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Artificial Intelligence and Green Total Factor Productivity: The Moderating Effect of Slack Resources

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Abstract: With the emergence of the digital economy, digital technologies—such as artificial intelligence (AI)—have provided new possibilities for the green development of enterprises. Green total factor productivity is a key indicator of green sustainable development. While traditional total factor productivity does not consider the constraints of natural resources and the environment, green total factor productivity remedies this deficiency by incorporating environmental protection indicators, such as pollutant emissions, into the accounting system. To further clarify the relationship between AI technology and corporate green total factor productivity, this study uses a two-way fixed effects model to examine the impact of AI technology on the corporate green total factor productivity of A-share listed companies in China from 2013 to 2020 while examining how corporate slack resources affect the relationship between the two. The results show that the AI application positively contributes to the green total factor productivity of enterprises. Meanwhile, firms' absorbed, unabsorbed, and potential slack resources all positively moderate the positive impact of AI technology on firms' green total factor productivity. This study offers a theoretical basis for a comprehensive understanding of digital technology and enterprises' green development. It also contributes practical insights for the government to formulate relevant policies and for enterprises to use digital technology to attain green and sustainable development.

Keywords: artificial intelligence; green total factor productivity; slack resources; sustainable development; environmental protection

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1. Introduction

According to the International Energy Agency, the total global energy-related greenhouse gas emissions have increased dramatically from 31.78 billion tons in 1990 to 41.3 billion tons, and climate warming and environmental pollution have become increasingly serious. In recent years, China's rapid development has led to massive energy consumption and greenhouse gas emissions; to improve environmental management, China is shifting its development focus from rapid economic growth to sustainable economic growth [1]. Therefore, accomplishing green and sustainable development is one of the main challenges currently confronting China.

Green total factor productivity (GTFP) is a key indicator to assess green and sustainable development. Traditional total factor productivity (TFP) does not consider the constraints of natural resources and the environment [2]. In addition, it has been argued that multifactor productivity (MFP) can be equivalently substituted with total factor productivity (TFP). However, multifactor productivity mostly tends to reflect the difficulty of output growth [3] rather than focusing on the sustainability of output. Therefore, the indicator of green total factor productivity is chosen for this study. Green TFP both compensates for the shortcoming of traditional TFP, that does not consider environmental constraints, and also focuses on the sustainable growth of output. GTFP remedies this deficiency by incorporating environmental protection indicators, such as pollutant emissions, into the accounting system. This indicator system reflects environmental factors in economic development and balances the relationship between economic development and environmental protection [4,5]. Along with the transformation of China's economic development philosophy, the mode of economic development has gradually started relying on the promotion of GTFP [6]. In short, GTFP is a necessary condition for environmentally friendly economic development—a process that considers both environmental and economic benefits [7], and is an essential metric to reflect the degree of high-quality development, which is directly related to the implementation of national sustainable development strategy goals [8]. However, in recent years, the GTFP of many enterprises has decreased [9,10], which is unfavorable for green sustainable development. Therefore, improving the GTFP of enterprises is a problem that must be urgently addressed.

As the digital economy grows, digital technologies, such as artificial intelligence (AI) provide new possibilities for green development. AI is a new technological science that imitates and performs human cognitive functions through technologies such as machine learning, computer vision, and deep learning. Following the continuous advancement of current digital technologies, AI has encompassed fields such as medicine, science, business, engineering, food, and art, leading to a new technological revolution and industrial upgrades [11,12]. The application of AI has also reshaped the operational modes of enterprises and has far-reaching effects on socioeconomic development [13]. Due to the continuous digitization process in recent years, the application of AI in enterprises has accelerated, and it is becoming increasingly important to analyze its impact on enterprises. Studies have shown that AI can enhance corporate creativity and innovative thinking [14] and reduce the cost of principal–agent relationships within a firm [15]. In addition, AI can overcome technological limitations, optimize business processes and resource allocation, enhance resource utilization and productivity [16], and positively impact corporate sustainability goals [17]. However, AI is not always beneficial [18]. While AI has great potential, it can often have potentially negative impacts on sustainable development due to technical complexity and environmental diversity [19]. In this context, it is important to explore whether AI technologies can enhance enterprises' GTFP and help them achieve green development.

New and emerging technologies are usually considered key factors in enhancing productivity [20]. AI, as a typical emerging technology, has opened new paths to promote green economic growth and sustainable development. Existing studies have shown that AI can reduce enterprises' carbon emissions by optimizing their green supply chain management systems [21], improving energy efficiency, and reducing their environmental impact [22], while integrating and optimizing their environmental processes to enhance their green performance [23]. AI can also promote the upgrade of traditional equipment and processes and green technological innovation in enterprises [24]. It is clear that the application of AI technologies solves many cutting-edge business problems by reducing corporate costs, increasing corporate productivity, and reducing the negative effects of organizational inertia in order to effectively improve corporate performance [25,26] and greatly contribute to the prosperity of business [27]. It is noteworthy that most studies have only focused on the impact of AI on business operations and performance and are still in the nascent stage of exploring whether it can contribute to the green development of enterprises, especially because research on the impact of AI on GTFP is insufficient.

Slack resources play an important role in enterprise management [28]. Slack resources refer to resources that can be reused and redeployed to achieve corporate goals and are beyond the actual needs of the organization—or are not yet used by the enterprise—which can support the enterprise in the face of various external environmental and technological impacts [29,30]. Resource buffers can enhance operational resilience and aid in resisting vulnerability to ensure sustainable development [31], especially in complex and unstable markets and institutional environments where slack resources are of great importance [32]. Studies show that slack resources are beneficial for enterprises in improving their strategic capabilities, seizing new opportunities for development [33], facilitating their entry into new market areas, and providing more freedom for strategic exploration and innovation [34]. AI applications are typical technological innovations and provide a new path for enterprises to explore green and sustainable development. A large amount of investment and resources are required for enterprises to carry out AI technology applications, which require full consideration of the allocation of slack resources, as they play an important role in enterprises' efforts to explore innovation, cultivate green industries, and promote green development [35,36]. Depending on their availability, slack resources are classified into three types: absorbed, unabsorbed, and potential slack. Each type of slack resource may play an important role in the relationship between AI technologies and enterprises' GTFP and should not be ignored.

Therefore, to comprehensively understand the relationship between digital technology and enterprises' green development, and further clarify the impact of AI technology on enterprise GTFP, this study selects A-share listed companies in China from 2013 to 2020 as the research sample to explore the impact of AI on enterprises' GTFP. It also takes slack resources as the boundary condition to explore the impact of absorbed, unabsorbed, and potential slack resources on the relationship between AI technology and enterprises' GTFP, respectively.

The contributions of this study are as follows. First, it expands the research literature related to digital technology and enterprise green development and provides a theoretical basis for enterprises to promote green development with the help of digital technology. Second, unlike previous studies that used a single indicator to measure enterprises' green development level, this study applies the super-SBM model to measure GTFP, which enriches the measurement indicators of the green development capability of enterprises. Third, this study expands the literature on GTFP from a micro perspective and broadens the antecedent research on the GTFP of enterprises. Fourth, we reveal the applicability conditions of slack resources and clarify the boundary conditions of digital technology and green development of enterprises. The findings of this study also provide references for the policy formulation and management of the government and related departments on the one hand, and provide insights for the application of digital technology and the enhancement of the green development capability of enterprises on the other.

2. Theoretical Background and Hypotheses

2.1. Artificial Intelligence and Corporate GTFP

The theory of endogenous growth holds that technological progress is a decisive factor in ensuring economic growth and is the key to total factor productivity improvement [37]. Liu et al. (2022) believed that technological innovation leads to talent aggregation, enhances the market competitiveness of enterprises at home and abroad, and is an effective influencing factor of GTFP [38], which shows that applying AI technology might have an impact on GTFP. In general, AI can influence enterprises' GTFP in four ways: increasing resource utilization efficiency, controlling and reducing environmental pollution, fostering green industries, and promoting clean energy use [2]. Studies have demonstrated that AI can facilitate the development of enterprises' green economy [39], while at the same time it can dramatically boost the green technological efficiency of enterprises and positively affect green technological innovation [40]. The application of AI technology—for example, industrial robots—can have a positive effect on the GTFP of enterprises, thereby reducing carbon emission intensity [41] and improving their green productivity [42]. Liu et al., (2022) analyzed the impact of the digital economy, including elements of big data, cloud computing, and AI, on GTFP from a holistic perspective; their findings indicated that the digital economy enables efficient exchange of digital information, reduces resource mismatch (thus improving overall productivity), breaks the barriers of information exchange to reduce the cost of information communication, promotes GTFP, and accelerates the green economic transformation of enterprises [43–45]. In summary, the following hypothesis is proposed:

Hypothesis 1 (H1). *Artificial intelligence positively affects the GTFP of enterprises.*

2.2. The Moderating Effect of Slack Resources

The theory of business behavior asserts that the role of slack resources is crucial in enterprises. First, firms need a certain amount of slack resources to relieve and adapt to the pressure of the external environment, which enhances their external environmental adaptability. Second, the existence of slack resources enhances the flexibility of a firm's decision making; as the resources available to the firm increase, the firm's ability to cope with the complex environment—and thereby achieve its diversified strategic goals—increases, and higher levels of slack resources contribute to providing better conditions for the firm's exploration and innovation [46–48]. In addition, slack resources can alleviate internal conflict among the top management of a firm [49]. Finally, the existence of idle resources in a firm enables managers to focus on long-term sustainability, rather than being forced to address short-term poor performance [50]. From the resource-based perspective, a firm's resources are the source of its competition and development, and slack resources ensure available funds in a complex environment, alleviating the problem of financing constraints and providing opportunities for green growth [51]. As the digital economy continues to develop, the ability of enterprises to reintegrate and reconfigure resources is directly related to their sustainability. According to resource availability, this study classifies slack resources into unabsorbed, absorbed, and potential slack resources [52,53] to explore the impact of different types of slack resources on the relationship between AI and enterprise GTFP.

2.2.1. The Moderating Effect of Absorbed Slack Resources

"Absorbed slack" refers to administrative resources invested in the reproduction process of an enterprise beyond what is needed for normal operations; this includes selling and management expenses, which are relatively inflexible and cannot be easily reconfigured [54]. Although it is difficult to recover such resources, they help firms create a long-term competitive advantage. The more resources an enterprise absorbs, the more likely it is to focus on its strategic activity, which has a buffering effect on its long-term development strategy [55] and provides a favorable internal enterprise environment for the application of AI technologies. In addition, absorbed slack resources help enterprises reduce the cost of fulfilling social responsibility, increase the efficiency of resource utilization, reduce shortsighted managerial behavior, and enable the effective reallocation of production capacity, personnel, and equipment in response to unforeseen situations [56]. Enterprise GTFP is basically a reflection of the weight of enterprise resource input and output, and the more slack resources have been absorbed, the better the resource utilization efficiency, which precisely provides favorable conditions for the improvement of enterprise GTFP to a certain extent. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 2 (H2). *Absorbed slack resources promote the positive impact of AI on the GTFP of enterprises.*

2.2.2. The Moderating Effect of Unabsorbed Slack Resources

Unabsorbed slack refers to excess, uncommitted resources that are not invested in reproduction, such as cash and marketable securities, which are the most liquid and easily accessible, and can be effortlessly absorbed into a firm's technological activities to meet its diverse capital needs [57]. If a company has a large amount of unabsorbed slack resources, it is likely to invest in more valuable investment projects and explore new products and development models [28], which provide resource support and security for the application of AI technologies. Unabsorbed slack resources can supply stable financial support for enterprises to cope with risks, make strategic decisions, and ensure their innovation activities. Moreover, the cost of capital reallocation is low because of their high liquidity, which can alleviate the problem of financing constraints [58]. Unabsorbed slack resources, which offer more incentives to managers, improve the performance of the firm [59]. In addition, unabsorbed slack resources can alleviate internal conflicts among R&D personnel and ease competition for limited resources in developing new technologies, which has a favorable effect on both promoting innovation and raising firm performance [60]. This is conducive to the application of AI technologies in firms and provides an excellent internal firm environment for further enhancement of GTFP. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 3 (H3). *Unabsorbed slack resources promote the positive impact of AI on corporate GTFP.*

2.2.3. The Moderating Effect of Potentially Lack Resources

Potential slack resources are available to managers and are defined as additional resources that a firm obtains from the external environment by increasing its debt. Potential slack alleviates firms' concerns about future risks and performance and encourages better strategic management and innovation [52]; this, in turn, presents a better prerequisite for the application of AI technologies in firms. According to Maria et al., (2020), the rational use of potentially slack resources has a favorable impact on firms' long-term performance [61], and a high level of potentially slack resources means that firms have a greater likelihood of being able to fully seize strategic opportunities, which ultimately contributes to the improvement of corporate performance [62]. At the same time, the enhancement of firm performance delivers sufficient internal firm resources for the optimization of GTFP. Potential slack reflects a firm's ability to borrow and deploy external funds [63] that are highly disposable to managers [64], providing both solid resources for firms to carry out digital technology applications and ample possibilities for management to optimize the firm's GTFP. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 4 (H4). *Potentially slack resources promote a positive effect of AI on corporate GTFP.*

Figure 1 presents the framework of this study.

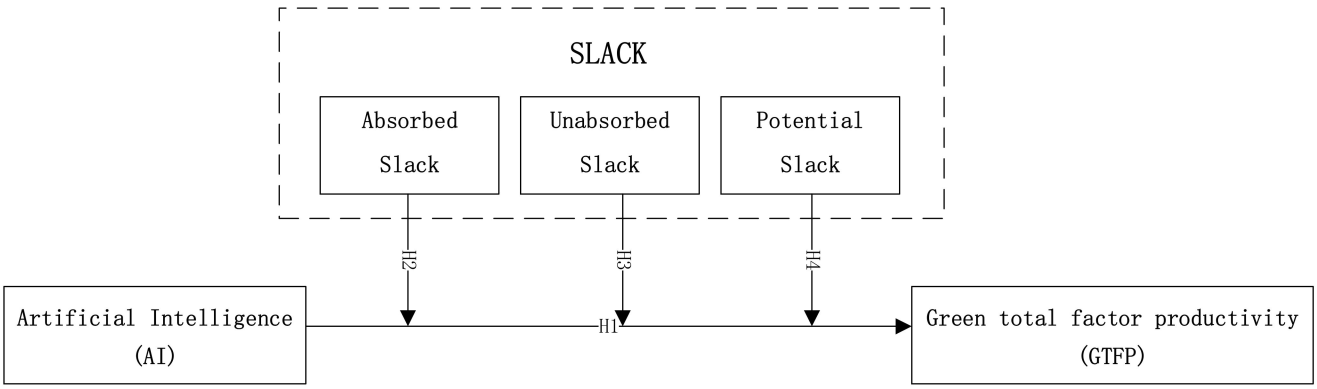

Figure 1. Research Framework.

3. Methodology

3.1. Definition and Measurement of Variables

3.1.1. Dependent Variable

This study uses the super-SBM model to measure the total factor productivity of enterprises. With reference to existing studies [65], the input–output indicators of enterprise GTFP are calculated as follows: (1) expected output indicator: enterprise sales revenue; (2) unexpected output indicator: enterprise carbon dioxide emissions; and (3) input indicators: labor, capital, and energy. The number of enterprise employees was measured as labor input, the net value of enterprise fixed assets was measured as enterprise capital, and energy consumption was measured as energy input. Finally, the input–output indicators were imported into the super-SBM model for calculation, and the GTFP of the enterprise was obtained.

3.1.2. Independent Variable

Along with the application of text analysis and machine learning methods in economics, it has become feasible to use text analysis methods for enterprise AI technology applications [13,66]. The level of enterprise AI technology application was measured according to the following steps: In the first step, a keyword lexicon for AI technology application was constructed, with reference to existing studies [67] (Table 1). In the second step, the annual reports of enterprises listed in A-share companies in China were compiled using Python software 3.8, and the text contents of all enterprise annual reports were extracted through Java PDFbox 2.08. In the third step, we used the constructed AI technology keyword thesaurus to search, match, and count the total extracted annual report text. Finally, we obtained the word frequency of AI technology application then by drawing on existing research [68]. The ratio of the word frequency of AI technology applications to the total text length of the annual report of the enterprise was used to measure the level of AI technology application of the enterprise.

Table 1. Keywords of AI.

AI	Business Intelligence	Image Understanding
Investment decision support system	Intelligent data analysis	Intelligent robot
Machine learning	Deep learning	Semantic search
Biometric identification technology	Face recognition	Speech recognition
Authentication of identity	Autonomous driving	Natural language processing

3.1.3. Moderating Variables

This study proposes the introduction of slack resources as a moderating variable to explore their effects on the relationship between AI technology applications and firms GTFP. There are three main classifications of slack resources in the literature: absorbed slack (AS), unabsorbed slack (UAS), and potential slack (PS). Referring to existing studies [69], this study uses selling, general, and administrative expenses (SG&A), current, and equity-to-debt ratios to measure absorbed slack (AS), unabsorbed slack (UAS), and potential slack (PS), respectively.

3.1.4. Control Variables

As there are additional relevant variables that may affect the GTFP of firms, this study refers to the existing literature on firm GTFP [65,70–72] to reduce the effect of omitted variables and controls for the following variables: firm size (Size), board size (Board), return on assets (ROA), cash flow ratio (Cashflow), nature of corporate ownership (SOE), and years of corporate listing (ListAge). In addition, to ensure the accuracy of the findings, industry dummy variables (INDUSTRY) and year dummy variables (YEAR) were set up, with industry dummy variables taking the value of 1 if the firm belonged to the industry and 0 if it did not belong to the industry. The same system also applied to year dummy variables. Table 2 lists the names, abbreviations, and definitions of the variables.

3.2. Model Design

Four models were established to test the proposed hypotheses. In the four models, $GTFP_{i,t}$ is the explanatory variable, which represents the GTFP of firm i in year t. $\Sigma Control_{i,t}$ represents the overall level of control variables, φ_Y and γ_I represent year dummy variables and industry dummy variables, respectively, and $\varepsilon_{i,t}$ represents the residual term.

Table 2. Definition and measurement of the variables.

	Variables	Symbol	Definitions
Dependent variable	Green total factor productivity	GTFP	Super-SBM model
Independent variable	AI	AI	Frequency of AI keywords in the annual report/total number of words in the annual report
Moderating variables	Absorbed slack	AS	SG&A expense ratio = (administrative expenses + selling expenses)/sales revenue
	Unabsorbed slack	UAS	Current ratio = current assets/current liabilities
	Potential slack	PS	Equity to debt ratio = net assets/total liabilities
Control variables	Size of enterprise	Size	Logarithm of total assets
	Size of board	Board	Logarithm of the number of board members
	Net profit rate on total assets	ROA	Net profit/average balance of total assets
	Nature of enterprise property right	SOE	It is 1 for state-owned enterprises and 0 otherwise
	Cash flow ratio	Cashflow	Net cash flow from operating activities/total assets
	Year of listing	ListAge	Logarithm of the year of listing plus 1
	Dummy variable of industry	Industry	Belonging to the industry is 1 and 0 otherwise
	Dummy variable of year	Year	Belonging to the year is 1 and 0 otherwise

In Model (1), $AI_{i,t}$ is an explanatory variable representing the level of AI technology application at firm i in year t. The larger the value, the higher is the level of AI technology application by the firm in that year. The model tests the relationship between AI applications and the enterprise GTFP. If β_1 is positive and passes the significance test, it means that enterprise AI technology application positively affects enterprise GTFP, which supports Hypothesis 1. If β_1 does not pass the significance test or β_1 is negative and passes the significance test, it means that AI technology application cannot affect the GTFP of the enterprise, meaning that Hypothesis 1 is not valid.

Models (2) to (4) examine the moderating effects of absorbed, unabsorbed, and potential slack between AI applications and firms' GTFP, respectively. As in Model (2), the model incorporates the interaction term between AI application and absorbed slack ($AI_{i,t} \times AS_{i,t}$) to verify the moderating effect of absorbed slack. If β_2 is positive and passes the significance test, and β_1 is positive and passes the significance test, it means that the higher the level of absorbed slack, the stronger the promotion effect of AI technology application on the GTFP of the enterprise, and Hypothesis 2 is valid. If β_2 is negative and passes the significance test, while the coefficient of β_1 passes the significance test, then the firm's absorbed slack negatively moderates the positive impact of AI application on the firm's GTFP. The interpretation of Models (3) and (4) is similar to that of Model (2) and will not be repeated.

$$GTFP_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \Sigma Control_{i,t} + \varphi_Y + \gamma_I + \varepsilon_{i,t} \quad (1)$$

$$GTFP_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 AI_{i,t} \times AS_{i,t} + \beta_3 AS_{i,t} + \Sigma Control_{i,t} + \varphi_Y + \gamma_I + \varepsilon_{i,t} \quad (2)$$

$$GTFP_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 AI_{i,t} \times UAS_{i,t} + \beta_3 UAS_{i,t} + \Sigma Control_{i,t} + \varphi_Y + \gamma_I + \varepsilon_{i,t} \quad (3)$$

$$GTFP_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 AI_{i,t} \times PS_{i,t} + \beta_3 PS_{i,t} + \Sigma Control_{i,t} + \varphi_Y + \gamma_I + \varepsilon_{i,t} \quad (4)$$

3.3. Sample Selection

This study selected data on Chinese A-share listed companies from 2013 to 2020 as the research sample. The reason for selecting 2013 as the starting year of the sample is that, on the one hand, the Chinese government started to consider AI as an important development area in 2013 and put forward a series of policies to encourage companies to develop AI technologies [73]. On the other hand, some scholars believe that digital technologies represented by AI and big data started to develop rapidly in China since 2013 [74]. This provided the possibility of obtaining relevant data for this study. The year 2020 was chosen as the sample termination year because some of the input–output indicators used to measure the GTFP of enterprises are updated only up to 2020.

The data of China's A-share listed firms from 2013 to 2020 served as the study's initial sample. To avoid interference of abnormal data, this study screened and processed the data according to the following criteria. The abnormal data involved in this study refer to missing values, abnormal operating values and extreme values. These abnormal data will reduce the accuracy of the study and cannot be controlled by the increase or decrease in variables, so they need to be eliminated. The specific steps are as follows. First, the data of companies in the financial industry were excluded. This is because the financial industry and the non-financial industry in China use different accounting standards. This will cause a lot of mistakes in the data, so it needs to be excluded [75]. Second, the data of companies classified as ST, ST*, or PT owing to abnormal financial status were excluded. ST companies represent negative net profits for two consecutive fiscal years, ST* companies represent negative net profits for three consecutive fiscal years, and PT companies represent companies that have stopped trading and are awaiting delisting [76]. The above three types of companies will be given special treatment in China, and the company data is inconsistent with the facts, so they need to be eliminated [77]. Third, (data) companies with serious abnormal observations were excluded. This step refers to the relevant literature and eliminates the sample data with null values [74]. Finally, to avoid the influence of extreme values [78], in this study, the variables were subjected to a 1% tailoring process, and 8511 sample observations were obtained. The independent, dependent, and moderating variables were also logarithmised. All the data used in this study were obtained from the China Stock Market & Accounting Research Database[1], the WIND Database[2], and Chinese Research Data Services[3], and the data processing software involved were Stata 17.0, MATLAB 9.8, and Python 3.8.

4. Results

4.1. Descriptive Statistics

The results of the descriptive statistics are presented in Table 3. The mean value of GTFP among enterprises is −0.81, and the standard deviation is 0.519, indicating a large difference in the level of GTFP among enterprises. The negative value of this variable was due to data skewness in the distribution of the value; therefore, it was logarithmically processed. The mean value of AI technology application is 0.02 with a standard deviation of 0.043, which means that the level of AI technology application differs from one enterprise to another and varies widely. The minimum value is 0.000, which shows that some enterprises are not practicing AI technology application. Descriptive statistical analyses of other variables were not repeated. The sample data used in this study complied with the standard. The skewness and kurtosis of all data met the requirements of a normal distribution, and the data form was good.

4.2. Correlation

The correlation results for all variables are presented in Table 4. A Pearson's correlation coefficient was used to analyze the correlations between all variables. As shown in Table 4, the correlation coefficient between AI technology application and firm GTFP is 0.081 and is significant at the 1% level. This indicates a highly positive correlation between AI technology application and firm total factor productivity before controlling for the relevant variables, which tentatively indicates that AI technology application positively affects factor productivity. It is not appropriate to judge the relationship based only on the correlation coefficient, and further regression analyses are required. Additionally, to ensure the rigor of the study, the model variables were tested for multiple cointegrations. After the calculation, the variance inflation factors (VIF) were all less than three, and there was no obvious multicollinearity problem.

Table 3. Descriptive statistics.

Variables	*N*	Mean	SD	Min	Median	Max	Skewness	Kurtosis
GTFP	8511	−0.81	0.519	−2.1027	−0.7846	0.7431	0.0479	3.3058
AI	8511	0.02	0.043	0.0000	0.0000	0.1429	1.9365	5.4033
AS	8511	−2.13	0.753	−4.2230	−2.1083	−0.4944	−0.2365	3.0217
UAS	8511	0.52	0.675	−1.2103	0.4571	2.5380	0.3860	3.6602
PS	8511	0.30	0.951	−1.9796	0.2635	2.7114	0.1238	2.8214
Size	8511	22.54	1.304	19.5511	22.3420	26.3978	0.6501	3.1580
ROA	8511	0.04	0.051	−0.1224	0.0330	0.1669	−0.3344	4.8416
Board	8511	2.14	0.194	1.6094	2.1972	2.7080	−0.2649	3.9718
SOE	8511	0.39	0.488	0.0000	0.0000	1.0000	0.4553	1.2073
ListAge	8511	2.44	0.574	0.6931	2.4849	3.3322	−0.5364	2.6238
Cashflow	8511	0.05	0.064	−0.1965	0.0475	0.2568	−0.0215	4.0417

SD: Standard deviation; GTFP: Green total factor productivity; AI: Artificial intelligence; AS: Absorbed slack; UAS: Unabsorbed slack; PS: Potential slack; ROA: Net profit rate on total assets; SOE: Nature of enterprise property right.

Table 4. Correlation.

	GTFP	AI	AS	UAS	PS	Size	ROA	Board	SOE	ListAge	Cashflow
GTFP	1										
AI	0.081 ***	1									
AS	−0.219 ***	0.035 ***	1								
UAS	−0.040 ***	0.066 ***	0.359 ***	1							
PS	−0.181 ***	0.028 **	0.399 ***	0.769 ***	1						
Size	0.278 ***	0.048 ***	−0.445 ***	−0.427 ***	−0.541 ***	1					
ROA	0.069 ***	−0.0110	−0.00300	0.281 ***	0.329 ***	0.044 ***	1				
Board	0.024 **	−0.075 ***	−0.144 ***	−0.174 ***	−0.160 ***	0.264 ***	0.033 ***	1			
SOE	0.055 ***	−0.090 ***	−0.271 ***	−0.269 ***	−0.293 ***	0.345 ***	−0.089 ***	0.247 ***	1		
ListAge	0.104 ***	0.062 ***	−0.238 ***	−0.308 ***	−0.349 ***	0.400 ***	−0.091 ***	0.142 ***	0.448 ***	1	
Cashflow	−0.022 **	−0.0120	−0.059 ***	−0.005	0.153 ***	0.061 ***	0.404 ***	0.055 ***	−0.0140	0.023 **	1

Note: *** $p < 0.01$, ** $p < 0.05$. GTFP: Green total factor productivity; AI: Artificial intelligence; AS: Absorbed slack; UAS: Unabsorbed slack; PS: Potential slack; ROA: Net profit rate on total assets; SOE: Nature of enterprise property right.

4.3. Regression Results and Analysis

A Hausman test was conducted to ensure the fit of the research model. The results demonstrated that this study was more applicable to fixed-effects models. Therefore, this study used a fixed effects model that incorporated both industry and year fixed effects.

The regression results are presented in Table 5. The first column presents the relationship between the independent and dependent variables, and the coefficient of AI technology application is 0.6346, passing the significance test at the 1% level and suggesting that there is a positive effect of the firm's AI technology application level on its GTFP, which precisely verifies Hypothesis 1.

The second to fourth columns of Table 5 illustrate the moderating effects of the three moderating variables. In the second column, the coefficient of the interaction term between AI technology application and a firm's absorbed slack (AI × AS) is 0.5087 and passes the significance test, while the coefficient of AI technology application (AI) is significantly positive, meaning that the higher a firm's level of absorbed slack, the stronger the contribution of its AI technology application to its total factor productivity, which supports Hypothesis 2. Similarly, the results in the third and fourth columns indicate that both unabsorbed slack (UAS) and potential slack (PS) positively moderate the positive effect of AI technology application (AI) on firm total factor productivity (GTFP), verifying Hypotheses 3 and 4, respectively.

Table 5. Regression results.

Variables	(1) GTFP	(2) GTFP	(3) GTFP	(4) GTFP
AI	0.6346 *** (3.9551)	0.5419 *** (3.4217)	0.5450 *** (3.4474)	0.6120 *** (3.8659)
AS		−0.1760 *** (−8.5976)		
UAS			−0.0420 ** (−2.2119)	
PS				−0.0584 *** (−3.9321)
AI × AS		0.5087 ** (2.4866)		
AI × UAS			0.8740 *** (3.5667)	
AI × PS				0.3438 * (1.9610)
Size	0.1151 *** (6.0726)	0.0838 *** (4.4910)	0.1066 *** (5.5251)	0.0908 *** (4.7013)
ROA	0.5356 *** (3.7515)	0.1683 (1.1461)	0.6119 *** (4.2237)	0.7086 *** (4.8220)
Board	−0.0601 (−1.2350)	−0.0628 (−1.3039)	−0.0623 (−1.2847)	−0.0566 (−1.1718)
SOE	−0.1076 ** (−2.0070)	−0.0921 * (−1.7566)	−0.1022 * (−1.8989)	−0.1083 ** (−2.0152)
ListAge	0.2853 *** (6.3954)	0.2485 *** (5.6847)	0.2392 *** (5.4139)	0.2321 *** (5.1927)
Cashflow	0.1559 (1.5193)	0.1018 (1.0168)	0.1500 (1.4610)	0.1604 (1.5638)
Constant	−3.8400 *** (−9.0264)	−3.5517 *** (−8.6202)	−3.5131 *** (−8.0221)	−3.1854 *** (−7.2384)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	8511	8511	8511	8511
R-squared	0.124	0.143	0.116	0.116

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. SD: Standard deviation; GTFP: Green total factor productivity; AI: Artificial intelligence; AS: Absorbed slack; UAS: Unabsorbed slack; PS: Potential slack; ROA: Net profit rate on total assets; SOE: Nature of enterprise property right.

4.4. Robustness Test

The regression results suggest that corporate adoption of AI technology positively affects corporate GTFP. However, higher levels of corporate total factor productivity support resources, to a certain extent, to promote corporate AI technology adoption, which may be endogenous. To address this issue, this study substituted the research model and constructed instrumental variables for re-regression using the two-stage least squares method to verify the robustness of the findings.

The endogeneity problem is mainly caused by a correlation between the current period's independent variables and the disturbance terms of the current period; that is, the covariance between the current period's independent variables and the current period's disturbance terms is not zero. Moreover, the lagged one-period independent variables tend to be uncorrelated with the perturbation terms in the current period. Referring to the existing literature [13], we used a one-period lagged corporate AI technology application (AI_{t-1}) as the instrumental variable and applied the two-stage least squares method for validation.

Table 6 presents the results of the robustness tests. The first column presents the first stage of the instrumental variables approach, in which the lagged one-period AI technology application (AI_{t-1}) and current-period AI technology application (AI) are regressed as explanatory and explanatory variables, respectively. The coefficient of AI_{t-1} is 0.2460 and is significant at the 1% level, suggesting that the instrumental variable is positively correlated with the independent variable. Meanwhile, the Cragg-Donald Wald *F*-statistic is 232.409 and the *p*-value of the unidentifiable test is 0.000, indicating that the instrumental variable passed the weak instrumental variables test and the unidentifiable test, which means that the instrumental variable is appropriate. The second column presents the second stage of the instrumental variable method, where the fitted value calculated in the first stage—that is, the value after removing the endogenous part of the independent variable—is regressed as the explanatory variable in the second stage. The coefficient of AI is 1.6366, which also passes the significance test, demonstrating that the application of AI technology positively contributes to the total factor productivity of the firm. Thus, Hypothesis 1 holds after solving the endogeneity problem.

Table 6. Robustness Test: Results of 2sls.

Variables	**First Stage AI**	**Second Stage GTFP**
AI_{t-1}	0.2460 *** (15.2450)	
AI		1.6366 ** (2.1896)
Size	0.0046 *** (2.6388)	0.1138 *** (5.5304)
ROA	−0.0078 (−0.5624)	0.4930 *** (3.1105)
Board	0.0135 ** (2.3191)	−0.0795 (−1.1890)
SOE	−0.0114 ** (−2.4737)	−0.0401 (−0.7512)
ListAge	0.0046 (0.8221)	0.1155 * (1.7967)
Cashflow	0.0127 (1.2119)	0.3686 *** (3.0669)
Constant	−0.1338 *** (−2.9658)	
Industry FE	YES	YES
Year FE	YES	YES
Observations	5106	5106
R-squared	0.224	0.101
Underidentification test *p*-value	0.000	
Cragg-Donald Wald *F* statistic	232.409	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. SD: Standard deviation; GTFP: Green total factor productivity; AI: Artificial intelligence; AS: Absorbed slack; UAS: Unabsorbed slack; PS: Potential slack; ROA: Net profit rate on total assets; SOE: Nature of enterprise property right.

5. Discussion and Conclusions

5.1. Discussion

In the current digital economy era, and with the intensification of environmental pollution problems that accompany economic growth, much attention has been paid to the practical application of digital technologies to promote environmental protection, enhance resource utilization efficiency, and attain green and sustainable development [79]. As a typical example of emerging digital technologies, AI provides new opportunities for solving environmental protection problems and improving resource utilization efficiency. Some scholars found that AI enables firms to mitigate environmental pollution emissions and consequently promote their environmental performance [80], while others found that AI technologies assist firms in identifying and improving manufactured products and processes, thereby improving their resource utilization efficiency [81].

Existing studies have focused on the impact of AI technology on the efficiency of enterprise resource utilization or environmental protection issues, which is not conducive to a comprehensive understanding of the impact of digital technology on the environmental and resource efficiency dimensions of enterprises. Because it is difficult to measure both productivity and environmental quality using a single indicator [82], this study selected GTFP, which differs from traditional total factor productivity in that it considers both the input and output of resources as well as the impact of environmental pollutant emissions, such as carbon dioxide [83]. Therefore, the choice of GTFP as an outcome variable for exploring the impact of AI technology on green sustainable development is conducive to fully revealing and understanding the integrated impact of digital technology on economic performance and the ecological environment.

Currently, most existing studies on GTFP focus on the macro- and meso-levels; that is, they mostly focus on regional [84], urban [85], and industry GTFP [86]. Few studies have focused on micro level GTFP, meaning that few have focused on the GTFP of individual enterprises. In addition, China's path toward balanced economic and environmental development has received worldwide attention in recent years [87], and it is imperative to explore the drivers of GTFP in the Chinese context. Therefore, this study analyzes the impact of AI technology on the GTFP of enterprises, which, on the one hand, compliments academic research on GTFP at the enterprise level and, on the other, reveals the driving logic of green sustainable development of Chinese enterprises in the digital economy, which may provide insights for enterprises in other countries or regions to attain green development.

This study found that artificial intelligence is advantageous for increasing the green total factor productivity of businesses, which is crucial for attaining green and sustainable business development. The application of artificial intelligence can assist businesses in improving resource efficiency, controlling and reducing environmental pollution, fostering green industries, and promoting the use of renewable energy. Thus, it can increase the green total factor productivity of businesses in order to attain sustainable green development. When businesses encounter bottlenecks in sustainable green development, they can use AI technology to enhance the situation.

To further increase the depth of the study, we selected corporate slack resources as the moderating variable from the perspective of behavioral theory. Based on the classification of slack resources in the existing literature [53], the moderating roles of absorbed, unabsorbed, and potential slack in the relationship between AI and corporate GTFP were explored. The boundaries of the relationship between the two were further expanded to enhance the practical value of this study and guide enterprises on how to apply enterprise resource conditions to enhance the contribution of digital technology to the sustainable development of enterprises. This study found that all three redundant resources are beneficial in promoting the role of AI in enhancing the green total factor productivity of firms. This provides confidence for firms to create redundant resources. Although redundant resources have been found to have adverse moderating effects in some aspects [88], they are highly beneficial and feasible for applying AI technologies to enhance the green sustainability of enterprises. This also provides the possibility for further research and the expansion of redundant resources.

5.2. Conclusions

As a key indicator for measuring sustainable green development, GTFP compensates for the shortcomings of traditional total factor productivity, which does not consider natural resources and environmental constraints, by incorporating environmental protection indicators such as pollutant emissions into the accounting system. Most previous studies have focused on regional GTFP [84], urban GTFP [85], and industry GTFP [86] as the research dimensions of green total factor productivity. This study focuses on green TFP at the firm level, completing the relevant research at the microlevel. At the same time, previous studies have shown that there is often a strong positive correlation between a company's green practices and its performance [89]. Therefore, improving the green practice capability of enterprises is particularly important to enhance enterprise performance and achieve sustainable development. This study focuses on the relationship between AI technology and GTFP, with a view to provide insights into new paths by which enterprises can use digital technology to pursue green and sustainable development.

Using a two-way fixed effects model, this study selected A-share listed companies in China from 2013 to 2020 as the research sample to examine the impact of AI technology applications on enterprise total factor productivity. The results show that the application of AI technology has a positive impact on the GTFP of enterprises. By enhancing the level of AI technology application, enterprises can significantly improve their own GTFP level, which is also consistent with the claim of endogenous economic growth theory—that the application and advancement of innovative technology offers a solid guarantee for economic growth. These findings provide empirical insights for enterprises to further study and apply AI technologies.

The theory of business behavior asserts that the role of slack resources in a firm is critical. This study investigates how absorbed, unabsorbed, and potential slack affect the relationship between AI technology applications and factor productivity, using slack resources as moderating variables. The results revealed that, first, absorbed slack resources positively moderated the relationship between AI technology application and enterprise GTFP, and the more absorbed slack resources an enterprise has, the more obvious the promotional effect of AI technology application on enterprise GTFP. This finding verifies the previous theoretical analysis that the more resources an enterprise absorbs, the more likely it is to focus on a specific strategic activity. Second, the higher the level of unabsorbed slack in an enterprise, the stronger the positive contribution of AI technology application to the GTFP of the enterprise. Unabsorbed slack resources are extremely mobile and can be easily invested in a company's various technological activities. If a large amount of unabsorbed slack resources exists in an enterprise, it can provide solid resources for the application of AI technology, thus improving the enterprise's GTFP. Third, the level of potential slack in enterprises can strengthen the positive impact of AI technology application on the GTFP of enterprises. Potential slack is the additional resources obtained by enterprises from the external environment through increasing debts, which provides good prerequisites for the application of AI technology by enterprises and better promotes them to enhance the GTFP of enterprises, which is also consistent with the results of previous theoretical analysis.

5.3. Implications

The study offers contributions at theoretical and practical levels.

The theoretical contributions are as follows. First, this study further expands the literature related to digital technology and enterprise green development and explores the impact of AI on enterprise green development as a typical digital technology, which contributes to exploring the driving factors of enterprise green development and provides theoretical evidence for enterprises to promote green development, with the support of digital technology. It also expands research on the outcome effects of AI technology applications. Second, rather than using a single indicator to measure the green development level of enterprises, this study applies the super-SBM model to comprehensively incorporate the input–output indicators related to the green development of enterprises and calculates the GTFP of enterprises, which enriches the measurement basis of their green development capability. Third, research on GTFP is mostly focused on the regional development level, which means that GTFP is studied from a macroscopic perspective, such as provinces, cities, and industries, but is rarely explored at the microscopic level. This study focuses on the relationship between AI and enterprise GTFP at an individual enterprise level, which broadens the understanding of the driving factors behind green total a microscopic perspective. Finally, this study focuses on the indirect effects of slack resources in enterprises, classifies slack resources into absorbed, unabsorbed, and potential slack, in accordance with existing criteria, and it investigates their moderating effects on AI and GTFP. The results revealed the applicability of different types of slack resources in the strategic development of enterprises and facilitating a comprehensive understanding of the relationship between digital technology and enterprise green development.

The practical contributions are as follows. At the macro level, the research findings verify the accuracy of vigorous AI development, offer directional guidance for the policy formulation of relevant digital technology development, and provide reference to the management and guidance of the government and relevant departments regarding digitalization. At the micro level, the research findings point in the direction of development of AI technology and provide a reference for enterprises to promote GTFP and enhance green development capability. Simultaneously, research findings on slack resources also contribute to rational resource allocation for enterprises in order to adapt to their strategic development.

5.4. Limitations and Future Research

As the models, methods, and data involved in this study are limited, the findings may have limitations. To further indicate possible future research directions, this study has identified the following shortcomings. First, the keyword lexicon of AI technology applications constructed in this study is based on the development characteristics of AI technology in Chinese enterprises, and the lexicon has strong localization characteristics. Thus, the applicability of the research findings to enterprises in other countries and regions is weak. In future, the AI technology development characteristics of other countries and regions should be combined to further expand and improve the keyword lexicon of AI technology to verify the universality of the findings of this study. Second, this study uses a composite index to measure the application level of AI technology in enterprises but fails to conduct a classification study of AI to explore the relationship between different dimensions of AI technology and the green development of enterprises. Additionally, the relationship between other types of digital technologies and enterprise green development has not been carefully examined, and the impact of multidimensional AI or other digital technologies on enterprise green development should be explored in the future.

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Notes

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[2] https://www.wind.com.cn. accessed on 10 March 2023.

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