (Cui et al. 2019; Stekelorum et al. 2022; Yu et al. 2019). Government policies and regulations create coercive pressure on firms, promoting innovation and sustainability, especially in environmental practices (Dewick and Foster 2018; Martínez-Ferrero and García-Sánchez 2017). IT posits that regulatory pressure compels firms to adapt their practices to social and environmental expectations, frequently leading to technological advancements like BDA and AI to achieve performance targets and evade penalties. Regulatory pressure, which includes environmental laws, compliance requirements, and penalties imposed by governmental bodies, is essential in promoting sustainability among firms (Berrone et al. 2013; Jin et al. 2024; Liao 2018). For instance, environmental regulators in China impose significant fines or sanctions on companies for discharging toxic gases or untreated wastewater, utilizing their authority and the clarity of environmental regulations (He et al. 2025; He et al. 2023; Scott 2005). Consequently, firms under coercive pressure aim to minimize or eliminate their production processes' environmental impact, thereby enhancing their commitment to sustainable innovation (Chen et al. 2018; Wang et al. 2023).

Recent developments in the ESG framework have expanded environmental regulations to include social and economic dimensions, representing a form of institutional coercion. While resource-constrained firms may only adopt BDA and AI under strong institutional coercion, proactive or innovative firms may pursue digital sustainability initiatives irrespective of external mandates. This suggests that regulatory pressure may not always be linear, with initial influence potentially diminishing once compliance thresholds are met or returns decrease beyond a certain point. In China, institutional arrangements, including mandatory CSR reporting, supplier contracts with social responsibility clauses, labor welfare disclosure standards, and sustainability-linked financing policies, are setting regulatory expectations for social outcomes (Cui et al. 2025). As such, regulatory pressure affects how firms address labor practices, employee well-being, and social responsibility, though their responses can vary significantly. Moreover, the strength of the BDA–AI–sustainability relationship may vary across three dimensions, influenced by sectoral priorities, firm size, and regional enforcement patterns. We therefore propose the following hypotheses:

H3. *Regulatory pressure positively moderates the relationship between BDA capabilities and (a) environmental performance, (b) social performance, and (c) economic performance.*

H4. *Regulatory pressure positively moderates the relationship between AI integration and (a) environmental performance, (b) social performance, and (c) economic performance.*

2.5 | Moderating Role of TMS

TMS refers to the extent to which senior executives provide leadership, allocate resources, and align strategic priorities to support digital renovation and sustainability initiatives (Wen et al. 2023). The successful integration of advanced BDA and AI requires not only technical proficiency but also a strong leadership commitment to corporate sustainability frameworks. Top management plays a particularly critical role in sustainability performance efforts, where decision-making often involves significant resource allocation and transformative changes to business operations (Liu et al. 2020). Based on RBV and DCV, top management significantly influences firm-specific capabilities through strategic vision, innovation-oriented culture, and organizational learning (Gunasekaran et al. 2024). These managers are instrumental in integrating BDA and AI into sustainability strategies, ensuring alignment with ESE goals.

Hierarchical organizational structures and cultural dynamics can either enable or restrict the influence of top management on digital sustainability transitions. Liu et al. (2020) highlight that executive leadership significantly influences firms' genuine engagement in green practices, with top managers' internal commitment and environmental philosophy being more crucial for successful implementation (Wijethilake and Lama 2019). Moreover, proactive top management can extend sustainability efforts beyond regulatory compliance, embedding them into the strategic core and organizational culture (Burki et al. 2019).

Evidence suggests that TMS enhances BDA and AI effectiveness by facilitating cross-functional collaboration and translating data insights into actionable sustainability practices across departments (Birkinshaw et al. 2016). The strategy aligns digital initiatives with long-term sustainability goals, fostering innovation despite uncertainty or resistance (Helfat and Peteraf 2015; Ocasio 1997). Additionally, top managers promote technological change by providing legitimacy, direction, experimentation, and resource commitment for scaling digital sustainability solutions (Wüstenhagen et al. 2007). For instance, firms with leaders prioritizing environmental and social goals invest in BDA and AI for long-term sustainability and competitive advantage, promoting technological innovation (Chu et al. 2017; Ilyas et al. 2020). Thus, TMS not only facilitates the use of digital tools but also ensures their purposeful deployment toward sustainability performance objectives (Kiron et al. 2017; Bocken et al. 2019). Consequently, TMS can enhance the impact of digital technologies on sustainability performance by promoting strategic coherence, aligning firm values with environmental and social needs, and facilitating resource mobilization. Despite the recognized importance of TMS (Chu et al. 2017; Yeung et al. 2007; Liu et al. 2020), empirical research examining its moderating role in the relationship between digital technology adoption and corporate sustainability performance remains limited. Therefore, we propose the following hypotheses:

H5. *TMS positively moderates the relationship between BDA and (a) environmental performance, (b) social performance, and (c) economic performance.*

H6. *TMS positively moderates the relationship between AI integration and (a) environmental performance, (b) social performance, and (c) economic performance.*

To summarize, Figure 1 presents our research conceptual framework, outlining the relationships between the hypotheses.

3 | Methodology

3.1 | Sampling and Data Collection

We chose manufacturing in China because it is undergoing a digital revolution, prioritizing intelligent manufacturing, industrial upgrading, and environmental protection (Li and Branstetter 2024; Wübbeke et al. 2016). This study focuses on chemical, electronics, automotive, and publishing and printing sectors because they face significant environmental and regulatory pressures (Al-Swidi et al. 2023), making them ideal for studying the impact of BDA and AI on corporate sustainability. Specifically, our sample was drawn from Eastern China's manufacturing firms, such as Jiangsu, Zhejiang, and Shanghai. These economically advanced regions are known for high innovation and strong adoption of digital technologies, where 73% of firms are recognized among China's top performers in technological innovation and sustainability (Fang and Li 2024; Li and Branstetter 2024).

We collected data using a structured questionnaire between November 2024 and April 2025, comprising demographics, firm profile data of Chinese manufacturing firms, and measurement constructs based on 5 Likert scale. The questionnaire was structured in two sections. The first section asked respondents about firms' profiles, and the remainder asked questions about the variables. The questionnaire was created in English, with a panel of academics reviewing and translating it into Chinese. The Chinese version was translated back into English and compared to the original English version to ensure its reliability. A pretest was conducted among finance and sustainability experts to evaluate the questionnaire's relevance, clarity, and alignment

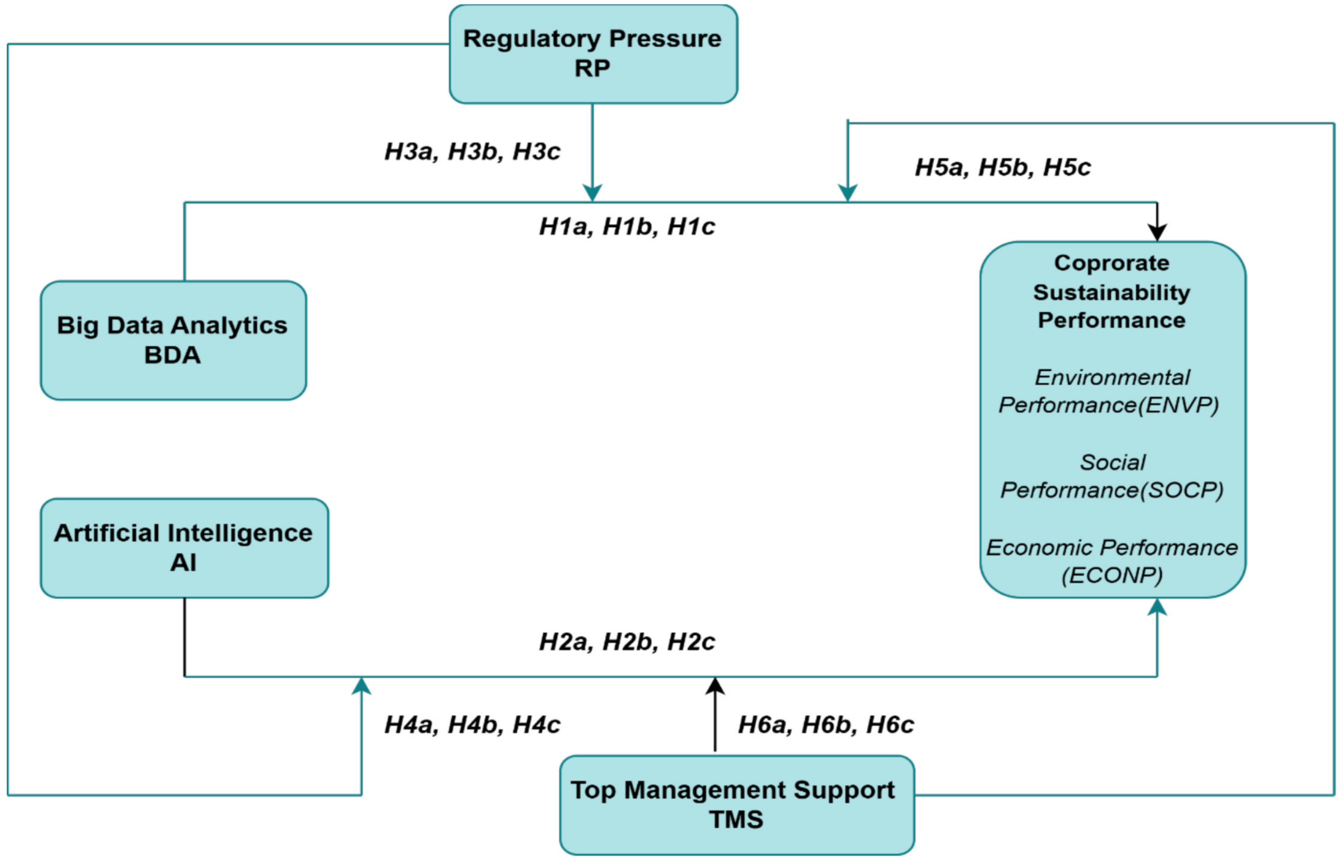

FIGURE 1 | Conceptual framework.

with study objectives and target population comprehension. Following that, three academics, each from China and UK universities, were contacted to guarantee the questionnaire's content validity and accurate capture of key constructs and dimensions. The questionnaire was revised to improve its representation, reliability, and coverage of study variables while maintaining contextual relevance. Following the content validity, we conducted a pilot test with 30 managers of manufacturing firms, which enhanced the instrument's clarity and relevance by addressing ambiguities and ensuring the questions were comprehensible to the target population. The questionnaire provided guidelines for participants, and assurance of their identities remained confidential and anonymous.

We distributed an online survey to 500 manufacturing firms that have used BDA and AI for at least 2 years. We used Chinese social media platforms, such as WeChat and Sina Weibo, to distribute the questionnaire. Purposive sampling was employed to select a sample of companies, following the approach commonly used in related studies (Seman et al. 2019). Through their connections, the authors contacted firms by phone to explain the aims and purpose of our research and urged their participation. Upon agreement, we collected data through a structured questionnaire from top and middle managers overseeing digital innovation and sustainability efforts. We approached top and middle managers, considering their strategic and operational roles in implementing AI and BDA initiatives. Practically, they possess firsthand knowledge of sustainability practices and digital adoption. Meanwhile, their insights align with RBV, IT, and DCV, focusing on managerial capabilities in resource mobilization, institutional response, and dynamic transformation.

We received 220 completed responses, representing a 44% response rate, with 52.6% males and 47.45% females among the respondents. The online survey's nature and data collection resulted in a dataset without missing values, as participants could not advance to subsequent questions without a specific response. Table 1 presents the results of respondents' demographics. Data was validated by evaluating non-response bias, following the recommendations (Hsu et al. 2019) method of comparing late (70) and early (150) collections of responses using the *t*-test. Our results showed a significant difference ($p > 0.05$), indicating that non-response bias was not a significant issue. Following this, we tested and evaluated probable common method bias, considering our developed questionnaire from the same instrument. Thus, we followed previous studies utilizing robust approaches for evaluation. Before that, we provided a comprehensive introduction in Chinese to the questionnaire, elucidating the questionnaires and constructs that facilitated the accurate response of participants. In addition, we randomized our construct measurement items to prevent respondents from acknowledging causal nexus variables. Second, we used the Harman single method, revealing 26.3%, which is one factor lower than the 50% benchmark (Fuller et al. 2016). To enhance Harman's single factor, we utilized the Marker variable (Lindell and Whitney 2001), using gender as a theoretically unrelated marker variable and one research variable (sustainability performance). The test

TABLE 1 | Respondents' profile.

Profiles		Number ($N = 220$)	Percentage (%)
Managerial status			
	Top manager	145	66%
	Middle-level manager	75	34%
Firm age			
	1–10 years	56	25%
	11–20 years	89	40%
	21 and above	75	35%
Number of employees			
	< 299	91	41.2%
	300–999	59	26.8%
	> 701	70	32%

Note: This table presents the demographic characteristics of the study respondents. Percentages may not total 100 due to rounding. $N = 220$.

found no evidence of common method bias, suggesting that the data is unlikely to be significantly impacted by this bias.

3.2 | Constructs Measures

Our study used validated items from the extant literature tailored to the research context. BDA were measured with five items adapted from (Wamba et al. 2017). AI was evaluated with five items adopted from (Davenport and Ronanki 2018; Lopes de Sousa Jabbour et al. 2025). Sustainability performance was classed into social, environmental and economic (business performance). Notably, four items for social performance were measured from (Lopes de Sousa Jabbour et al. 2025; Younis et al. 2016), environmental performance items was evaluated from (Lopes de Sousa Jabbour et al. 2025; Zhu and Sarkis 2004) and economic performance was adopted from (Henri and Journeault 2010; Lopes de Sousa Jabbour et al. 2025). Regulatory pressure were measured with five items adapted and tailored to the study context from (Liao 2018; Ye et al. 2013). Finally, TMS was adapted from (Ilyas et al. 2020; Liu et al. 2020), with items modified to achieve the study objectives.

Previous studies have recommended that the firm size (FS), firm age (FS), managers' experience, and educational background of top managers are relevant control variables of Manufacturing sustainability performance and technology adoptions to reduce spurious results (Cui et al. 2019; Stekelorum et al. 2022; Yu et al. 2019). Specifically, FS was measured using the natural logarithm of the number of employees (continuous variable), as larger firms often have greater access to financial and technological resources that may influence sustainability initiatives (Gupta and Batra 2016). FA is determined by the natural logarithm of the years of firm's establishment (continuous variable), suggesting that older firms may adopt behaviors shaped by established practices or institutional inertia (Gupta and Batra 2016). Managers' education level was assessed as ordinal categorical variable code as (1 = high school, 2 = bachelor's degree, and 3 = postgraduate) following (Bonsu 2024). Educational background can influence managerial cognition, openness to innovation, and understanding of sustainability principles (Ahn et al. 2017). Finally, managerial experience was included as a continuous variable measured in years, assuming experienced managers may have different decision-making patterns or risk preferences when adopting new technologies (Ferri et al. 2021).

3.3 | Reliability and Validity Checks

Our study employed confirmatory factor analysis (CFA) using Cronbach's alpha (CA), factor loadings, composite reliability (CR), and average variance estimates (AVEs) on 33 items, namely, (i) five items each for BDA and AI, (ii) five items each for regulatory pressure, (iii) five items for TMS, and (iv) four items each for social performance and environmental performance and three items for economic performance for checking the convergent validity. Finally, we test the correlation coefficient and the square root of AVE of each construct to check the discriminant validity. The test results are presented in Tables 2 and 3, respectively. Before estimating the validity and convergent tests, we utilized SPSS to evaluate the data's sample adequacy and fitness, achieving a significance level of 0.73, surpassing the standard 0.6 benchmark (Hair et al. 2010). Resultantly, factor loadings for constructs exceed 0.7, validating the indicator's validity (Bonsu et al. 2025). Additionally, CA values exceeded the 0.7 benchmark, confirming the internal consistency of constructs. Finally, CR and AVE values were higher than the 0.7 and 0.5 threshold respectively (Hair et al. 2010). The results evince convergent reliability and validity of the construct.

Discriminant validity was also assessed using Fornell–Larcker's criterion. Table 3 indicates that the diagonal element was larger than each correlation value, promoting the constructs' discriminant validity. In addition, variance inflation factors (VIFs) were evaluated to check for evidence of multicollinearity among the explanatory variables. As the VIFs were never larger than 10, we may conclude that multicollinearity did not pose a problem in our research (Bonsu et al. 2025).

3.4 | Data Analysis

We used the hierarchical regression analysis, a relevant approach and a conservative technique to test our research hypotheses. The moderation model suggests that BDA and AI are positively associated with ESE performance, and this relationship is moderated by regulatory pressure and TMS (see Figure 1). To test the moderation effects hypothesized, we followed Cohen et al. (2003) recommendation for examining interaction effects. Thus, we proceeded with the analysis in three steps to the hypothesis, by first performing a basic regression analysis with BDA and AI predicting SP (ENVP, SOC, ECONP) and moderators (RP and TMS) to check the individual significance of paths, including the control variables. Second, we introduced the interaction terms (BDA × RP, BDA × TMS AI × RP, and AI × TMS) into the model. All predictor and moderator variables were

TABLE 2 | Reliability and validity test.

Variables	Items	Loadings (> 0.70)	CA (> 0.70)	CR (> 0.70)	AVE (> 0.50)
Big data analytics	BDA1	0.84	0.89	0.82	0.61
	BDA2	0.86			
	BDA3	0.84			
	BDA4	0.83			
	BDA5	0.76			
Artificial intelligence			0.79	0.81	0.69
	AI1	0.83			
	AI2	0.82			
	AI3	0.84			
	AI4	0.85			
	AI5	0.78			
Economic performance	ECP1	0.76	0.88	0.78	0.67
	ECP2	0.83			
	ECP3	0.84			
Environmental	ENV1	0.79	0.87	0.72	0.59
	ENV2	0.80			
	ENV3	0.85			
	ENV4	0.84			
Social performance			0.91	0.77	0.69
	SOCP1	0.89			
	SOCP2	0.87			
	SOCP3	0.74			
	SOCP4	0.84			
Regulatory pressure			0.89	0.89	0.65
	RP1	0.83			
	RP2	0.84			
	RP3	0.85			
	RP4	0.78			
	RP5	0.89			
Top management support			0.87	0.78	0.78
	TMS1	0.81			
	TMS2	0.85			
	TMS3	0.81			
	TMS4	0.84			
	TMS5	0.83			

Note: This table presents the reliability and validity tests of the research. CA and CR values exceed 0.70, and AVE values exceed 0.50, indicating satisfactory reliability and convergent validity.
Abbreviations: AVE = average variance extracted; CA = Cronbach's alpha; CR = composite reliability.

TABLE 3 | Descriptive and correlation.

Constructs	Mean	STD	BDA	AI	ENVP	SOCP	ECONP	RP	TMS
BDA	18.401	5.716	***0.781***						
AI	23.350	7.065	0.208***	***0.831***					
ENVP	14.115	4.066	0.364***	0.116***	***0.818***				
SOCP	14.293	4.199	0.432***	0.373***	0.297***	***0.768***			
ECONP	14.252	4.058	0.155***	0.290***	0.205***	0.220***	***0.831***		
RP	23.841	6.488	0.352***	0.188***	0.315***	0.302***	0.302***	***0.812***	
TMS	22.176	4.312	0.263***	0.507***	0.202***	0.387***	0.193***	0.257***	***0.883***
Obs	220	220	220	220	220	220	220	220	220

Note: Means and standard deviations are reported along with inter-construct correlations. Diagonal elements in bold represent the square root of the average variance extracted (AVE).
Abbreviations: AI = artificial intelligence; BDA = big data analytics; ECONP = economic performance; ENVP = environmental performance; Obs = number of observations respectively; RP = regulatory pressure; SOCP = social performance; TMS = top management support.
***,
**, and
*denote 1%, 2%, and 5% significance values, respectively.

mean centered before creating interaction terms, following the guidelines of Aiken et al. (1991), to reduce multicollinearity and improve interpretability. Finally, a statistically significant interaction coefficient, along with a significant increase in R^2 (ΔR^2), was used to confirm the presence of a moderation effect.

4 | Results and Discussion

Utilizing hierarchical regression to present both direct and moderating effects results, as shown in Table 4. Notably, there are three sets of models for each outcome: Models 1, 4, and 7 serve as the base models (including only control variables); Models 2, 5, and 8 add the independent variables (BDA, AI, RP, TMS); and Models 3, 6, and 9 include interaction terms. Table 4 (Models 2, 5, and 8) indicates that BDA is positively associated with environmental performance ($B=0.155$, $pv<0.001$), social performance ($B=0.021$; $pv<0.001$) and economic performance ($B=0.103$, $pv<0.001$) of Chinese manufacturing firms. This supports H1a, H2b, and H1c suggesting that incorporating BDA into manufacturing firms in China enhances their ESE performance, thereby improving overall corporate sustainability performance. These findings can be explained by the RBV and DCV theories indicating that BDA acts not only as a valuable, rare, and inimitable resource but also as a dynamic capability that enables firms to reconfigure their operations, make informed decisions, and innovate in response to environmental and market changes. Notably, the findings validate previous studies that established positive effects of BDA on firms' sustainability performance (Cheng et al. 2023; Ertz et al. 2025; Jaouadi 2022; Jum'a et al. 2022; Lopes de Sousa Jabbour et al. 2025). Recently, Ertz et al. (2025) revealed that BDA has a positive and significant effect on the economic, social, and environmental dimensions of firms listed on the US SandP 500 Index and the Canadian SandP/TSX60 Index. We demonstrate that BDA is vital in emerging economies, especially China's rapidly evolving manufacturing sector, and is relevant in both technologically mature and transitioning industrial contexts. Based on both previous and our findings, we add novel empirical evidence to the ongoing debate on the nexus between BDA and firm sustainability performance, addressing a significant gap in studies examining how BDA is viewed as both a capability and a strategic resource contributes to the corporate sustainability of Chinese manufacturing firms. Overall, we suggest that manufacturing firms, particularly in emerging markets, should invest in BDA capabilities to enhance sustainability outcomes by optimizing efficiency and supporting ESEs.

In Table 4, H2a, H2b, and H2c showed positive and significant effects of AI on environmental ($B=0.389$, $pv<0.001$), social ($B=0.136$, $pv<0.001$), and economic ($B=0.148$, $pv<0.001$) (ESE) performance of Chinese manufacturing firms, consistent with previous studies (Acemoglu and Restrepo 2018; Chen et al. 2025; Dauvergne 2022; Goralski and Tan 2020; Kar et al. 2022; Vinuesa et al. 2020). This suggests that AI improves sustainability by automating processes, improving predictive capabilities, and enabling technological decision-making, enhancing agility, environmental responsiveness, and stakeholder engagement for sustainable growth (Lopes de Sousa Jabbour et al. 2025). Our findings support RBV and DCV theories, highlighting AI as a strategic resource and reconfigurable capability, enabling firms to respond to sustainability pressures, optimize resources, and continuously innovate (Barney 1991). AI can enhance manufacturing efficiency and sustainability by facilitating real-time decision-making, ensuring regulatory compliance, reducing waste, and improving ESG disclosures in global and Chinese manufacturing firms. We provide new evidence on AI's role in driving corporate sustainability performance, highlighting the underexplored relationship between ESE sustainability dimensions (Kopka and Grashof 2022). In national settings, the nexus between AI and sustainability performance is consistent across both emerging-developing countries like China, Pakistan, and Malaysia (Khan 2025; Rashid et al. 2025) and developed countries, including Qatar (Al Halbusi et al. 2025) and France (Lopes de Sousa Jabbour et al. 2025). AI is adaptable, improving resource efficiency, supply chain management, and integrating sustainability initiatives like real-time emissions tracking and carbon reduction strategies across various industries (Frank

TABLE 4 | Hierarchical results.

Variables	ENVP Model 1	ENVP Model 2	ENVP Model 3	SOCP Model 4	SOCP Model 5	SOCP Model 6	ECONP Model 7	ECONP Model 8	ECONP Model 9
Controls variables									
ME	0.189*** (3.009)	−0.145*** (0.672)	−0.046*** (0.666)	0.191*** (3.148)	0.697*** (0.803)	0.032***(0.845)	0.244*** (3.987)	1.526*** (0.761)	2.056*** (0.041)
MEP	0.193*** (3.162)	−0.029** (0.450)	−0.107*** (0.453)	0.183*** (3.016)	−0.040*** (0.537)	−0.011*** (−0.299)	0.143*** (2.323)	−0.732*** (0.509)	−1.504*** (0.134)
FS	0.100*** (1.436)	−0.017*** (0.610)	−0.238*** (0.610)	0.152*** (2.184)	1.392*** (0.728)	0.077*** (1.812)	0.065*** (0.931)	−0.313*** (0.690)	−0.820*** (0.413)
FA	−0.218*** (−0.134)	0.001*** (0.592)	0.067*** (0.587)	−0.239*** (3.458)	−0.632 (0.707)	−0.040 (−0.938)	−0.188*** (−0.693)	0.198*** (0.670)	0.261*** (0.794)
Main predictors									
BDA		0.155*** (1.049)	0.382*** (0.382)		0.021*** (0.316)	−0.681*** (0.179)		0.103*** (1.638)	−0.445*** (2.577)
AI		0.389*** (6.883)	0.477*** (0.477)		0.136*** (1.898)	0.352*** (0.145)		0.148*** (2.180)	0.361*** (2.586)
Moderators									
RP		0.255*** (4.040)	0.237*** (0.237)		0.231*** (2.894)	0.548*** (0.173)		0.217*** (2.866)	0.448*** (2.687)
TMS		0.274*** (4.787)	0.021*** (0.122)		0.493*** (6.796)	−0.457*** (0.195)		0.437*** (6.337)	−0.247*** (1.313)
Interaction terms									
BDA×RP			0.352*** (0.474)			0.078*** (0.938)			0.341 (0.392)***
AI×RP			0.493*** (0.570)			1.099*** (0.273)			0.618 (0.610)***
BDA×TMS			0.844*** (1.448)			2.907*** (0.004)			1.937*** (2.835)
AI×TMS			0.347*** (0.510)			0.134*** (0.893)			0.449*** (0.563)
Constant	15.274*** (28.619)	−0.140*** (−0.227)	2.261*** (1.143)	15.671*** (29.290)	3.133*** (4.232)	9.147*** (4.050)	15.435*** (28.657)	2.228*** (3.178)	5.486*** (2.514)

(Continues)

TABLE 4 | (Continued)

Variables	ENVP Model 1	ENVP Model 2	ENVP Model 3	SOCP Model 4	SOCP Model 5	SOCP Model 6	ECONP Model 7	ECONP Model 8	ECONP Model 9
Model summary									
Adj R^2	0.105	0.212	0.788	0.144	0.648	0.689	0.097	0.683	0.708
R^2	0.199	0.780	0.787	0.127	0.659	0.703	0.112	0.692	0.721
ΔR^2	0.199	0.668	0.519	0.127	0.532	0.405	0.110	0.582	0.229
Obs	220	220	220	220	220	220	220	220	220

Note: Standardized regression coefficients (β) are presented. Models are built hierarchically, with controls entered first, followed by independent and moderating variables. All variables are mean centered before creating interaction terms. Significance levels:
Abbreviations: FA = firm age; FS = firm size; ME = managers' education; MEP = managers' experience; RP = regulatory pressure; TMS = top management support.
***= $p < 0.01$ significance value. ENVP, SOCP, and ECONP denote environmental, social, and economic performances respectively.

2021). Therefore, our paper suggests that AI can serve as a technological enabler and a sustainability catalyst, enabling firms to meet operational and societal demands, future-proof operations, and enhance long-term value creation.

H3a, H3b, and H3c and H4a, H4b, and H4c were supported indicating that AI and BDA effects on firms' ESE performance are positively and significantly moderated by regulatory pressure (see Table 4). This suggests that external institutional forces like government regulations, environmental laws, and policy incentives significantly enhance the effectiveness of digital technologies in promoting sustainability outcomes (Liao 2018; Zhang et al. 2020). Specifically, our results of RP positively and significantly moderating BDA effects on ESE indicate that regulations can encourage firms to enhance their data analytics capabilities for sustainable transformation. For example, the Chinese government's "Made in China 2025" initiative and carbon neutrality pledges are promoting greener practices and digital technologies performance tracking among firms (Miao et al. 2025; Zhang et al. 2024). BDA is a tool that efficiently monitors environmental performance indicators, predicts sustainability risks, optimizes resource allocation, and produces precise sustainability reports that meet governmental standards. Similarly, our results suggest that firms are incorporating AI solutions to exceed regulations requiring higher standards for social responsibility, environmental compliance, and economic transparency. In China, high RP in electronics, automotive, and chemical manufacturing sectors prompts firms to invest in AI for carbon monitoring, predictive maintenance, and AI-driven workforce safety systems (Zhu et al. 2007). Globally, AI is being increasingly utilized in Europe and North America for ESG reporting, supply chain visibility, and automated sustainability auditing. Therefore, we suggest that manufacturing companies should view regulatory pressure as a catalyst for innovation and sustainable transformation, motivating strategic deployment of BDA and AI capabilities for performance gains. While previous studies have examined the impact of institutional and regulatory pressure on sustainability and technology innovation, existing literature offers limited insights into how such pressures moderate the relationship between emerging technologies and sustainability outcomes. Therefore, we provide new empirical evidence on the moderating role of regulatory pressure in the AI and BDA–CSP nexus, guided by IT, RBV, and DCV, complementing the existing literature. We highlight that firms respond more effectively to sustainability challenges when they align their technological capabilities with institutional expectations, driving competitive advantage and environmental stewardship.

Finally, our results confirmed both (H5a, H5b, H5c) and (H6a, H6b, H6c) indicating that AI and BDA influence on firms' ESE performance is positively and significantly moderated by TMS. This suggests that top management's strong commitment and involvement are crucial for firms to effectively utilize digital technologies for sustainability transformation. Top management's strategic direction, resource allocation, and digital innovation can significantly improve the effectiveness of AI and BDA in achieving sustainability objectives. Particularly, the positive relationship between BDA and sustainability performance under TMS suggests that successful BDA initiatives are more successful when integrated into the company's strategic vision. Indeed, top leaders can promote collaboration across departments, technological decision-making, and analytics investments that align with ESE goals (Wilms et al. 1994). This support is highly influential in Chinese manufacturing firms, where hierarchical leadership structures are prevalent. For instance, leadership endorsement can facilitate the implementation of BDA systems for energy consumption tracking, supply chain emission optimization, and stakeholder reporting enhancement. Similarly, the positive moderating role of TMS on the relationship between AI and sustainability performance validates successful implementation of AI tools such as predictive analytics, machine learning algorithms, and natural language processing tools for waste reduction and ESG reporting transparency. Top managers who prioritize sustainability are likely to encourage employees to adopt AI-driven initiatives, thereby integrating sustainability into the organization's culture and processes. Notably, our research supports RBV and DCV theories, highlighting the importance of top management in transforming digital resources like BDA and AI into strategic capabilities for sustainable competitive advantage. Top management drives technological impact by fostering innovation, ensuring capability development, and aligning technology use with sustainability goals. Therefore, we show that TMS is vital for maximizing the sustainability benefits of AI and BDA, promoting digital sustainability training, and establishing governance structures.

The results confirmed the main hypotheses and revealed several nuanced findings. Notably, Models 6 and 9 reveal a significant negative direct effect of BDA on social and economic performance (Model 6: $\beta=-0.681$, $p<0.001$; Model 9: $\beta=-0.445$, $p<0.001$). While BDA had a positive effect in earlier models, these results reflect its impact when TMS is at its mean, due to the inclusion of interaction terms in the full models. This suggests that BDA, when implemented without adequate strategic alignment or leadership backing, may fail to generate social and economic value. This aligns with prior research indicating that BDA adoption is resource-intensive, requiring not only technical infrastructure but also managerial capabilities to convert data into actionable insights. Without such support, firms may experience fragmented implementation, inefficiencies, or even negative stakeholder perceptions.

Further insight emerges from the role of TMS. Interestingly, TMS also shows a negative direct effect in both Model 6 ($\beta=-0.457$, $p<0.001$) and Model 9 ($\beta=-0.247$, $p<0.001$). This indicates that TMS, when not integrated with a robust digital strategy like BDA, may not improve performance and may potentially lead to overconfidence, resource misallocation, or operational goal misalignment. However, the positive interaction effects between BDA and TMS in both models suggest that TMS enhances the benefits of BDA when used together. This reinforces the argument that TMS is not inherently performance-enhancing in isolation, but functions as a critical enabler when aligned with digital technologies. These findings underscore the significance of strategic coherence in BDA's sustainability, highlighting the need for a capable top management team to ensure seamless integration across organizational functions and priorities.

In addition, our results show that RP has significant and positive effects across sustainability dimensions (ENVP: $\beta=0.255$, $pv=<0.001$), (SOCP: $\beta=0.231$, $pv=<0.001$), (ECONP: $\beta=0.217$, $pv=<0.001$), indicating that regulatory frameworks significantly influence organizations toward sustainable practices by fostering compliance and accountability. Firms are encouraged to adopt sustainable practices to avoid legal penalties and enhance their legitimacy. Our study supports IT, indicating that external pressures, especially from regulatory bodies, can positively influence organizations' compliance with sustainability standards, thereby enhancing environmental strategies and outcomes (Delmas and Toffel 2008). Moreover, TMS shows robust positive correlations across all sustainability dimensions, suggesting that effective leadership is vital for integrating sustainability into organizational strategy, enabling firms to mobilize resources, foster innovation, and drive performance across ESE domains. The study supports the RBV, emphasizing the importance of internal capabilities like leadership support in efficiently utilizing resources and achieving strategic goals. TMS demonstrates the leadership's commitment to integrating sustainability into the company's culture and strategic vision. We reveal that internal drivers, rather than external factors, are crucial in promoting socially responsible practices like employee well-being and community engagement.

Our control variables analysis offers valuable insights into the factors influencing a firm's sustainability performance dimensions. First managerial education consistently shows a strong and positive influence on sustainability performance across all models, indicating that higher educational attainment among managers is linked to improved sustainability practices, socially responsible behavior, and economic outcomes in a firm. The study emphasizes the significant role of cognitive and analytical skills, often linked to formal education, in strategic decision-making and innovation adoption. Managerial experience generally has a positive effect, although it has slightly lower magnitudes, indicating that experiential knowledge can enhance performance, but it may not be as influential as formal education, especially in dynamic or technology-driven environments. Additionally, our results reveal that firm size significantly impacts all three performance dimensions, with the most significant effect observed in social performance. Our study suggests that large firms are likely better resourced, more visible to stakeholders, and subject to greater regulatory and societal scrutiny, which may compel them to prioritize both environmental and social initiatives. However, the impact of size on economic performance is less pronounced, suggesting potential inefficiencies or diminishing returns to scale in larger organizational structures. However, our results indicate that firm age negatively impacts performance, particularly in the social and economic sectors. Older firms may be experiencing structural inertia, resistance to change, or outdated operational practices, which hinder their ability to adapt to changing stakeholder expectations or integrate new technologies. We suggest that firm maturity, while offering experience, may also decrease agility, potentially affecting overall performance negatively.

4.1 | Robustness Analysis

To ensure the robustness of our findings, we employed partial least squares structural equation modelling (PLS-SEM) as an alternative estimation technique. Recognized as a robust technique in the literature (Bonsu et al. 2025), PLS-SEM enables us to validate the consistency of the results derived from our primary analysis. As reported in Table 5, our PLS-SEM results validate our previous findings, thereby confirming the robustness of the relationships explored in this study. Specifically, the results show that both BDA and AI have statistically significant positive effects on ESE performance. Furthermore, the interaction terms (BDA×RP, AI×RP, BDA×TMS, and AI×TMS) also evidenced significant moderating effects, supporting the hypothesis that regulatory pressure and TMS strengthen the impact of BDA and AI on corporate sustainability performance dimensions of manufacturing firms in China. Thus, our findings confirm the robustness of our results across different analytical methods, reinforcing the validity of our conclusions.

4.2 | Additional Analysis

Our study conducted additional analysis to investigate the industry-specific variations in the impact of digital technologies on sustainability. First, we categorize the sample into three key manufacturing sectors: chemical, electronics, and automotive. This approach offers a comprehensive understanding of how BDA and AI, with regulatory pressure and TMS, impact ESE performance in various industrial contexts. Using regression analysis as reported in Table 6, the electronics sector demonstrated the strongest and most consistent positive effects of AI on all sustainability performance dimensions. Specifically, AI showed significant and positive improvements in environmental ($\beta = 0.145$), social ($\beta = 0.049$), and especially economic ($\beta = 0.570$) performance. Interaction effects such as AI×RP *and* AI×TMS also showed moderate yet meaningful impacts, indicating that firms in this sector are not only technologically mature but also more agile in aligning digital innovation with regulatory and managerial support. These findings suggest that electronics firms are well-positioned to exploit AI for driving sustainability, owing to their strong digital infrastructure and innovation-oriented culture. Practically, this indicates that managerial focus should be on scaling AI initiatives like smart production, energy optimization, and automated sustainability reporting, with policy opportunities to amplify these gains through targeted incentives and harmonized data-sharing frameworks.

TABLE 5 | Robustness test.

Hypothesis		ENVP	SOCP	ECONP
H1a, H1b, H1c	BDA	0.187 (4.239)***	0.221 (4.081)***	0.272 (5.475)***
H2a, H2b, H2c	AI	0.744 (16.888)***	0.656 (12.174)***	0.619 (12.530)***
H3a, H3b, H3c	BDA×RP	0.025 (3.060)***	0.542 (4.043) ***	0.260 (3.814)***
H4a, H4b, H4c	AI×RP	0.036 (3.417)***	0.056 (4.426)***	0.815 (4.389)***
H5a, H5b, H5c	BDA×TMS	0.026 (3.886)***	1.405 (3.900)***	0.029 (3.848)***
H6a, H6b, H6c	ATM×TMS	0.021 (2.477)	0.032 (3.102)	0.154 (3.3109)***
R^2		0.781	0.642	0.687
Obs		220	220	220

Note: This table reports robustness tests using partial least squares structural equation modeling (PLS-SEM). Standardized coefficients (β) are reported, with *t*-statistics shown in parentheses.
***represents significance at $p < 0.01$. ENVP, SOCP, and ECONP denote environmental performance, social performance, and economic performance.

TABLE 6 | Firm types of results.

	Chemical ($N = 69$)			Electronics ($N = 80$)			Automotive ($N = 71$)		
Variables	**ENVP**	**SOCP**	**ECONP**	**ENVP**	**SOCP**	**ECOP**	**ENVP**	**SOCP**	**ECONP**
BDA	0.027***	0.042**	0.068***	0.134***	0.035***	0.474***	0.272**	0.082***	0.077***
AI	0.011***	0.244***	0.035***	0.145***	0.049***	0.570***	0.619***	0.017***	0.176***
BDA*RP	0.021***	0.061***	0.054***	0.173***	0.084***	0.122***	0.260***	0.018***	0.053***
AI*RP	0.027***	0.117***	0.457***	0.134***	0.034***	0.045***	0.815***	0.021***	0.062***
BDA*TMS	0.126***	0.226***	0.681***	0.015***	0.035***	0.074***	0.029***	0.018***	0.054**
AI*TMS	0.030***	0.121***	0.352***	0.014***	0.014***	0.071***	0.154***	0.015***	0.046***
R^2	0.18	0.22	0.17	0.11	0.32	0.21	0.13	0.11	0.12
Obs		69			80			71	

Note: This table presents regression analysis results by firm type. For brevity, only standardized coefficients (β) are reported. Significance levels:
Abbreviations: RP = regulatory pressure; TMS = top management support.
***,
**, and
*= $p < 0.01$, 0.05, and 0.10, respectively. ENVP, SOCP, and ECONP denote environmental performance, social performance and economic performance.

In the automotive sector, both BDA and AI showed consistently positive effects across all sustainability dimensions. However, AI had a strong effect on environmental ($\beta = 0.619$) and economic ($\beta = 0.176$) performances. Additionally, the moderating effects showed significant interactions, reflecting that the effectiveness of digital tools is further enhanced by external regulatory frameworks and internal leadership commitment, suggesting that the automotive industry is increasingly utilizing BDA and AI for compliance, operational efficiency, and innovation. This advocates for continuous investment in digital twins, predictive analytics, and lifecycle carbon tracking systems, while urging policymakers to enforce digital sustainability standards and support AI-enabled automotive manufacturing.

The chemical sector showed some minor positive impacts of BDA and AI on sustainability outcomes, but these effects were generally modest. Notably, the interaction between AI and regulatory pressure on economic performance was positive, suggesting that the adoption of AI can potentially yield economic benefits in conservative industries, provided it is regulated appropriately. However, the overall limited impact across sustainability dimensions suggests that the chemical sector faces challenges in effectively utilizing digital technologies due to complex regulatory requirements, low digital maturity, and risk-averse organizational cultures. From a practical standpoint, chemical firms need to improve their digital readiness through tailored training, phased modernized technologies strategies, and cross-functional leadership to drive cultural and technological changes. Overall, our findings emphasize the significance of considering context when implementing digital technologies for sustainability. We argue that AI and BDA's effectiveness vary significantly across sectors due to differences in digital maturity, regulatory alignment, and managerial support. Thus, both practitioners and policymakers should develop sector-specific strategies to maximize the transformative potential of digital innovation in the manufacturing sector.

Second, we utilized PLS-SEM to analyze firms' size, categorizing firms into micro and small, medium, and large, providing insights into the impact of BDA and AI on ESE performance and their interactions with RP and TMS. In China, the Ministry of Industry and Information Technology and related authorities officially classify manufacturing enterprises based on factors like employee count and annual revenue (National Bureau of Statistics of China 2022). According to the prevailing standards, large manufacturing enterprises employ over 1000 people and generate 400 million RMB annually, while medium-sized enterprises have 300–999 employees and 20–400 million RMB annual revenues. Small enterprises, with 20–299 employees and annual revenues ranging between 3–20 million RMB, and micro enterprises with fewer than 20 employees, generate less than 3 million RMB. The classifications aid in statistical analysis, policymaking, and determining eligibility for government support programs, varying slightly by manufacturing subsector. From Table 7, both BDA and AI had weak and statistically insignificant effects on the sustainability performance of smaller firms, with only the connection between BDA and economic performance being significant ($\beta = 0.051$, $p = 0.039$), indicating that smaller businesses may face challenges in fully utilizing digital technologies due to limited resources, expertise, or digital infrastructure. The absence of significant moderation effects suggests a weaker alignment of regulatory or managerial enablers with technological integration. However, medium-sized firms established moderate improvements, particularly in the social sustainability performance. For instance, BDA significantly influenced social performance ($\beta = 0.081$, $pv = 0.043$),

TABLE 7 | Firm size results.

	Micro and small (<299)		Medium (300–999)		Large (>1000)	
Hypothesis	**β coefficient**	***p***	**β coefficient**	***p***	**β coefficient**	***p***
BDA → ENVP	0.027	0.123	0.043	0.251	0.121	0.201
BDA → SOCP	0.014	0.077	0.081	0.043	0.048	0.041
BDA → ECONP	0.051	0.039	0.093	0.111	0.192	0.005
AI → ENVP	0.081	0.119	0.042	0.079	0.087	0.018
AI → SOCP	0.041	0.073	0.066	0.041	0.061	0.017
AI →ECONP	0.033	0.086	0.022	0.072	0.103	0.009
BDA × RP → ENVP	0.028	0.154	0.048	0.091	0.127	0.019
AI × RP → ECONP	0.016	0.201	0.098	0.031	0.133	0.007
BDA × TMS → SOCP	0.061	0.073	0.094	0.017	0.157	0.002
AI × TMS → ECONP	0.049	0.088	0.085	0.034	0.196	0.001
Obs	91		59		70	

Note: This table presents PLS-SEM results by firm size.
Abbreviations: AI = artificial intelligence; BDA = big data analytics; ECONP = economic performance; ENVP = environmental performance; Obs = number of observations; RP = regulatory pressure; SOCP = social performance; TMS = top management support.
***,
**, and
*denotes $p < 0.01$, $p < 0.05$, and $p < 0.10$ significance, respectively.

while AI also demonstrated a significant relationship ($\beta = 0.066$, $pv = 0.041$). Additionally, the interaction of AI with RP positively impacted economic performance, demonstrating the growing capacity of mid-sized firms to adapt and benefit from structured governance. The study indicates that medium-sized firms are currently in a transitional phase, and enhanced managerial support and policy alignment could significantly enhance their digital sustainability outcomes. Large firms showed the most consistent positive impacts of AI on ESE performance across all sustainability dimensions. Moreover, the moderating effects of RP and TMS were more pronounced in all groups. For instance, the interaction of BDA and regulatory pressure significantly impacted environmental outcomes, while AI and RP significantly enhanced economic performance ($\beta = 0.133$, $p = 0.007$). Similarly, the interaction of BDA with TMS significantly boosted social performance ($\beta = 0.157$, $p = 0.002$), while AI with TMS had a notable impact on economic outcomes ($\beta = 0.196$, $p = 0.001$). These results suggest that large firms possess the necessary digital maturity, regulatory integration, and leadership structures to effectively utilize BDA and AI for sustainability (Table 7).

Our findings emphasize the need for size-specific strategies to promote digital sustainability. Small firms need training, financial subsidies, and digital infrastructure for BDA and AI potential, while medium-sized firms can align technology with sustainability goals through targeted interventions and governance mechanisms. Meanwhile, large manufacturing firms should utilize their advanced capabilities while also leading in implementing industry-wide innovations and sharing best practices.

Finally, we performed a regional difference since we collected data from three regions in China: Jiangsu, Zhejiang and Shanghai. Our results show distinct patterns in how BDA and AI influence sustainability outcomes across these regions (See Table 8). Overall, firms in Shanghai exhibited the strongest and most consistent positive effects, with significant coefficients across all sustainability dimensions. For instance, AI showed a notable impact on environmental ($\beta = 0.105$, $pv = 0.002$), social ($\beta = 0.084$, $pv = 0.001$), and economic performance ($\beta = 0.112$, $p = 0.001$), while the interaction of AI with regulatory pressure significantly enhanced economic outcomes ($\beta = 0.147$, $p = 0.002$). Similarly, BDA and its interactions with both regulatory pressure and TMS had the highest effect sizes in Shanghai (e.g., BDA × RP → ENV: $\beta = 0.139$, $p = 0.004$; BDA × TMS → SOC: $\beta = 0.159$, $p = 0.001$) (Table 8). These results suggest that firms in Shanghai may benefit from advanced digital infrastructure, mature regulatory environments, and robust managerial capabilities, making it a potential digital innovation hub.

In Zhejiang, we found consistently positive and significant effects, with moderate magnitudes. BDA had a stronger economic relevance ($\beta = 0.099$, $pv = 0.001$), while AI significantly affected both social ($\beta = 0.045$, $pv = 0.001$) and economic outcomes ($\beta = 0.067$, $pv = 0.001$). The region also showed responsiveness to institutional enablers, as evidenced by the significance of interactions like AI × RP → ECON ($\beta = 0.043$, $pv = 0.001$) and BDA × TMS → SOC ($\beta = 0.072$, $pv = 0.002$). These findings suggest that an adaptable digital ecosystem can improve firms' capacity to leverage technological investments through institutional alignment.

In Jiangsu, all paths were significant, but effect sizes were generally lower. The AI → ENV path had a significant coefficient of ($\beta = 0.034$, $p = 0.001$), while the AI × RP → ECON showed the weakest effect with ($\beta = 0.016$, $p = 0.004$) (See Table 8). This indicates that firms in Jiangsu are adopting digital technologies, but their transformation may be nascent or hindered by factors like industry structure, regulatory

TABLE 8 | Regional test results.

	Jiangsu ($N = 72$)		Zhejiang ($N = 68$)		Shanghai (N = 80)	
Hypothesis	**β coefficient**	***p***	**β coefficient**	***p***	**β coefficient**	***p***
BDA → ENV	0.051	0.001	0.041	0.001	0.089	0.001
BDA → SOC	0.045	0.001	0.076	0.001	0.095	0.005
BDA → ECON	0.063	0.001	0.099	0.001	0.122	0.001
AI→ENV	0.034	0.001	0.043	0.001	0.105	0.002
AI→SOC	0.043	0.001	0.045	0.001	0.084	0.001
AI→ECON	0.052	0.003	0.067	0.001	0.112	0.001
BDA × RP → ENV	0.054	0.001	0.036	0.001	0.139	0.004
AI×RP → ECON	0.016	0.004	0.043	0.001	0.147	0.002
BDA × TMS → SOC	0.078	0.003	0.072	0.002	0.159	0.001
AI × TMS → ECON	0.069	0.002	0.044	0.001	0.182	0.001
Obs	72		68		80	

Note: This table presents test results by region.
Abbreviations: AI = artificial intelligence; BDA = big data analytics; ECONP = economic performance; ENVP = environmental performance; Obs = number of observations respectively; RP = regulatory pressure; SOCP = social performance; TMS = top management support.
***and
**
*denotes $p < 0.01$, $p < 0.05$, and $p < 0.10$ significance, respectively.

constraints, or inadequate digital capabilities. From a practical standpoint, these results underline the importance of regional tailoring in digital sustainability strategies. Shanghai firms can lead sustainable innovation by leveraging digital maturity, while Zhejiang firms can accelerate momentum through cross-sector partnerships, institutional support, and targeted interventions.

4.3 | Endogeneity Test

We utilized a two-stage least squares (2SLS) instrumental variable approach to examine the potential endogeneity in the relationship between digital capabilities and sustainability outcomes. Many studies reveal that organizations frequently incorporate Fintech, like AI and BDA, into their daily business operations (Bonsu et al. 2025; Ghouri et al. 2022; Hu and Pan 2023). The research utilized a previous method to identify instrumental variables, focusing on AI-BDA routine use, ensuring exogenous conditions and selection rules are considered (Bonsu et al. 2025; Chen et al. 2021; Lin et al. 2024). First, regular use of AI/BDA in business influences decision-making by manufacturing companies and employees for problem-solving and innovation (Bonsu et al. 2025). Second, AI-BDA are primarily utilized for managing structured business tasks, but they can also be utilized to enhance sustainability performance within companies. This suggests that routine use of AI-BDA does not directly influence the ESE performance of firms. In the first stage, the routine use of AI-BDA technologies was used to predict firms' AI-BDA capabilities. The instrument demonstrated strong explanatory power, with a coefficient of 0.65 ($t=6.5$, $p<0.001$), and the first-stage F-statistic of 42.3 far exceeded the conventional threshold of 10 (Table 9), confirming instrument strength and mitigating concerns of weak instrumentation. In the second stage, the predicted values of AI-BDA were significantly associated with all three dimensions of sustainability. For environmental sustainability, the coefficient was ($B=0.42$, $p=0.0002$), indicating a robust and positive relationship. Similarly, social sustainability improved with AI/BDA capabilities ($\beta=0.30$, $p=0.034$), although the magnitude of this effect was comparatively smaller. The strongest effect was observed on economic sustainability, where the coefficient reached ($B=0.50$, $p<0.001$), emphasizing the financial benefits of advanced digital capabilities. These estimates were adjusted for relevant control variables (e.g., firm size, sector, and region), although their coefficients are omitted here for brevity. The overidentification test ($Chi^2=1.25$, $p=0.26$) validated the validity of the instrument, suggesting that the instrument is not linked to the error term in the second-stage regression due to the exclusion restriction in place.

5 | Conclusions

This study constitutes a pioneering effort in employing a unified empirical model to examine the relationships among key constructs using data from 220 manufacturing firms in China. Grounded in the DCV, RBV and IT, our findings indicate that both BDA and AI have a positive and significant effect on firms' ENVP, SOCP, and ECONP, collectively contributing to corporate sustainability performance. Furthermore, we uncover that RP serves as a significant positive moderator, strengthening the impact of BDA and AI on firms' ENVP, SOCP, and ECONP outcomes. Similarly, we demonstrate that TMS significantly enhances the impact of BDA and AI on ENVP, SOCP, and ECONP. By integrating BDA and AI within a multi-theoretical framework, we highlight the importance of regulatory environments and management commitment in enhancing the benefits of digital technologies for sustainable value creation. We offer practical guidance for managers to utilize digital capabilities for sustainability and encourage policymakers to establish supportive institutional frameworks for responsible technological adoption in high-impact industries.

5.1 | Theoretical Relevance

Our research provides relevant and novel academic contributions to the literature. First, while literature has extensively examined BDA effects on firm performance and sustainability (Ertz et al. 2025; Lopes de Sousa Jabbour et al. 2025), limited empirical evidence exists on how BDA, as a capability and resource, contributes to corporate sustainability transformations, especially in Chinese manufacturing firms amidst increasing environmental regulations and stakeholder expectations. Thus, we address the gap, demonstrating that manufacturing firms' BDA capabilities and resources enhance sustainability outcomes by optimizing efficiency and supporting ESE goals.

Second, we explore the influence of AI on sustainability performance in manufacturing firms in China, contrasting previous

TABLE 9 | Endogeneity tests.

Model stages		B	Std. error	t-stat	p
First stage	Routine use of AI-BDA → AI/BDA	0.655	0.123	6.521	0.001
Second stage	Predicted AI-BDA → ENVP	0.427	0.115	3.821	0.002
Second stage	Predicted AI-BDA → SOCP	0.361	0.149	2.144	0.034
Second stage	Predicted AI-BDA → ECONP	0.571	0.12	4.17	0.001
Diagnostics	First stage F-statistic	42.3			
Overidentification test			$Chi^2=1.25$		0.26

Note: This table presents the results of the two-stage least squares (2SLS) regression, including endogeneity and overidentification tests. Significance levels:
***,
**, and
*suggest $p<0.01$, $p<0.05$, and $p<0.10$, respectively.

research on AI impact sustainability improvements (Chen et al. 2025; Lopes de Sousa Jabbour et al. 2025; Shan et al. 2025). Notably, research calls for empirical scholarship on whether corporate sustainability performance could be improved by AI (Asokan et al. 2022; Dauvergne 2022; Khakurel et al. 2018). Thus, we highlight the significant positive impact of AI on the ESE sustainability performance of manufacturing firms, filling observed gaps in existing literature. Particularly, we provide insights on how Chinese manufacturing firms are utilizing AI to promote efficiency, sustainable innovation, and align with global sustainability objectives, demonstrating their transformative potential in emerging economies.

Third, previous studies have explored the influence of institutional and regulatory pressure on sustainability and innovation (Jin et al. 2024), but current literature lacks understanding of how regulatory pressure influences the relationship between emerging technologies and sustainability outcomes. Therefore, we confirm that combining technological capabilities with institutional expectations can enhance sustainability, provide a competitive edge, and promote environmental stewardship among firms. In addition, studies on the moderating role of TMS in BDA-AI adoption and corporate sustainability performance are limited, especially in China, considering its hierarchical organizational structures and cultural dynamics. Our study addresses this gap, validating that TMS is vital for maximizing the sustainability benefits of AI and BDA, expanding the ESE performance of Chinese manufacturing firms. Finally, we explore how regulatory pressure and TMS influence the impact of BDA and AI on the sustainability of manufacturing firms, expanding the institutional, DCV and RBV theories. The study highlights the significance of external regulation and internal leadership in transforming digital capabilities into sustainable outcomes, emphasizing the strategic value of aligning resources with institutional demands. Our study presents a novel framework for practitioners and policymakers to effectively utilize BDA and AI, backed by regulation and leadership, for sustainable manufacturing transformation.

5.2 | Practical Implications

Our findings have significant implications for practice. First, we establish that both BDA and AI are positively and significantly enhancing corporate sustainability performance. Therefore, managers of manufacturing firms should prioritize the strategic integration of these technologies into their application. This includes investment in AI-driven systems for energy efficiency, predictive maintenance, waste reduction, and utilizing BDA for real-time monitoring of environmental performance. Specifically, (1) Electronics firms should focus on integrating digital innovation functions, automating ESG reporting, and utilizing AI for real-time energy management. (2) Automotive manufacturers should integrate AI initiatives with circular economy goals by utilizing digital twins and lifecycle analytics. (3) Chemical firms with lower digital maturity need a phased transformation involving foundational digital infrastructure, workforce reskilling, and risk-reduction frameworks. Small enterprises need low-cost cloud-based BDA and AI platforms, medium-sized firms are integrating digital tools with governance, and large firms are piloting AI-based sustainability solutions as innovation hubs.

Second, we highlight the importance of TMS in interacting with BDA and the AI impact on sustainability performance. This emphasizes the necessity for senior leaders to support digital transformation, provide adequate resources, and cultivate a culture that prioritizes data-driven decision-making for sustainability. In practice, top managers must approve investments in AI and BDA while also offering visible leadership, establishing clear sustainability targets, and encouraging departmental collaboration. Manufacturing firms in China can successfully achieve environmental and operational performance goals by aligning technological capabilities with leadership commitment in response to the changing regulatory environment.

Finally, our findings indicate that regulatory pressure enhances the positive impact of AI and BDA on corporate sustainability, suggesting that manufacturing firms in China should see regulations as strategic catalysts for digital and sustainability transformation. Thus, managers must align AI and BDA initiatives with environmental standards and sustainability requirements to ensure compliance, drive innovation, and enhance long-term competitiveness. Firms that adapt proactively to regulatory changes leverage data and AI insights, improving their ability to meet targets, reduce risks, and obtain green financing or government incentives.

5.3 | Policy and Social Implications

Alongside the practical insights, we provide both policy and social practice implications. First, governments should establish regulatory frameworks that promote sustainability standards and foster digital innovation. The initiative aims to promote the adoption of BDA and AI in sustainability-driven projects through tax incentives, grants, and public funding mechanisms. In addition, policymakers should use digital sustainability maturity indices and sectoral audits to assess progress, pinpoint inefficiencies, and improve intervention strategies. These tools assist businesses in identifying digital capability gaps, resource inefficiencies, and compliance issues, offering tailored interventions like subsidies, technical support, and regulatory updates based on their digital and sustainability maturity levels. Second, government can enhance transparency, reporting, and sustainability in manufacturing by implementing AI and BDA exemplified by initiatives such as China's Made 2025 and carbon neutrality objectives. Policymakers should promote the adoption of AI and BDA among firms to enhance resource optimization, emissions tracking, and real-time monitoring. This convergence enhances China's industrial sector's global competitiveness and regulatory adherence, while accelerating its move toward carbon neutrality.

Third, we highlight that national frameworks for data governance, AI ethics, and sustainability reporting standards can help firms scale their digital sustainability efforts responsibly and uniformly. Establishing clear guidelines for the moral application of AI and sustainability data accuracy will ensure compliance across industries and build stakeholder confidence. These guidelines support businesses in harmonizing innovation with responsibility by integrating AI and BDA into essential manufacturing processes that promote environmental sustainability and national development objectives.

Fourth, firms should promote digital sustainability through proactive workforce development strategies, especially in low-tech and small-scale manufacturing sectors. This includes cross-functional training, digital literacy initiatives, and reskilling programs designed to promote innovation and shared responsibility across all organizational levels. Governments and business leaders must focus on digital inclusion to guarantee fair access to digital resources, infrastructure, and education. This is important to inhibit increasing socioeconomic disparities and to allow all workers and regions to engage in the changes brought about by AI and BDA.

Finally, firms need to confirm that AI-driven decisions are transparent, equitable, and responsible to maintain public confidence and regulatory approval. Through predictive analytics and customized interventions, AI-powered systems enhance workplace safety, optimize resource allocation, and promote employee well-being, contributing to the social and environmental aspects of sustainability.

5.4 | Limitations and Further Studies

Despite the valuable results, we encountered the following limitations. First, we used cross-sectional data from a questionnaire survey conducted among Chinese manufacturing firms, suggesting the potential for longitudinal research to enhance its applicability. Additionally, we focus on managers' insights rather than objectivity, despite our careful operationalization of the item design to improve the indicators' validity and reliability. Thus, utilizing more objective data sets may be more interesting to forecast the effects of BDA and AI on sustainability. Finally, we investigate the influence of AI and BDA on sustainable performance, suggesting further research on integrating digital technologies like blockchain in supply chain tracking for enhanced transparency.

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