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The Impact of Artificial Intelligence Adoption Intensity on Corporate Sustainability Performance: The Moderated Mediation Effect of Organizational Change

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Abstract: With the rapid development of the economy and society, enterprises are increasingly prioritizing environmental and social sustainability alongside economic benefits. As a critical driver of technological innovation, the effective application of artificial intelligence (AI) to enhance corporate sustainability performance has garnered considerable attention from both academia and industry. This study explores the impact of AI adoption intensity on corporate sustainability performance, with a particular focus on the mediating role of organizational change and its moderated mediation effect. Employing an empirical analysis approach, this study collected 451 employee survey responses from manufacturing enterprises. The results indicate that AI adoption intensity substantially enhances corporate sustainability performance, reflected in comprehensive improvements in economic, environmental, and social benefits. Furthermore, organizational change serves as a crucial mediator between AI adoption and sustainability performance, with this mediation effect moderated by internal and external environmental factors. The study finds that enterprises with high digital capabilities and innovative cultures are more effective in leveraging AI to enhance sustainability performance. This suggests that in promoting AI applications, enterprises should not only focus on technology adoption but also emphasize internal organizational change and the development of digital capabilities to fully achieve sustainability goals. Through empirical analysis, this study provides an in-depth understanding of the application paths and mechanisms of AI in corporate sustainability, offering a theoretical foundation and practical guidance for corporate managers in strategy and policymaking.

Keywords: artificial intelligence adoption intensity; corporate sustainability performance; organizational change; digital capability

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1. Introduction

In recent years, the focus of global leadership and business management has shifted from mere economic growth to a more comprehensive pursuit of sustainability, particularly in environmental and social domains [1]. Initiatives like the United Nations' "2030 Agenda for Sustainable Development" call for nations and industries to adopt sustainable practices across all levels of production and consumption. As a major contributor to economic stability, manufacturing plays a pivotal role in achieving these goals, particularly in China, where the sector is a cornerstone of the economy [2]. To foster high-quality development, manufacturing enterprises must integrate both environmental and social responsibilities into their business operations [3]. Concurrently, the digital economy is reshaping industries, with artificial intelligence (AI) emerging as a transformative technology that can enhance innovation, efficiency, and sustainability across sectors [4]. This is particularly relevant for traditional large-scale manufacturing industries in China, which are essential for integrating the digital and real economies [5]. AI adoption is becoming crucial in driving corporate sustainability, offering tools to optimize operations, reduce costs, and

strengthen competitive advantages [6]. Despite its promise, research into the specific intersection of AI adoption and sustainability remains limited, particularly regarding how AI adoption intensity influences corporate sustainability performance during organizational transformations [7].

The existing literature largely focuses either on AI or sustainability in isolation, without exploring their intersection in depth [8–10]. This leaves a significant gap in understanding how AI adoption intensity drives sustainability outcomes, especially in the context of organizational change [11,12]. There is a need to examine how AI adoption can foster corporate sustainability by enhancing both operational efficiency and environmental and social performance. Additionally, there is limited research on how digital capabilities moderate this relationship, making it critical to explore their combined effects on corporate sustainability [13–15].

Based on the research background, this study addresses these research questions by posing the following key questions. First, how does AI adoption intensity influence corporate sustainability performance, and what mechanisms drive this relationship? Second, how does organizational change mediate the relationship between AI adoption intensity and corporate sustainability performance? Third, how do digital capabilities moderate the effect of AI adoption intensity on organizational change and, subsequently, on sustainability performance? In presenting these research questions, the main objectives of this study are as follows. We aim to identify the level of AI adoption intensity in the Chinese organizational context and to clarify the causal relationship through its impact on corporate sustainability performance. In addition, we do not simply verify the impact of AI adoption intensity on corporate sustainability performance, but rather clarify the process of how corporate sustainability performance is induced. In this regard, we aim to clarify the indirect effect of organizational change on the impact of AI adoption intensity on corporate sustainability performance. According to this, we focus on identifying one important process through which AI adoption intensity leads to corporate sustainability performance and verifying the mediating effect of organizational change. Furthermore, as a way to increase the influence on the core role of organizational change, we clarify the role of the interaction between AI adoption intensity and digital possibilities and verify the moderating effect. Finally, by integrating AI adoption, organizational change, and corporate sustainability performance into a unified framework, this study seeks to provide both theoretical insights and practical recommendations for manufacturing enterprises, particularly in China, where AI is central to digital and intelligent transformation.

Finally, in previous studies, most studies have been conducted on factors affecting corporate sustainability performance, such as stakeholder pressure and responsible innovation [16], environmental regulation [17], mechanisms of environmental information disclosure [18], Integration of Environmental, Social, and Governance (ESG) criteria [19], and green innovation and organizational culture [20]. However, the topic related to AI adoption is quite lacking in the research topic of corporate sustainability performance. In addition, most studies simply focus on the exploration of antecedent factors affecting corporate sustainability performance, moderating effects, or mediating effects. This can be seen as a gap in previous studies. Therefore, this study identifies the role of AI adoption intensity as a new factor that improves the level of corporate sustainability performance and verifies its influence. Furthermore, it proposes a moderated mediating research model related to ways to improve corporate sustainability performance. Overall, we aim to expand the research field of corporate sustainability performance and fill the gap in previous studies, thereby contributing to the academic field related to corporate sustainability performance.

2. Theoretical Background and Hypotheses

2.1. AI Adoption Intensity and Organizational Change

AI adoption intensity is defined as the frequency of using AI systems to understand, learn from, and continuously upgrade based on external data to achieve specific goals [21]. Moreover, the dynamic nature of AI requires continuous learning and agility from the work-

force, thereby redefining traditional roles and responsibilities within organizations [22]. We emphasize that both the innovation diffusion theory and the dynamic capabilities theory provide a theoretical foundation to explain how AI adoption triggers organizational change by enabling firms to continuously adapt to technological advances and market dynamics. From the perspective of the innovation diffusion theory [23], AI adoption can be seen as a process of organizational innovation diffusion. As AI technologies are introduced, they spread throughout the organization, leading to gradual changes in organizational structures and processes. Companies that adopt AI early in the diffusion curve gain competitive advantages by being the first to benefit from enhanced operational efficiency and data-driven decision-making. Furthermore, advances in AI adoption are expected to lead to innovation and organizational change. In addition, the dynamic capabilities theory [24] offers another lens to understand the relationship between AI adoption and organizational change. According to this theory, firms with strong dynamic capabilities are better equipped to integrate new technologies, such as AI, into their operational processes. AI adoption can be viewed as a dynamic capability that enables organizations to continuously reconfigure and renew their internal resources and processes to remain competitive in rapidly changing environments. By adopting AI technologies, firms enhance their ability to adapt to market demands, optimize resources, and foster innovation, all of which are crucial for organizational transformation.

At the organizational level, organizational change refers to the process of an organization transitioning from one state to another [25]. Organizational change involves various aspects of management, including structures, systems, processes, and considerable personnel changes. The application of AI is likely to induce system-wide transformations within organizations [26]. AI enhances operational efficiency and decision-making accuracy through automation and intelligent technologies. This not only reduces operational costs but also frees up human resources, allowing employees to focus on more creative tasks, thus driving organizational restructuring and change [21]. For example, AI in manufacturing can significantly improve production efficiency and product quality through automation and intelligent control systems, reducing human errors and resource wastage [27]. This technological advancement forces companies to redesign their production processes and organizational structures to adapt to new production methods and efficiency demands, thereby triggering organizational change. Furthermore, AI provides advanced data processing and analysis tools, enabling companies to better extract valuable information from data and convert it into knowledge and action [28]. This capability enhancement forces companies to establish more comprehensive knowledge management systems and learning mechanisms internally, thus promoting organizational change.

In conclusion, by drawing on the innovation diffusion theory and the dynamic capabilities theory, it becomes evident that AI adoption intensity acts as a catalyst for organizational change, as firms continuously evolve their internal processes and capabilities to accommodate the transformative potential of AI technologies. Therefore, this study speculates that AI adoption intensity has a significant positive impact on organizational change. Specifically, AI enhances operational efficiency and decision-making capabilities, boosts market competitiveness and innovation capabilities, and improves organizational learning and knowledge management capabilities, prompting companies to make changes in technology, management, and culture. Thus, this study proposes the following hypothesis:

H1: *AI adoption intensity positively influences organizational change.*

2.2. Organizational Change and Corporate Sustainability Performance

Corporate sustainability performance is assessed using economic, environmental, and social metrics, adhering to the "triple bottom line" framework [29]. Effective corporate sustainability performance integrates valuable, rare, and non-substitutable resources and capabilities to maintain a competitive advantage [30]. The impact of organizational

change on corporate sustainability performance is explained through the corporate social responsibility (CSR) theory. CSR theory emphasizes that organizations have obligations to various stakeholders beyond shareholders, including employees, customers, suppliers, and the wider community. Organizational change is a critical mechanism through which companies can fulfill their CSR obligations, particularly by adopting sustainable business practices and promoting ethical behavior. Through CSR-driven organizational change, firms can improve their environmental practices, enhance employee welfare, and engage more effectively with the communities they operate in, all of which contribute to improved sustainability performance [31]. According to the theoretical statement above, this study emphasizes that organizational change is a factor that improves corporate sustainability performance. CSR theory further supports this by suggesting that organizational change enables companies to respond more effectively to stakeholder needs, such as improving working conditions, increasing employee engagement, and participating in community development projects. These CSR initiatives lead to improved social performance, enhancing a company's reputation and strengthening its relationships with key stakeholders [31].

Organizational change involves various aspects of management, including structure, systems, processes, and significant personnel changes such as mergers, hierarchy changes, new performance appraisal systems, technology adoption, and management shifts [32]. These changes not only improve internal efficiency and collaboration but also enhance the organization's sensitivity to and response speed to external environmental changes, thereby promoting corporate sustainability performance.

In addition, from the perspective of organizational learning theory, organizational change is a vital process through which firms can enhance their learning capacity and adaptability in the face of evolving environmental and social demands [33]. By fostering a learning-oriented culture, organizations can better integrate sustainability practices into their daily operations, continuously improving their performance across economic, environmental, and social dimensions. Organizational learning allows companies to absorb new knowledge, innovate, and implement sustainable solutions that enhance their long-term sustainability performance. For example, through continuous learning, companies can improve their waste management processes, reduce carbon footprints, and enhance stakeholder engagement [34].

Organizational learning theory further posits that this capacity to learn and innovate is crucial for sustaining long-term improvements in economic, environmental, and social performance, as firms continuously adapt to new sustainability challenges. For instance, by introducing new technologies and innovative management models, companies can accelerate technological innovation and product development, meeting diverse market and customer needs, and thereby maintaining competitive advantage and sustainable development in an ever-changing market environment [35].

Based on the above analysis, it can be deduced that organizational change enhances corporate sustainability performance by improving economic, environmental, and social performance, thus strengthening the company's sustainability capabilities. Therefore, this study proposes the following hypothesis:

H2: *Organizational change positively influences corporate sustainability performance.*

2.3. AI Adoption Intensity and Corporate Sustainability Performance

AI adoption intensity substantially improves economic performance by optimizing resource allocation and increasing production efficiency, which helps companies reduce operational costs and increase profit margins. AI's predictive analytics capabilities enable companies to forecast market demand and consumer behavior more accurately, optimizing production plans and marketing strategies to further enhance economic performance [36]. Thus, higher AI adoption intensity correlates with better resource utilization and economic benefits, promoting corporate sustainability.

The Technology–Organization–Environment (TOE) framework provides a comprehensive explanation of how AI adoption influences corporate sustainability performance. According to the TOE framework, the adoption of innovative technologies such as AI is shaped by three key dimensions: technology, organization, and environment [37]. AI adoption enables organizations to enhance operational efficiency (technological dimension), restructure internal processes and resources (organizational dimension), and respond to external regulatory and market demands (environmental dimension). By leveraging AI, firms can better meet environmental regulations, reduce resource consumption, and align with market expectations for sustainable practices, ultimately improving corporate sustainability performance across economic, environmental, and social metrics.

From the perspective of the resource-based view (RBV), AI adoption intensity can be viewed as a critical organizational capability that provides firms with a sustainable competitive advantage. According to the RBV, valuable, rare, inimitable, and non-substitutable resources drive a firm's long-term success. AI technology enhances a company's ability to efficiently allocate resources, optimize processes, and generate superior environmental and social outcomes. For instance, AI's data-driven decision-making capabilities enable firms to better manage their environmental impact by reducing waste and improving resource utilization [38]. This advantage allows firms to achieve economic gains while simultaneously addressing environmental and social concerns, thus contributing to their overall sustainability performance.

AI adoption intensity also enhances social performance by enabling companies to fulfill their social responsibilities and build closer relationships with stakeholders. AI improves customer service by analyzing customer feedback and behavior data to provide personalized products and services, enhancing customer satisfaction and loyalty [39]. Additionally, AI applications in employee management can improve job satisfaction and experience. For instance, AI-driven performance evaluation systems and training platforms can more effectively identify and develop talent, promoting employee career growth [40]. Therefore, increased AI adoption intensity not only boosts economic and environmental performance but also enhances social responsibility and image, driving comprehensive corporate sustainability.

Based on the above analysis, it can be deduced that AI adoption intensity positively impacts economic, environmental, and social performance, thereby strengthening corporate sustainability capabilities. Therefore, this study proposes the following hypothesis:

H3: *AI adoption intensity positively influences corporate sustainability performance*.

2.4. Mediating Effect of Organizational Change

According to Change Management Theory, the successful adoption of new technologies like AI requires significant organizational adjustments [41]. AI adoption often entails deep structural and cultural changes within organizations, as it reshapes business processes, decision-making systems, and employee roles. Change Management Theory emphasizes the importance of effectively managing these changes to ensure that AI technology can be integrated into the organization's daily operations, which, in turn, enhances corporate sustainability performance. Properly managed organizational change allows firms to align AI's potential with their sustainability goals, driving improvements in environmental, social, and economic outcomes.

In addition, institutional theory further supports the role of organizational change by emphasizing how external pressures, such as regulations and societal expectations, shape organizational behavior [42]. Companies often adopt AI technologies in response to institutional pressures related to environmental regulations, social responsibility, and market expectations. Organizational change allows firms to adapt to these external demands, restructuring their internal processes to align with societal norms and legal requirements. As companies implement AI technologies to meet regulatory standards, such as reducing

carbon emissions or improving social governance, organizational change acts as the mechanism that connects AI adoption to corporate sustainability performance. This theory helps explain why organizational change is essential for translating AI's capabilities into tangible sustainability outcomes.

Sustainability, as a dynamic organizational capability promoting organizational change by enhancing a company's adaptability and innovation capacity, further promotes corporate sustainability performance [43]. During the transformation process, companies optimize their organizational structures, improve management processes, and cultivate an innovation culture, effectively addressing external environmental changes and challenges. For instance, through AI technology, companies can more accurately predict market demand and customer behaviors, adopting more effective strategies in product development and marketing [36]. This not only boosts economic performance but also promotes efficient resource utilization and environmental protection, thus enhancing corporate sustainability performance. Additionally, organizational change improves social responsibility by enhancing employee management and customer service, thereby improving a company's social image and brand value [44,45].

The mediating role of organizational change between AI adoption intensity and corporate sustainability performance can be realized by enhancing overall corporate synergy. Specifically, the application of AI technology requires adjustments not only at the technological level but also in management and culture. These changes facilitate better integration of resources and capabilities and the achievement of higher operational efficiency and performance [46]. By optimizing internal communication and collaboration mechanisms, companies can respond more quickly to market changes and customer needs, maintaining a competitive edge in the market [36]. Thus, from both Change Management Theory and institutional theory perspectives, organizational change is a key mediator that bridges the gap between AI adoption intensity and improved corporate sustainability performance, ensuring that the technology is fully utilized to meet both internal and external sustainability goals. Therefore, organizational change acts as a bridge between AI adoption and corporate sustainability performance, promoting a positive interaction between the two.

Based on the above analysis, it can be deduced that organizational change plays a key mediating role between AI adoption intensity and corporate sustainability performance. Specifically, AI technology enhances corporate sustainability performance by promoting organizational change. Therefore, this study proposes the following hypothesis:

H4: *Organizational change mediates the relationship between AI adoption intensity and corporate sustainability performance*.

2.5. The Moderated Mediation Effect of Digital Capability

Digital capability plays a crucial role in modern enterprises and is defined as an organization's ability to acquire, analyze, and utilize digital technologies to innovate and enhance performance [47]. This capability not only improves operational efficiency but also enhances flexibility and responsiveness to market changes. Specifically, digital capability, by increasing the accuracy and efficiency of data processing and information analysis, enhances the effectiveness of AI applications in enterprises, thereby promoting organizational change.

When enterprises engage in digital transformation, the decision-making and support of top management teams are crucial factors in building digital capabilities [48]. The digital sense-making of top managers influences the participation of organizational members in the digital transformation process, thereby enhancing the organization's digital capabilities [49]. Additionally, digital literacy, digital culture, and organizational learning considerably impact the formation of digital capabilities [50]. Investment in digital infrastructure and digital talent with relevant skills is also essential for enhancing digital capabilities [51].

By enhancing digital capability, enterprises can achieve more efficient operational models and stronger innovation capabilities, thereby maintaining a competitive advantage in rapidly changing market environments [47]. Furthermore, high levels of digital capability ensure that enterprises can effectively integrate and utilize AI technologies, fostering changes in organizational structure, processes, and culture. The stronger the digital capability, the higher the adaptability and innovation of the enterprise in the face of technological change, thereby enhancing the effect of AI adoption on organizational change [52].

Research indicates that AI technologies can promote corporate sustainability performance by optimizing resource allocation, enhancing production efficiency, and reducing environmental damage [27]. However, this promoting effect often needs to be realized through organizational change. Organizational change encompasses various actions and strategies that enterprises employ to adapt to external environmental changes, optimize internal management structures, and improve operational efficiency [25]. Digital capability plays a critical role in this process, enhancing the ability of enterprises to cope with and implement change through improved information processing and technology application capabilities [53]. When an enterprise possesses high levels of digital capability, AI applications can more effectively drive organizational change, thereby indirectly enhancing corporate sustainability performance. Based on this, this study proposes the following hypotheses:

H5: *Digital capability positively moderates the relationship between AI adoption intensity and organizational change. That is, the stronger the digital capability, the stronger the effect of AI adoption intensity on promoting organizational change.*

H6: *Digital capability positively moderates the mediating effect of AI adoption intensity on corporate sustainability performance through organizational change. That is, the stronger the digital capability, the stronger the effect of AI adoption intensity on promoting corporate sustainability performance through organizational change.*

3. Methods

3.1. Research Model

This study focuses on verifying the effect of AI adoption intensity on corporate sustainability performance. Furthermore, the significance of the mediating effect of organizational change is verified in the process of AI adoption intensity leading to corporate sustainability performance. Finally, it verifies whether digital capability moderates the mediating effect of organizational change on the relationship between AI adoption intensity and corporate sustainability performance. Based on these hypotheses, we provide the research model in Figure 1. In addition, the hypotheses of this study are organized into a table, as in Table 1, below.

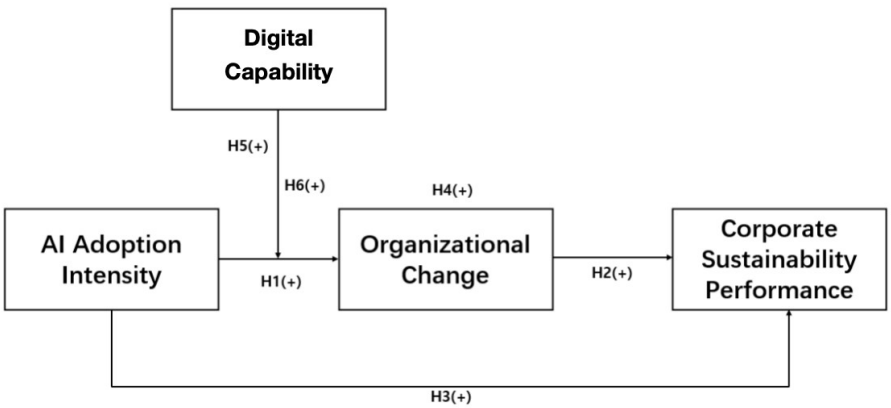


Figure 1. Research model.

Table 1. Hypotheses and contents.

Hypotheses	Contents
Hypothesis H1	AI adoption intensity positively influences organizational change.
Hypothesis H2	Organizational change positively influences corporate sustainability performance.
Hypothesis H3	AI adoption intensity positively influences corporate sustainability performance.
Hypothesis H4	Organizational change mediates the relationship between AI adoption intensity and corporate sustainability performance.
Hypothesis H5	Digital capability positively moderates the relationship between AI adoption intensity and organizational change. That is, the stronger the digital capability, the stronger the effect of AI adoption intensity on promoting organizational change.
Hypothesis H6	Digital capability positively moderates the mediating effect of AI adoption intensity on corporate sustainability performance through organizational change. That is, the stronger the digital capability, the stronger the effect of AI adoption intensity on promoting corporate sustainability performance through organizational change.

3.2. Sample Characteristics

Data collection for this study was initiated in March 2024, with samples drawn from employees of six manufacturing enterprises located in eastern, southern, and central China. These regions are among China's most densely populated and dynamic manufacturing areas, making the selected enterprises representative of the broader industry.

For this study, we adopted the bidirectional translation method, introducing English measurement scales [54]. Items on the scales related to AI adoption intensity, organizational transformation, and corporate sustainability performance were translated into Chinese. Two PhDs with extensive research experience in management were then invited to back-translate the Chinese items into English. This process helped identify and correct discrepancies, thereby refining the measurement scales. Subsequently, five managers from relevant companies and three professors specializing in related research fields were consulted to discuss the questionnaire. They provided suggestions for improvement, which were incorporated into the final questionnaire. The scales were further optimized to align with the specific research context, enhancing the rationality and validity of the indicators and ensuring the rigor of the study.

Due to the logistical constraints of conducting the survey from South Korea while the target respondents were located in China, an online survey was chosen over a face-to-face approach. The project and research objectives were introduced in detail to the enterprise leaders. Employees were informed that the survey data would be used exclusively for scientific research and that all information would be kept strictly confidential. They were encouraged to select options that best reflected their actual work experiences. Enterprise leaders were also requested to remind employees to complete the survey. Following persistent efforts, the survey was conducted in June 2024, targeting 500 employees from various companies, ultimately resulting in the collection of 476 self-reported questionnaires, yielding a response rate of 95.2%. After excluding incomplete responses and those completed within an unreasonably short period, 451 valid questionnaires were retained, resulting in an effective response rate of 88.2%.

Among the survey sample, 51.0% were male and 49.0% were female. Regarding their age, 11.3% were under 25 years old, 24.0% were between 26 and 30 years old, 31.7% were between 31 and 35 years old, 16.0% were between 36 and 40 years old, 11.5% were between 41 and 50 years old, and 5.5% were over 51 years old. Concerning education, 12.9% had a high school education or below, 29.1% had a vocational education, 42.8% had a bachelor's degree, 11.7% had a master's degree, and 3.6% had a doctoral degree. Regarding work tenure, 40.6% had 1 to 5 years of experience, 37.3% had 6 to 10 years, 11.1% had 11 to 15 years, 5.8% had 16 to 20 years, and 5.3% had more than 20 years. As for job levels, 59.0% were regular employees, 29.3% were junior managers, 10.2% were middle managers, and

0.9% were senior managers. Regarding the time working with their current supervisor, 11.1% had been working together for less than 6 months, 22.0% for more than 6 months but less than 1 year, 22.0% for more than 1 year but less than 1 year and 6 months, 26.2% for more than 1 year and 6 months but less than 2 years, and 18.9% for 2 years or more. As for company size, 3.3% had 50 or fewer employees, 8.0% had 51 to 100 employees, 34.8% had 101 to 150 employees, 37.5% had 151 to 200 employees, and 16.4% had more than 201 employees. Table 2 shows the sample characteristics.

Table 2. Sample characteristics.

		Quantities	Percentages (%)
Gender	Female	221	49.00
	Male	230	51.00
Education	High school education or below	58	12.86
	Junior college	131	29.05
	College graduates	193	42.79
	Master's degrees	53	11.75
	Doctoral degrees	16	3.55
Age	Under 25 years old	51	11.31
	26–30	108	23.95
	31–35	143	31.71
	36–40	72	15.96
	41–50	52	11.53
	51 or over	25	5.54
Service years	1–5	183	40.58
	6–10	168	37.25
	11–15	50	11.09
	16–20	26	5.76
	21 or over	24	5.32
Job levels	Regular employees	266	58.98
	Junior managers	135	29.93
	Middle managers	46	10.20
	Senior managers	4	0.89
Working with the current immediate leader	6 months or less	50	11.09
	6 months to 1 year or less	99	21.95
	1 year to 1 year and 6 months or less	99	21.95
	1 year and 6 months to 2 years or less	118	26.16
	2 or more years	85	18.85
Company size	50 or below	15	3.33
	51–100	36	7.98
	101–150	157	34.81
	151–200	169	37.47
	201 or over	74	16.41
Total		451	100.0

3.3. Measurement

3.3.1. Measurement of AI Adoption Intensity

AI adoption intensity refers to the frequency with which a system comprehends and learns from external data, continuously upgrading to achieve specific goals and tasks [21]. In this study, the measurement of AI adoption intensity employs a unidimensional scale developed by Baabdullah et al. [55], consisting of four items. These items are measured

using a 7-point Likert scale. Sample items include "AI is a mainstream technology that will be dominant in our industry" and "AI is well accepted by the top management in our company". The Cronbach's alpha for this scale is 0.87.

3.3.2. Measurement of Organizational Change

Organizational change is the process by which an organization transitions from one state to another [25]. In this study, the measurement of organizational change utilizes a unidimensional scale developed by Hetty van Emmerik et al. [56], consisting of eight items. These items are measured using a 7-point Likert scale. Sample items include "Most change initiatives do not end up with positive results" and "Change initiatives within this faculty usually make sense". The Cronbach's alpha for this scale is 0.94.

3.3.3. Measurement of Corporate Sustainability Performance

Corporate sustainability performance is typically measured through economic, environmental, and social dimensions, following the "triple bottom line" theory [29]. In this study, the measurement of CSP employs a unidimensional scale developed by Huang et al. [57], consisting of six items. These items are measured using a 7-point Likert scale. Sample items include "The company pays great attention to environmental protection" and "The company's economic performance is outstanding compared to its peers". The Cronbach's alpha for this scale is 0.91.

3.3.4. Measurement of Digital Capability

Digital capability refers to the advanced ability of a company to think about and solve problems using digital skills [58]. In this study, the measurement of digital capability uses a unidimensional scale developed by Khin and Ho [47], consisting of five items. These items are measured using a 7-point Likert scale. Sample items include "Identifying new digital opportunities" and "Responding to digital transformation". The Cronbach's alpha for this scale is 0.90.

Table 3 below summarizes the variables and operational definitions.

Table 3. Variable and operational definitions.

Variables	Operational Definitions	Source
AI adoption intensity	AI adoption intensity refers to the frequency with which a system comprehends and learns from external data, continuously upgrading to achieve specific goals and tasks.	Haenlein & Kaplan (2019) [21]
Organizational change	Organizational change is the process by which an organization transitions from one state to another.	Lewin (1951) [25]
Corporate sustainability performance	Corporate sustainability performance is typically measured through economic, environmental, and social dimensions, following the "triple bottom line" theory.	Elkington (1998) [29]
Digital capability	Digital capability refers to the advanced ability of a company to think about and solve problems using digital skills.	Khurana et al., (2022) [58]

3.3.5. Control Variables

The first section of the questionnaire collected demographic information from respondents. As prior research suggests, individual variables may to some extent influence employee work behavior and attitudes. Therefore, certain individual variables were selected as control variables in this study, including gender, age, education level, years of work experience, job position, duration working with the current leader, and company size.

4. Results

4.1. Confirmatory Factor Analysis and Reliability Analysis

The applicability of the model can be confirmed by a confirmatory factor analysis [59]. The results of the confirmatory factor analysis are as follows. The absolute fit indexes were χ^2 (p)= 341.467 (0.000), χ^2/df = 1.518, and RMSEA = 0.034. Second, the incremental fit indexes were IFI = 0.982 and CFI = 0.982. Third, the parsimonious adjusted indexes were PNFI = 0.845 and PGFI = 0.765.

This study analyzed the values of average variance extracted (AVE) and composite reliability (CR). Regarding average variance extracted (AVE), the value of AI adoption intensity was 0.588, organizational change was 0.588, corporate sustainability performance was 0.560, and digital capability was 0.561; these values were all greater than 0.5. Regarding composite reliability (CR) values, AI adoption intensity was 0.760, organizational change was 0.828, corporate sustainability performance was 0.770, and digital capability was 0.736; all of these values were greater than 0.7. An AVE higher than 0.5 and a CR higher than 0.7 indicate that the measurements have adequate convergent validity and discriminant validity.

A reliability analysis assesses the consistency or stability of survey results. Therefore, this study also analyzed the Cronbach's value. For the α Cronbach, the value of AI adoption intensity was 0.866, organizational change was 0.936, corporate sustainability performance was 0.910, and digital capability was 0.899; a Cronbach's alpha higher than 0.7 suggests a high reliability. The results are shown in Table 4.

Table 4. Results of confirmatory factor analysis and reliability analysis.

Variables		Estimate	S.E.	C.R.	*p*	Standardized Regression Weights	AVE	CR	Cronbach's Alphas
AI Adoption Intensity (A)	A1	1			-	0.666	0.588	0.706	0.866
	A2	1.022	0.07	14.617	***	0.67			
	A3	1.342	0.093	14.415	***	0.852			
	A4	1.329	0.088	15.145	***	0.857			
Organizational Change (B)	B1	1			-	0.699	0.588	0.828	0.936
	B2	1.25	0.059	21.259	***	0.794			
	B3	1.212	0.057	21.448	***	0.798			
	B4	1.166	0.059	19.878	***	0.763			
	B5	1.206	0.06	19.971	***	0.765			
	B6	1.176	0.06	19.514	***	0.754			
	B7	1.201	0.06	20.102		0.768			
	B8	1.226	0.059	20.925		0.787			
Corporate Sustainability Performance (C)	C6	1			-	0.7	0.560	0.770	0.910
	C5	1.163	0.061	18.957	***	0.752			
	C4	1.151	0.06	19.021	***	0.754			
	C3	1.153	0.061	19.018	***	0.754			
	C2	1.116	0.059	18.972	***	0.753			
	C1	1.187	0.06	19.814	***	0.773			
Digital Capability (D)	D5	1			-	0.704	0.561	0.736	0.899
	D4	1.171	0.061	19.177	***	0.765			
	D3	1.121	0.062	18.058	***	0.735			
	D2	1.191	0.062	19.193	***	0.765			
	D1	1.203	0.062	19.518	***	0.774			

Model fit index: χ^2 (p) = 341.467(0.000), χ^2/df = 1.518, RMSEA = 0.034, IFI = 0.982, CFI = 0.982, TLI = 0.980, PGFI = 0.765, PNFI = 0.845. *** $p < 0.001$.

4.2. Descriptive Statistics and Correlation Analysis

Table 5 shows the descriptive statistics and correlation analysis. The descriptive statistics analysis included the mean and standard deviation (SD). The mean values for AI adoption intensity, organizational change, corporate sustainability performance, and digital capability were 4.445, 4.489, 4.413, and 4.438, respectively. In addition, the SDs of AI adoption intensity, organizational change, corporate sustainability performance, and digital capability were 1.369, 1.380, 1.353, and 1400, respectively.

Table 5. Results of descriptive statistics and correlation analysis.

	Mean	Standard Deviation	AI Adoption Intensity	Organizational Change	Corporate Sustainability Performance	Digital Capability
AI Adoption Intensity	4.445	1.369	-			
Organizational Change	4.489	1.380	0.376 ***	-		
Corporate Sustainability Performance	4.413	1.353	0.377 ***	0.435 ***	-	
Digital Capability	4.383	1.400	0.343 ***	0.461 ***	0.400 ***	-

(*** $p < 0.001$).

To verify the correlation among variables, this study conducted a correlation analysis, and the results are summarized as follows: AI adoption intensity was positively associated with organizational change ($r = 0.376$, $p < 0.001$), corporate sustainability performance ($r = 0.377$, $p < 0.001$), and digital capability ($r = 0.343$, $p < 0.001$). Organizational change was positively associated with corporate sustainability performance ($r = 0.435$, $p < 0.001$) and digital capability ($r = 0.461$, $p < 0.001$). Digital capability was positively associated with corporate sustainability performance ($r = 0.400$, $p < 0.001$). Table 5 shows the results of the descriptive statistics and correlation analysis.

4.3. Path Analysis

SPSS Process Model 4 was used to analyze the mediation effect of organizational change. The results show that AI adoption intensity has a positive impact on corporate sustainability performance (estimate = 0.242, $p < 0.001$) and organizational change (estimate = 0.373, $p < 0.001$). In addition, the results show that organizational change has a significant impact on corporate sustainability performance (estimate = 0.344, $p < 0.001$). Therefore, Hypothesis 1, Hypothesis 2, and Hypothesis 3 are supported.

Hypothesis 4 posits that organizational change mediates the relationship between AI adoption intensity and corporate sustainability performance. The indirect effect was 0.125. The bootstrapped confidence intervals were Boot LLCI = 0.084 and Boot ULCI = 0.173, as 0 was not included between Boot LLCI and Boot ULCI. These results indicate that the mediation effect of organizational change is significant. This finding suggests that AI adoption intensity increases corporate sustainability performance through organizational change. Thus, Hypothesis 4 is supported. Table 6 shows the results of the path analysis.

Table 6. Results of path analysis.

Path			Estimate	S.E.	*t*	*p*	LLCI	ULCI
AI Adoption Intensity	→	Corporate Sustainability Performance	0.242	0.045	5.442	0.000	0.1549	0.3299
AI Adoption Intensity	→	Organizational Change	0.373	0.045	8.344	0.000	0.2850	0.4606
Organizational Change	→	Corporate Sustainability Performance	0.344	0.044	7.584	0.000	0.2476	0.4209
Indirect Effect(s) of X on Y								
Indirect Effect			Effect	Boot SE	Boot LLCI		Boot ULCI	
AI Adoption Intensity → Organizational Change → Corporate Sustainability Performance			0.125	0.023	0.084		0.173	

4.4. Moderating Effect of Digital Capability

Hypothesis 5, which postulates on the moderating role of digital capability, has been validated. To mitigate issues related to multicollinearity, centralization was applied to the independent variable (AI adoption intensity) and the moderating variable (digital capability). Subsequently, a product term was introduced into the regression equation. As indicated in Table 7, the product term of AI adoption intensity and digital capability is significantly and positively associated with organizational change ($\beta = 1.125$, $p < 0.001$). These results indicate that digital capability moderates the relationship between AI adoption intensity and organizational change. Therefore, Hypothesis 5 receives support.

Table 7. The result of the moderating effect of digital capability.

	Model 1		Model 2		Model 3		
	β	*t*	*β*	*t*	*β*	*t*	VIF
AI Adoption Intensity(A)	0.376 ***	8.609	0.247 ***	5.744	−0.425 ***	−3.172	1.142
Digital Capability(B)			0.376 ***	8.735	−0.300 ***	−2.226	1.172
Interaction					1.125 ***	5.281	1.061
R^2 (Adjusted R^2)	0.142 (0.140)		0.267 (0.263)		0.310 (0.305)		
ΔR^2 (Adjusted R^2)			0.125 (0.123)		0.043 (0.042)		
F	74.112 ***		81.422 ***		66.834 ***		

(*** $p < 0.001$).

To vividly illustrate the moderating effect of digital capability on the relationship between AI adoption intensity and organizational change, the present study employs a simple slope analysis method to test and graphically depict the moderating role of digital capability, as depicted in Figure 2. For organizational change and strong digital capabilities, AI adoption intensity significantly enhances organizational change. In contrast, for organizational change and weak digital capabilities, the positive impact of AI adoption intensity on organizational change is not statistically significant. This observation further validates Hypothesis 5.

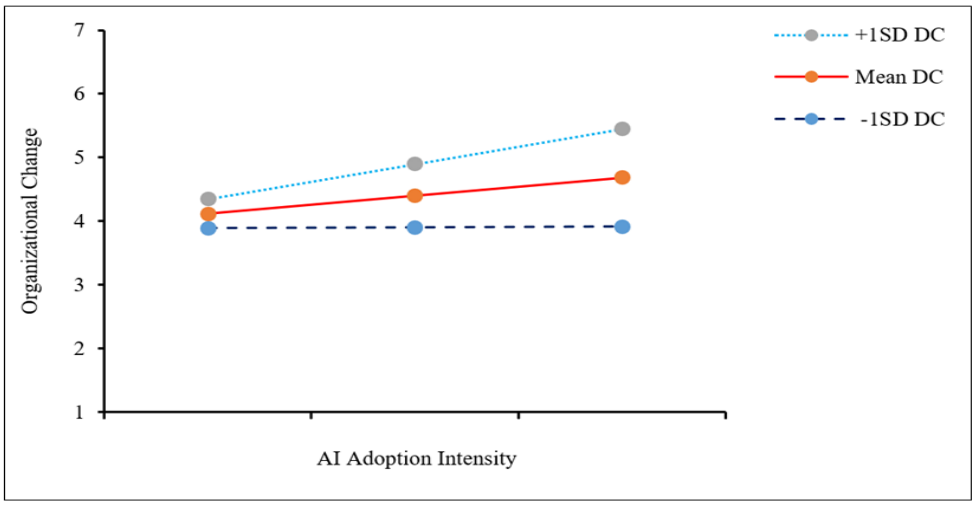


Figure 2. Moderating effect of digital capability on the relationship between AI adoption intensity and organizational change. Note: DC = digital capability (moderating variable).

4.5. Moderated Mediation Test of Digital Capability

Table 8 presents the moderating effect of digital capability. Hypothesis 6 posits that digital capability positively moderates the indirect effect of AI adoption intensity on corporate sustainability performance through organizational change. To test this moderated mediation model, SPSS Process Macro 4.1 Model 7 was employed, utilizing a bootstrap method with 5000 resamples and generating 95% confidence intervals. The analysis entails evaluating the conditionally indirect effects of AI adoption intensity on corporate sustainability performance at three different levels of moderation (−1 SD, mean (M), and +1 SD) of digital capability.

Table 8. Results of moderated mediation test of digital capability.

Dependent Variable: Corporate Sustainability Performance					
Moderator	**Level**	**Conditional Indirect Effect**	**Boot SE**	**Boot LLCI**	**Boot ULCI**
Digital Capability	−1 SD (−1.4003)	0.0031	0.0209	−0.0407	0.0422
	M (0.0000)	0.0690	0.0171	0.0373	0.1041
	+1 SD (1.4003)	0.1348	0.0246	0.0903	0.1872
Index of Moderated Mediation					
	Index		Boot SE	Boot LLCI	Boot ULCI
	0.0470		0.0108	0.0280	0.0698

Based on the analysis, at the −1 SD (standard deviation) confidence interval level, the range between Boot LLCI and Boot ULCI includes 0. However, at the mean level (M) and the +1 SD (standard deviation) confidence interval level, the range between Boot LLCI and Boot ULCI does not include 0. Therefore, this study concludes that the moderating effect is confirmed and statistically significant.

Furthermore, the index of the moderated mediation effect is 0.047, with a Boot SE of 0.0128, a Boot LLCI of 0.0280, and a Boot ULCI of 0.0698. Since the confidence interval between Boot LLCI and Boot ULCI does not include 0, this underscores the importance of the guided confidence interval. Therefore, Hypothesis 6 receives support.

5. Discussion

This study examines the mechanism underlying the impact of AI adoption intensity on corporate sustainability performance, investigates the mediating role of organizational change, and explores the moderating effect of digital capability. The results indicate that AI adoption intensity positively impacts corporate sustainability performance. Organizational change acts as a mediator between AI adoption intensity and corporate sustainability performance, meaning that AI adoption intensity exerts a positive influence on corporate sustainability performance through organizational change. Digital capability positively moderates the positive impact of AI adoption intensity on organizational change, indicating that the stronger the digital capability, the more pronounced the relationship between AI adoption intensity and organizational change. Additionally, digital capability positively moderates the mediating effect of AI adoption intensity through organizational change on corporate sustainability performance, suggesting that higher digital capability enhances the ability of AI adoption intensity to promote corporate sustainability performance through organizational change. In this study, all six hypotheses were supported by the statistical results, confirming the validity of each hypothesis. Supported by the results of the hypotheses, the study demonstrates that AI adoption intensity has a direct and substantial positive effect on corporate sustainability performance, mediated by organizational change (H1–H3). The empirical evidence supports the hypothesis that organizational change mediates the relationship between AI adoption intensity and sustainability performance (H4). Policies that enhance digital literacy and infrastructure are crucial in building the digital capabilities necessary for successful AI implementation (H5, H6). AI's impact on sustainability performance is contingent upon organizational change, highlighting the importance of effective change management (H2–H4). By demonstrating that AI adoption intensity leads to improved sustainability performance, the study highlights AI's role as a catalyst for technological advancements across industries (H1, H3).

The empirical findings provide insights into how Chinese manufacturing enterprises can leverage emerging technologies such as AI to achieve sustainable development, offering guidance on potential pathways for growth. The conclusions are summarized below.

5.1. Theoretical Implication

The findings of this study significantly deepen the theoretical understanding of how AI adoption intensity impacts corporate sustainability performance through the mediating role of organizational change. This research emphasizes that AI is not merely a technological tool but is a transformative force that drives profound organizational changes. As companies adopt AI, they can enhance efficiency, streamline operations, and foster innovation, all of which are essential for achieving sustainability goals [60]. The study extends current theories by demonstrating that AI's effect on sustainability performance is mediated by an organization's capacity to adapt and transform, aligning with the dynamic capabilities framework [24]. This reinforces the notion that organizations must build dynamic capabilities to continuously improve their processes and sustainability practices.

Moreover, AI adoption is not a one-off technological upgrade but a dynamic process requiring constant updates and organizational learning, which supports the dynamic capabilities theory [61]. As AI adoption continues to evolve, organizations must continually adapt, integrate, and reconfigure their internal and external competencies to meet the demands of rapidly changing environments. In this context, AI becomes an essential enabler of iterative improvements in organizational sustainability [52]. Supported by the empirical evidence of AI's role in improving corporate sustainability across economic, environmental, and social dimensions, this study highlights the critical pathways—such as process automation, data-driven decision-making, and enhanced customer interactions—through which AI facilitates organizational transformation.

This study bridges the theoretical gap between technology adoption and sustainability, which have traditionally been examined in isolation. The integration of AI adoption intensity with corporate sustainability performance, viewed through the lens of organizational

change, offers a novel perspective. This research demonstrates that AI adoption goes beyond operational enhancements, necessitating a comprehensive rethinking of organizational processes and structures, thereby aligning with the resource-based view [62] and the triple-bottom-line approach [63]. AI enhances organizational resources and capabilities, leading to improvements across economic, environmental, and social performance dimensions.

By incorporating elements of innovation diffusion theory, this study suggests that AI adoption is a form of organizational innovation that fundamentally reshapes business operations and strategic direction. This supports Rogers' diffusion of innovations theory, which posits that new technologies spread through an organization over time, altering its internal structures and processes [23]. This study enriches this framework by linking innovation diffusion to sustainability outcomes, providing a comprehensive understanding of how technological advancements like AI drive sustainable business practices. Additionally, the study underscores the importance of the organizational context—such as culture, leadership, and employee engagement—in determining the success of AI-driven sustainability initiatives, further contributing to a more nuanced theoretical understanding of the interaction between technology adoption and sustainability.

This study offers new insights into how digital capabilities moderate the relationship between AI adoption and organizational change, which in turn impacts corporate sustainability performance. Organizations with higher digital capabilities are better equipped to implement AI effectively, enabling them to realize more substantial improvements in sustainability. This enriches the theoretical discourse on digital transformation and dynamic capabilities, as digital readiness and maturity emerge as critical factors in maximizing the potential of AI [64]. The study integrates these concepts with organizational change theory, illustrating how digital capabilities enhance an organization's capacity to leverage AI for sustainability goals.

Additionally, the findings highlight the evolving nature of digital capabilities. Organizations that invest in digital literacy, advanced data analytics platforms, and robust IT infrastructures are better positioned to adopt AI technologies successfully [65]. This investment enables not only smoother AI integration but also greater flexibility in responding to technological shifts and market demands. Digital capabilities, therefore, act as catalysts for organizational change, facilitating continuous adaptation and innovation. This is particularly relevant in fostering a learning organization, where the workforce's upskilling and ongoing development are crucial for maintaining a competitive advantage in a dynamic business environment [66].

5.2. Practical Implications

The findings of this study offer valuable insights into how AI adoption can significantly enhance industry practices, especially in manufacturing, where the pressures of sustainability and efficiency are most pronounced. Specifically, the adoption of AI enhances operational efficiency, reduces waste, and improves product quality—key components of economic and environmental performance [62]. By automating processes and utilizing AI-driven data analytics, companies can streamline their operations and optimize resource utilization, thus addressing environmental concerns while boosting economic returns [24,67]. For manufacturing industries facing competitive pressures and sustainability regulations, this study presents a clear pathway for integrating AI into strategic operations to drive long-term sustainable growth. The empirical findings underscore that organizations with higher AI adoption intensity experience improvements in sustainability performance due to their ability to align technology with dynamic organizational capabilities. This not only helps businesses meet regulatory requirements but also enables them to exceed industry standards, setting benchmarks for others to follow [10].

In addition, this study provides essential guidance for policymakers in promoting sustainable innovation through AI integration. Policymakers can encourage the use of AI by focusing on fostering organizational change and digital transformation. This aligns with

innovation diffusion theory, which posits that successful technology adoption requires a supportive organizational context [23]. To accelerate AI adoption, governments could introduce targeted initiatives, such as tax incentives and subsidies for companies investing in AI technologies aimed at improving sustainability outcomes. Moreover, by promoting such policies, governments can stimulate economic growth, enhance corporate sustainability performance, and support environmental stewardship and social responsibility [61,63].

Furthermore, for business leaders, the study offers practical insights into how AI adoption can be strategically aligned with corporate sustainability objectives. Managers should, therefore, focus on integrating AI technologies into their strategic frameworks to ensure that the benefits of AI adoption are fully realized across economic, environmental, and social dimensions [44,62]. In particular, the findings emphasize the importance of building a culture of innovation and agility within organizations. This is critical for leveraging AI to drive continuous improvement in sustainability practices [66]. Managers should implement AI-driven strategies that foster employee engagement and encourage a learning-oriented environment, enabling organizations to respond effectively to market changes and environmental challenges. This approach not only improves operational efficiency but also strengthens the competitive positioning of firms in a rapidly evolving market focused on sustainability [24].

Finally, the broader economic implications of AI adoption are evident from this study, particularly its potential to drive technological innovation and stimulate economic development. The empirical evidence shows that companies with strong digital capabilities are better positioned to adopt AI technologies, which in turn enhances their overall sustainability and competitiveness [52].

For technology developers and entrepreneurs, this research provides insights into the commercial viability of AI solutions in addressing sustainability challenges. By aligning AI innovations with sustainability goals, firms can create high-impact solutions that not only address pressing environmental issues but also contribute to economic value creation. The study underscores the importance of collaboration between industry, academia, and government in building ecosystems that support AI-driven innovation and promote sustainable development [66]. This collaboration is crucial for ensuring that AI technologies are effectively integrated into business strategies and contribute to broader societal and environmental goals.

5.3. Limitations and Future Research

First, the methodological limitations of this study are noteworthy. Although this study employed empirical analysis through survey data collection and structural equation modeling, the latter being advantageous for capturing complex causal relationships, the use of cross-sectional data may limit the accuracy of causal inferences. Longitudinal research designs can better reveal the dynamic relationship between AI adoption intensity and corporate sustainability performance. Future research should consider using longitudinal data to further validate the findings of the present study. Additionally, this study relied heavily on self-reported data, which may have introduced subjective biases. Future studies could incorporate multiple data sources, including actual operational data and financial reports of companies, to enhance the reliability and validity of the findings [68].

Second, the study sample was primarily concentrated in manufacturing enterprises. While this choice reflects the importance of manufacturing in digital transformation and sustainable development, it also limits the generalizability of the findings. Different industries may have considerably different AI application scenarios and sustainability challenges, and the applicability of the results to other sectors remains untested. Future research could expand the sample to include a wider variety of enterprises and industries to examine the broad applicability of the findings. For example, exploring how service, agriculture, and information technology sectors achieve sustainable development goals through AI would provide additional insights [69]. By comparing case studies across different industries,

future research can offer a more comprehensive understanding of how AI operates in various contexts.

Finally, this study mainly explores the impact of AI adoption intensity on corporate sustainability performance at the current stage. However, both AI technology and market environments are rapidly evolving, and the results may not fully capture future trends. Future research should consider the dynamic nature of AI advancements and changes in market and policy environments. As AI algorithms and hardware technologies continue to progress, AI adoption will become more widespread, creating new application scenarios and challenges [70]. Additionally, changes in policy environments, such as government support and regulatory policies for AI technology, will substantially influence corporate AI adoption behaviors. Future research could track the development of AI technologies and study their long-term impact on corporate sustainability performance across different stages, providing more forward-looking insights.

6. Conclusions

This study empirically investigates the impact of AI adoption intensity on corporate sustainability performance, with all six hypotheses supported. The findings indicate that AI adoption significantly enhances sustainability performance across economic, environmental, and social dimensions. The reason for this is that AI, through automation, data analytics, and intelligent decision-making, effectively drives organizational change, which is identified as a crucial mediator in achieving better sustainability outcomes. Moreover, digital capability, serving as a moderating variable, amplifies the positive impact of AI adoption on sustainability performance, highlighting the necessity for organizations to invest in digital infrastructure and skills to fully realize AI's potential. However, this study has certain limitations. The cross-sectional data used limits the ability to infer causality, and the reliance on self-reported data may introduce subjectivity and bias. Future research should consider employing longitudinal data to capture the dynamic nature of AI adoption and its long-term impact on sustainability. Expanding the scope of research to include other industries would also enhance the generalizability of the findings. Theoretically, this study bridges the gap between technology adoption and sustainability practices, offering new insights into how AI can be integrated into corporate strategies. Practically, it provides actionable guidance for managers, emphasizing the importance of aligning AI initiatives with organizational change and sustainability goals. Future research should continue to explore the broader implications of AI across various sectors and contexts to deepen understanding of its long-term effects.

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