AIMS Environmental Science

AIMS Environmental Science, 12(5): 887–915.
DOI: 10.3934/environsci.2025039
Received: 03 September 2025
Revised: 13 October 2025
Accepted: 24 October 2025
Published: 29 October 2025

https://www.aimspress.com/journal/environmental

Research article

Uncovering the role of financial technology for total factor energy efficiency in China: based on machine learning methods

Yaning Zhang and Yong Liu*

School of Economics, Sichuan University, Chengdu 610065, China

* **Correspondence:** Email: 16600246575@163.com; yonghopeliu@sina.com.

Abstract: In the context of China's long-standing extensive economic growth model and increasing environmental pressures, improving total factor energy efficiency (TFEE) has become crucial for environmental protection and sustainable development. Financial technology (FinTech), as an emerging technology-driven financial innovation model, offers potential solutions; however, empirical evidence on its environmental impact remains limited. Based on balanced panel data of 268 Chinese cities from 2011 to 2021, we employed a double machine learning approach and the SHAP value algorithm to assess the impact of FinTech on TFEE as well as its nonlinear effects, with Random Forest being the primary estimation model. The major findings were as follows: (1) FinTech has a significant promoting effect on improving TFEE, which has passed multiple robustness tests. (2) In terms of mediation mechanisms, FinTech exerts its positive influence on TFEE by promoting green finance development, facilitating industrial structure optimization, and driving green technological innovation. (3) Heterogeneity analysis indicates that the role of FinTech in enhancing TFEE is more pronounced in eastern China, non-old industrial bases, and large cities. (4) According to the distribution trend of SHAP value, the impact of FinTech on TFEE exhibits a nonlinear effect, and its positive driving force can be effectively exerted only after its development level exceeds a specific threshold around 4.2. This study provides empirical evidence on the role of FinTech in advancing TFEE, offering valuable insights for policymakers seeking to harness FinTech as an effective tool to advance energy efficiency and support sustainable economic transformation.

Keywords: financial technology (FinTech); total factor energy efficiency (TFEE); double machine learning; SHAP value; mediation mechanism; nonlinear effect; China

1. Introduction

For a long time, China's extensive economic growth model and "GDP competition" mindset have led to misallocation of resources, low energy efficiency, and increased pressure on the ecological environment [1]. Especially due to technical limitations, China generates substantial greenhouse gases and industrial waste during energy consumption. The urban systems in China face the dual challenges of economic growth and environmental governance [2]. To effectively alleviate the adverse impact of climate warming and environmental pollution on socio-economic development, improving total factor energy efficiency (TFEE) is a powerful measure [3]. As the world's largest energy consumer and carbon emitter, China plays an important role in global environmental governance. To this end, the Chinese government set ambitious "dual carbon" goals in 2020, namely achieving "carbon peak" before 2030 and "carbon neutrality" before 2060. Against this background, China has been seeking a sustainable development path to achieve coordination between the economy, society, and environment.

Traditionally, the financial system has played a core role in resource allocation [4]. However, traditional finance faces bottlenecks such as information asymmetry, high transaction costs, insufficient service coverage, and complex risk assessment [5], which limit its empowerment in enhancing energy efficiency. In recent years, financial technology (FinTech), driven by cutting-edge information technology, has developed rapidly, not only reshaping the financial industry and service models, but also injecting vitality into promoting economic growth and sustainable development [6,7]. FinTech is defined as financial innovation driven by technologies such as big data, artificial intelligence, blockchain and the Internet of Things, which promotes sustainable practices by creating new financial products, services, and business models aligned with environmental goals [8]. According to World Bank data, more than 200 countries have introduced policies to promote FinTech development [9]. In 2022, the People's Bank of China released the "FinTech Development Plan (2022-2025)", emphasizing that FinTech development in China should adhere to green and low-carbon principles, thereby contributing to achieving "dual carbon" and sustainable development goals. In 2024, the Third Plenary Session of the 20th CPC Central Committee also highlighted the need to implement financial policies and standards that support green and low-carbon development to promote the construction of an economic system for green, low-carbon, and circular development. Therefore, examining the impact and mechanisms of FinTech on TFEE is not only related to achieving environmental protection goals, but also important for promoting high-quality economic development, with both theoretical value and practical urgency.

Based on the collected literature analysis, scholars have conducted extensive research on TFEE influencing factors, covering the urbanization process, digital technology, foreign trade, carbon rights trading, environmental information disclosure, and environmental regulation [10–15]. These studies establish important foundations for understanding TFEE determinants but have not sufficiently incorporated modern financial innovations. Moreover, although FinTech's role in improving economic efficiency has been widely studied and recognized [16,17], systematic research on its impact on environmental governance is in its infancy. For instance, research indicates that FinTech development has reduced carbon emissions in BRICS nations [18], while some scholars believe FinTech has increased energy consumption and carbon emissions in G7 countries [19]. Evidently, there is inconsistency in the literature regarding FinTech's impact on TFEE. Considering the booming development of FinTech, research exploring its impact on TFEE remains insufficient. Therefore, whether FinTech enhances or suppresses TFEE, or whether nonlinear effects exist, requires further empirical testing, especially based on Chinese city data.

In addition, urban TFEE improvement is a complex systematic project involving the combined effect of multiple factors [20,21]. Investigations into TFEE determinants have utilized traditional econometric frameworks, predominantly including panel regression models with fixed effects. While these approaches have yielded substantial insights, they exhibit inherent methodological constraints. Specifically, they often struggle with high-dimensional covariate spaces, leading to potential overfitting or omitted variable bias when introducing many control variables. Furthermore, these models typically presuppose linear or parametrically specified nonlinear relationships, which may not adequately capture the complex, data-driven interactions characteristic of real-world socio-economic and environmental systems. A recent development, double machine learning (DML), bridges this gap by integrating flexible machine learning estimators with causal inference principles. This method is particularly adept at handling settings with many potential confounders and complex, nonlinear functional forms [22]. It employs techniques like orthogonalization to isolate the causal effect of a treatment variable, thereby producing unbiased and consistent estimates even when using regularized, non-parametric machine learning models for nuisance parameter estimation. Concurrently, the field of explainable artificial intelligence has produced frameworks such as SHAP (SHapley additive exPlanations) value, which quantifies the contribution of each feature to individual predictions based on cooperative game theory. This enables researchers to move beyond aggregate model performance and probe specific nonlinearities and threshold effects [23]. Despite these advanced methodologies' clear advantages, their adoption in TFEE research is nascent, and this study positions itself at this methodological frontier.

The relationship between FinTech and environmental outcomes is an emerging area of scholarly interest, yet it remains underdeveloped, especially regarding TFEE. Existing studies on TFEE influencing factors are plentiful but have not sufficiently incorporated modern financial innovations. While prior research acknowledges FinTech's economic benefits, its environmental implications, particularly within China's urban landscapes, are not well understood. Therefore, we aim to address these gaps by systematically investigating the impact and mechanisms of FinTech on TFEE in China. Specifically, we seek to answer the following research questions: (1) Does FinTech have a significant direct impact on TFEE in China? (2) What are the mediation mechanisms, specifically through green finance, industrial structure upgrading, and green technology innovation? (3) Does the impact exhibit heterogeneity across regions, city types, and sizes? (4) Are there nonlinearities or threshold effects in the relationship?

We address these gaps by providing novel empirical evidence from China, utilizing a comprehensive city-level panel dataset from 2011 to 2021. The focus on China is strategically significant given its status as the largest energy consumer and its ambitious national climate targets, offering a unique contextual focus. Theoretically, we move beyond establishing a simple direct relationship. It constructs and tests a multifaceted theoretical framework positing that FinTech influences TFEE indirectly through three critical mediating channels: Green finance development, industrial structure optimization, and green technological innovation. This framework offers a more nuanced understanding of the transmission mechanisms than previously available. Methodologically, we introduce significant innovation. The employment of DML model addresses limitations inherent in traditional econometrics when dealing with potential nonlinearities and high-dimensional confounders. Furthermore, the application of explainable machine learning techniques, specifically SHAP value analysis, enables identifying and interpreting complex nonlinear patterns and threshold effects, a capability often absent in conventional approaches. This methodological combination not only strengthens causal claims but also opens new avenues for analyzing complex socio-economic-environmental systems. Third, at the practical level, our empirical conclusions provide direct evidence for coordinating FinTech innovation and achieving environmental protection goals in many developing countries. The corresponding policy suggestions have practical guiding value for governments to precisely formulate sustainable development paths. By integrating a unique contextual setting, a novel theoretical mediation framework, and advanced machine learning methodologies, this research contributes empirically and theoretically to the evolving discourse on FinTech and sustainable development. It provides clarified insights into how FinTech can be harnessed as an effective tool for improving TFEE, thereby supporting environmental goals and economic transformation.

The structure of the rest of this paper is shown in Figure 1. First, we analyze the potential paths through which FinTech affects TFEE from a theoretical perspective. Subsequently, based on panel data of 268 Chinese cities from 2011 to 2021, the direct impact of FinTech on TFEE, as well as its heterogeneity and mediating transmission mechanism, is empirically examined using the DML method. In addition, we use explainable machine learning methods to explore the nonlinear relationship between FinTech and TFEE. Finally, we summarize the major findings and put forward policy recommendations to provide reference for urban environmental protection and sustainable development.

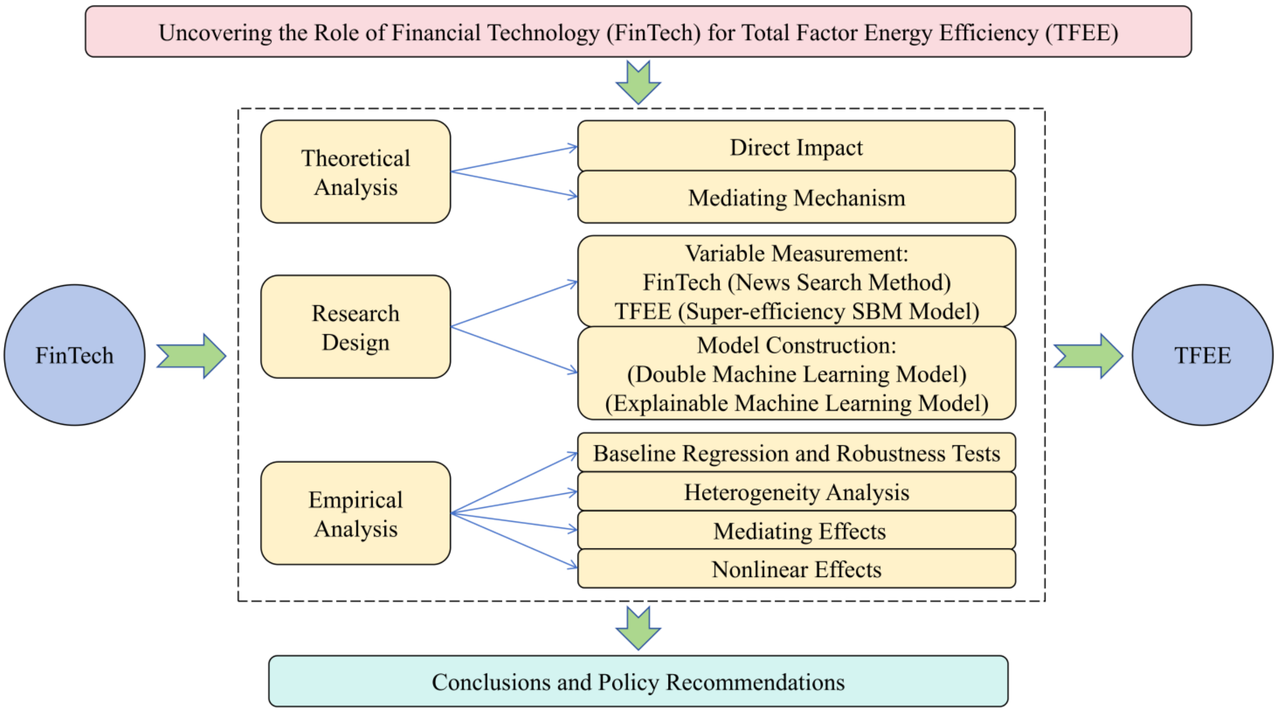

Figure 1. Research framework.

2. Literature review and research hypotheses

The theoretical underpinnings explaining how FinTech influences environmental performance remain underdeveloped in the literature. We address this gap by drawing upon Environmental Modernization Theory and the Triple Bottom Line framework. Environmental Modernization Theory posits that technological innovation and institutional restructuring are central to transforming economic systems onto more environmentally sustainable pathways [24]. It refutes the notion of an inherent conflict between economic development and environmental protection, arguing instead that modernization processes can be ecologically restructured. FinTech, as a technological innovation in the financial sector, embodies this potential by modernizing financial systems to better support ecological objectives, for instance, through enhancing capital allocation efficiency toward green projects [25]. Complementing this perspective, the Triple Bottom Line framework emphasizes that sustainable development necessitates interconnected and balanced consideration of economic prosperity, social equity, and environmental protection [26]. This framework provides a comprehensive lens to analyze FinTech's multifaceted impacts, ensuring that its effects are evaluated not just in economic terms but also for their social and environmental consequences, thereby aligning with holistic sustainability goals [27]. Building on these theoretical foundations, we propose that FinTech influences TFEE through multiple interconnected pathways. The direct effects operate primarily through improved resource allocation efficiency, enhanced risk assessment capabilities, and increased transparency in financial transactions. The indirect effects operate through three major mediating channels that represent distinct yet complementary mechanisms of environmental modernization and reflect the three pillars of the Triple Bottom Line. In the following sections, we synthesize empirical evidence and theoretical reasoning to develop specific hypotheses about these relationships.

2.1. The relationship between FinTech and TFEE (direct impact)

Environmental Modernization Theory suggests that technological innovations can directly improve environmental performance by enabling more efficient resource use. FinTech has brought profound changes to the traditional financial service model. This not only enables more enterprises and individuals to enjoy convenient and efficient financial services, but also lays a solid foundation for TFEE improvement. FinTech employs intelligent technologies to analyze user behavior and market trends, improving service precision and meeting diverse financial needs [28]. These capabilities enable personalized financial products that incentivize low-carbon choices, such as green loans or carbon-tracking investment portfolios. In addition, FinTech optimizes resource allocation and risk management, thereby improving TFEE. FinTech can utilize big data technology to mine and analyze vast information, achieving precise matching and efficient use of resources. For instance, by analyzing market trends, consumer behavior, and business operation data, FinTech can more accurately identify the potential value of green projects and enterprises, enabling precise capital allocation [29,30]. Furthermore, FinTech improves fund usage transparency and traceability through smart contract technologies [31,32], ensuring funds flow into green, environmentally friendly, and low-carbon areas, thus guaranteeing green investment effectiveness. These findings align with Environmental Modernization Theory's emphasis on technological innovation as a driver of environmental improvement.

However, theoretical perspectives also acknowledge potential countervailing effects that must be considered. Empirical research indicates that in early development stages, FinTech platforms might prioritize short-term profitability over environmental considerations, potentially channeling funds toward established, sometimes polluting, industries [33]. This empirical ambiguity reflects a theoretical tension between different potential development pathways for financial innovation. The inconsistent findings in the literature regarding FinTech's environmental impact further highlight the need for rigorous empirical testing of its net effect on energy efficiency.

Synthesizing these theoretical perspectives and empirical findings, we posit that the resource allocation improvements and transparency enhancements enabled by FinTech will produce a net positive effect on TFEE. The direct mechanisms of improved capital allocation to green projects, enhanced risk assessment for energy-efficient investments, and increased transparency in environmental financing are theoretically robust and empirically supported in related contexts. This leads to our first hypothesis.

Hypothesis 1. *FinTech can effectively enhance TFEE.*

2.2. The mediation mechanisms of FinTech affecting TFEE (indirect impact)

The Triple Bottom Line framework emphasizes that sustainability advancements often occur through interconnected economic, social, and environmental channels. FinTech's influence on TFEE operates through three such mediating pathways that represent distinct yet complementary mechanisms of environmental modernization.

2.2.1. Green finance development channel

FinTech promotes green finance development by providing more precise and efficient financial services. First, through big data analysis and artificial intelligence technologies, FinTech enhances market information transparency and reduces information asymmetry between financial institutions and investors [34,35], making green investment projects more likely to secure funding. Second, FinTech drives green financial product innovation such as green bonds and funds, guiding capital towards environmental and sustainable development sectors [36]. Additionally, traditional green finance requires substantial resources for due diligence, project evaluation, and risk control. FinTech, through automation and intelligent operations, reduces financial service intermediary steps and lowers transaction costs, enabling green projects to obtain funding at lower cost. On the other hand, green finance supports projects in environmental protection, clean energy, green transportation, and green buildings [37,38]. This ensures more financial resources are directed towards green, low-carbon, and environmentally friendly projects, which helps conserve resources, reduce pollution, and restore ecosystems, thus effectively improving TFEE. This channel resonates with the economic dimension of the TBL by fostering a financial system that supports environmental sustainability. Building on this empirical and theoretical foundation, we propose our second hypothesis.

Hypothesis 2. *FinTech enhances TFEE by promoting green finance development.*

2.2.2. Industrial structure optimization channel

FinTech supports emerging, high-tech, and green industries through efficient and innovative financial service models. First, blockchain technology application enhances transaction transparency and security, reduces traditional financial service intermediaries, and improves financial service efficiency. These changes promote financial industry innovation and lower business financing and transaction costs [39,40], thereby promoting emerging industry development. Second, FinTech guides more capital towards environmental and sustainable development sectors, accelerating industrial structure transformation towards green, low-carbon, and circular economies. This capital flow shift helps optimize and upgrade industrial structure. Furthermore, FinTech development has been supported by government policies, such as R&D subsidies and tax incentives, which facilitate green technology and industry development [41]. On the other hand, industrial structure optimization and upgrading signify a transition from traditional industries to high-tech and green industries. This transition improves resource utilization efficiency and effectively reduces energy consumption and environmental pollution, thereby contributing to sustainable economic development [42]. Furthermore, this mechanism aligns with the social dimension of the TBL by fostering structural economic change that can create new opportunities while mitigating environmental harm. Based on this theoretical mechanism and supporting empirical evidence, we propose our third hypothesis.

Hypothesis 3. *FinTech enhances TFEE by facilitating industrial structure optimization.*

2.2.3. Green technological innovation channel

FinTech enhances financial service efficiency and inclusiveness, stimulating technological innovation vitality and promoting scientific and technological achievement commercialization and application. First, FinTech provides precise data analysis and risk assessment, lowering financing thresholds and costs for green technological innovation projects. Artificial intelligence and big data analysis application enables financial institutions to more effectively identify and evaluate green technological innovation project value and risks, providing more reasonable financing solutions [43,44]. Additionally, as consumers' environmental protection and sustainable development awareness increases, green products and technologies with patents are more likely to gain market recognition [45]. This promotes enterprise green brand image construction and accelerates environmental technology promotion and application. On the other hand, green technological innovation improves energy efficiency in production processes and reduces production and environmental costs [46]. Moreover, technological innovation provides new solutions to address environmental pollution and ecological degradation, such as clean energy technologies, waste treatment, and recycling technologies. This pathway directly engages the environmental pillar of the TBL by fostering innovations that reduce ecological impact. Drawing on this empirical and theoretical foundation, we propose our fourth hypothesis.

Hypothesis 4. *FinTech enhances TFEE by driving green technological innovation.*

These mediating mechanisms collectively represent how FinTech contributes to environmental modernization through financial system transformation, structural economic change, and technological innovation. The interplay between these pathways illustrates the complex theoretical relationship between FinTech development and TFEE improvement, with each mechanism supported by both theoretical reasoning and empirical evidence from related contexts. To sum up, the theoretical mechanism of FinTech's impact on TFEE is shown in Figure 2. Whether FinTech can effectively improve TFEE and whether the possible mechanisms are valid require further empirical testing.

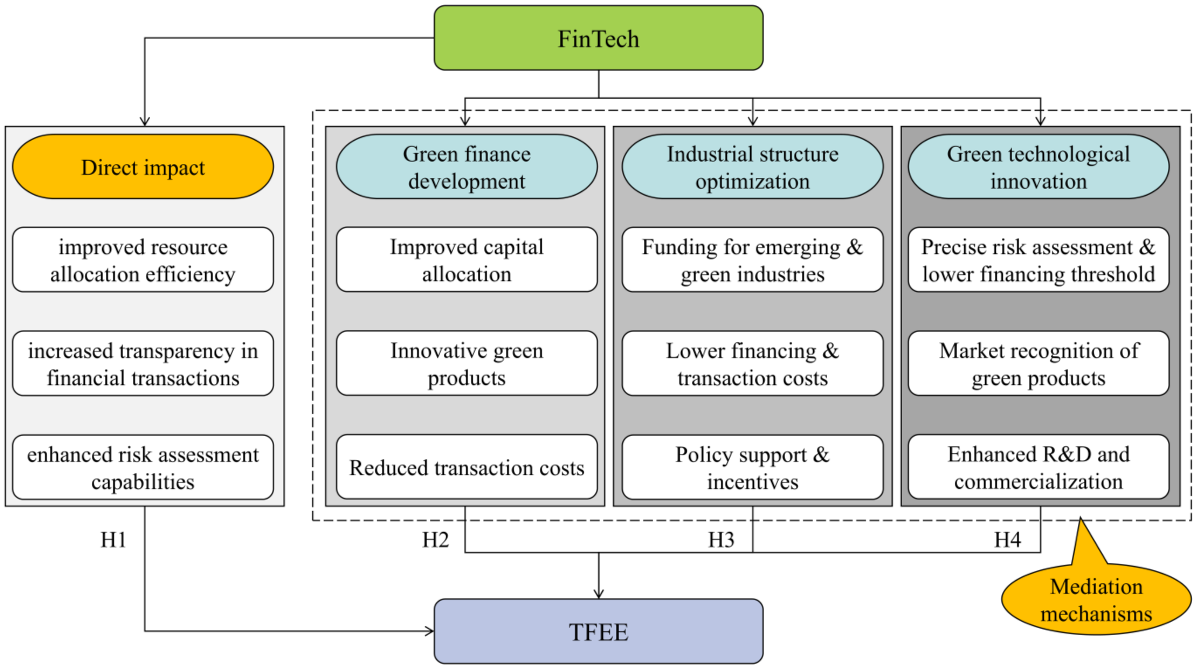

Figure 2. Theoretical analysis frame diagram.

3. Methods and data

3.1. Model construction

3.1.1. Double machine learning model

Compared to traditional econometric methods, the DML model has the following advantages. First, TFEE may be affected by different socioeconomic factors. To improve accuracy, it is necessary to control the interference of as many factors as possible on TFEE, which inevitably leads to the "curse of high-dimensional variables", affecting estimation accuracy [47]. Second, nonlinear relationships between variables are common, leading to estimation bias. The DML framework addresses these challenges through its unique orthogonalization procedure. This approach combines flexible machine learning algorithms with causal inference principles, enabling us to handle numerous control variables without incurring overfitting bias. The model's ability to capture complex nonlinear patterns makes it particularly suitable for examining the relationship between FinTech and TFEE. Therefore, we employ the DML model to estimate the potential impact of FinTech on TFEE. Referring to related literature [48], we construct a partially linear DML model as follows:

$$TFEE_{it} = \theta_0 FinTech_{it} + g(X_{it}) + U_{it} \tag{1}$$

$$E(U_{it} \mid FinTech_{it}, X_{it}) = 0 \tag{2}$$

where i represents the city, t represents the year, $TFEE_{it}$ is the dependent variable, $FinTech_{it}$ is the core explanatory variable, θ_0 is the coefficient of interest, indicating the impact and direction of

FinTech development on TFEE, X_{it} is a set of control variables and a machine learning algorithm is required to estimate the specific form of $g(X_{it})$, and U_{it} is the error term with a conditional mean of zero.

At this point, if the above two formulas are estimated directly, the estimates would be biased due to the high-dimensional or complex model settings. The Machine learning model has to introduce a regular term to reduce the dimensionality, which avoids the estimator's variance being too large, but also brings about the function's regularity bias, which makes it difficult for $\hat{\theta}$ to converge to θ_0.

To enhance the convergence speed of the model and ensure the unbiasedness of the coefficient estimates in small samples, we construct auxiliary regressions:

$$FinTech_{it} = m(X_{it}) + V_{it} \tag{3}$$

$$E(V_{it} \mid X_{it}) = 0 \tag{4}$$

where $m(X_{it})$ is the regression function of the high-dimensional control variables on the treatment variable, estimated using machine learning algorithms. The steps are as follows:

First, we use a machine learning model to estimate $m(X_{it})$ and obtain the estimate $m(X_{it})$, which in turn is calculated to obtain the estimate of the residual V_{it}.

$$\hat{V}_{it} = FinTech_{it} - \hat{m}(X_{it}) \tag{5}$$

Next, we use V_{it} as the instrument variable for $FinTech_{it}$, and then continue to use the machine learning algorithm to estimate $g(X_{it})$, which yields an unbiased estimate of:

$$\hat{\theta}_0 = \left(\frac{1}{n} \sum_{i \subseteq I, t \subseteq T} \hat{V}_{it}\ FinTech_{it} \right)^{-1} \frac{1}{n} \sum_{i \subseteq I, t \subseteq T} \hat{V}_{it} \left(TFEE_{it} - \hat{g}(X_{it}) \right) \tag{6}$$

The primary machine learning algorithm employed within the DML framework is the Random Forest (RF) regressor. This selection is justified by the algorithm's recognized capacity to capture complex nonlinear relationships and interactions among variables without requiring extensive feature engineering. Its inherent robustness to multicollinearity and its utility in providing feature importance measures represent additional advantages conducive to causal inference settings [49]. To ensure optimal model performance and generalizability, the dataset is partitioned into training and testing subsets with a 4:1 ratio. A five-fold cross-validation procedure is implemented on the training folds derived from the sample splits inherent in the DML approach, and the search for the optimal hyperparameter combination is conducted via a randomized search strategy. This rigorous procedure helps ensure that the machine learning models utilized within the DML framework avoid underfitting and overfitting, thereby enhancing the reliability of the final causal estimate [48]. The RF algorithm offers a solid foundation for such nonparametric estimation tasks within semiparametric models, and its application in this context follows established practices in the econometric machine learning literature [50,51].

3.1.2. Explainable machine learning model

In this paper, we use explainable machine learning to test whether there is a nonlinear effect of FinTech on TFEE. Conventional machine learning models often operate as a "black box", making it difficult to understand their operating mechanisms. In recent years, the SHAP (SHapley additive exPlanations) framework has provided a theoretical solution based on cooperative game theory [52]. This approach enables robust identification of critical nonlinear patterns that may remain obscured in parametric specifications, particularly threshold effects where FinTech's influence on TFEE undergoes significant transitions. The SHAP value algorithm is shown as follows:

$$\phi_i(v) = \sum_{S \subseteq N,\ \{i\}} \frac{|S|!(n-|S|-1)!}{n!}\left(v(S \cup \{i\}) - v(z)\right) \tag{7}$$

Among them, $\phi_i(v)$ represents the attribute value of each feature, S is all possible subsets of features except feature i, N is the set of all features, n is the number of features, $|S|$ is the number of feature S in the set, and $v(z)$ is the average predicted value of the model on the feature subset z. $\left(v(S \cup \{i\}) - v(z)\right)$ represents the change values before and after adding new features.

To ensure SHAP analysis robustness and interpretability, a structured procedure is implemented. The SHAP explanation relies on a RF model as the underlying predictive function, selected for its stability and proficiency in modeling complex feature interactions. All features from the primary double machine learning analysis are included, specifically the core explanatory variable FinTech and the complete set of ten control variables. Prior to model training, each feature is standardized to have zero mean and unit variance, which mitigates scale-induced bias in SHAP value computation. The dataset is divided into training and testing subsets using a 4:1 ratio. The RF model is trained solely on the training set. The TreeExplainer algorithm, an exact and efficient method tailored for tree-based models, is subsequently applied to compute SHAP values on the test set. This enables an efficient assessment of each feature's marginal contribution to individual predictions. To verify the stability of the identified nonlinear relationships and threshold effects, the analysis is repeated across multiple with varying random seeds. This approach confirms that the findings are robust and not an artifact of a particular data partition. TreeExplainer use aligns with established practices in explainable machine learning, providing consistent and theoretically grounded interpretations of complex model behaviors [53].

3.2. Variable measurement

3.2.1. Dependent variable

When evaluating TFEE, the traditional Data Envelopment Analysis (DEA) model has two key limitations: One is that it cannot handle both expected outputs and unexpected outputs simultaneously; the other is that it is difficult to distinguish efficiency differences among efficient decision-making units. Based on relevant literature and considering data availability, we measure TFEE using a super-efficiency SBM model containing undesirable outputs [11,13]. The model formulation is as follows:

$$\min\beta = \frac{\frac{1}{m}\sum_{i=1}^{m}(\frac{\overline{x}}{x_{ik}})}{\frac{1}{c_1+c_2}(\sum_{s=1}^{c_1}\frac{\overline{y^d}}{y_{sk}^d}+\sum_{q=1}^{c_2}\frac{\overline{y^u}}{y_{qk}^u})} \tag{8}$$

$$S.t.\begin{cases} \overline{x} \geq \sum_{j=1,\neq k}^{n} x_{ij}\gamma_j ; \overline{y^d} \leq \sum_{j=1,\neq k}^{n} y_{sj}^d \gamma_j \\ \overline{y^d} \geq \sum_{j=1,\neq k}^{n} y_{qj}^d \gamma_j ; \overline{x} \geq x_k ; \overline{y^d} \leq y_k^d ; \overline{y^u} \geq y_k^u \\ \gamma_j \geq 0; i=1,2,\cdots,m; j=1,2,\cdots,n; j \neq 0 \\ s=1,2,\cdots,c_1; q=1,2,\cdots,c_2 \end{cases} \tag{9}$$

where β is the efficiency value of the evaluation unit (DMU), assuming there are n DMUs, each consisting of inputs m, desired outputs c_1 and undesirable outputs c_2. x, y^d, and y^u represent the input matrix, desirable output matrix, and undesirable output matrix, respectively, and γ is the weight vector.

The specific indicator information is shown in Table 1. The input indicators encompass labor, capital, and energy consumption. Labor input is indicated by the number of employed people in each city. The actual capital stock is estimated using the perpetual inventory method for Chinese cities from 2011 to 2021, calculated at constant prices, with a depreciation rate of 10.96% [54]. Energy input is measured by the total energy consumption of each city, which includes natural gas, liquefied petroleum, and electricity and is converted into standard coal equivalent [55]. The desirable output is the local real GDP, and undesirable outputs included carbon emissions and three types of industrial emissions: Sulfur dioxide, industrial wastewater, and industrial smoke and dust.

Table 1. Indicator system of TFEE.

Measurement index	First-grade index	Second-grade index	Third-grade index
TFEE	Input indicators	Labor	Number of employed people
		Capital	Actual capital stock estimated by the perpetual inventory method
		Energy	Total energy consumption converted into standard coal equivalent
	Desirable output	GDP	Real GDP
	Undesirable output	Three types of industrial emissions	Industrial sulfur dioxide, Industrial wastewater, Industrial smoke and dust
		Carbon emissions	Carbon dioxide emissions

3.2.2. Independent variable

Following related scholars' practices [56], we utilize 48 keywords closely related to FinTech development, such as "big data", "blockchain", and "artificial intelligence". These keywords are paired with various Chinese cities and searched in the Baidu News advanced search function to retrieve the number of news reports containing specific city names and keywords annually. Based on this, we employ web crawling technology to extract the total number of search results from the source code of the Baidu News advanced search page. By aggregating the search results for all keywords for the same city, we construct an indicator reflecting FinTech activity level in each city. Given the positively skewed distribution of the original data, to ensure analysis normality and accuracy, we perform a logarithmic transformation of the total keyword search volume.

It is recognized that a search-based index may capture elements of media attention and public discourse alongside genuine FinTech activity. Within China's FinTech ecosystem, however, media coverage often corresponds closely to substantive developments. FinTech is a highly policy-sensitive sector where governmental announcements, corporate innovations, and regional pilot programs frequently attract substantial news reporting [57]. This makes news search volume a plausible proxy for regional FinTech vibrancy. Furthermore, alternative metrics such as transaction volumes or platform-specific penetration rates are often proprietary, unavailable at the city level, or limited to particular sub-sectors like digital payments. The Baidu search index provides extensive spatial and temporal coverage across 268 cities, facilitating a systematic macro-level assessment [58]. This methodological choice aligns with a growing body of scholarly work that utilizes digital informational footprints to analyze technological and financial development [59]. To address potential measurement concerns, an alternative proxy based on the number of registered FinTech firms is introduced in robustness checks, and the consistency of the major findings under this alternative measure supports the primary approach's validity.

3.2.3. Control variables

Based on data availability and completeness, we select 10 variables that affect TFEE. Economic Growth (per capita GDP), Population Density (population / regional land area), Economic Agglomeration (GPD/regional land area), Urbanization Level (proportion of urban population), Environmental Regulation (text analysis) [60], Government Intervention (public budget expenditure/GDP), Opening Up (import and export of goods/GDP), Education Expenditure (education expenditure/public budget expenditure), Technology Expenditure (science and technology expenditure/public budget expenditure), and Digital Economy (digital inclusive finance index) [61].

3.2.4. Mediating variables

(1) Green Finance: We construct a comprehensive indicator system for the development of green finance from 7 dimensions, including green credit, green investment, green insurance, green bond, green support, green fund, and green equity, and measure it using the entropy method [62]. (2) Industrial Structure: We measure the advancement of industrial structure using the ratio of the added value of the tertiary industry to the secondary industry [63]. (3) Green Innovation: we identify the number of green patent applications at the city level based on the IPC codes in the “International Patent Classification Green List” released by the World Intellectual Property Organization [64].

3.3. Data description

Based on data availability and completeness, we exclude cities with significant missing values and finally compiled panel data for 268 Chinese cities from 2011 to 2021, with a sample size of 2948. Missing data are imputed using interpolation. Core explanatory variable data come from the Baidu search engine and "Tianyancha", the most authoritative platforms in China. Other data are sourced from annual "China City Statistical Yearbooks", "China Environmental Statistical Yearbooks", "China Urban Construction Statistical Yearbooks", "China Industry Statistical Yearbooks", the State Intellectual Property Office, provincial and municipal statistical yearbooks, government work reports, the Digital Finance Research Center of Peking University, and the Emissions Database for Global Atmospheric Research (EDGAR). Descriptive statistics of each variable are shown in Table 2.

Figure 3 shows the violin diagrams of FinTech and TFEE. From the distribution pattern perspective, the FinTech violin width gradually shifts right and its pattern broadens over the years, indicating that its numerical distribution range has expanded and the overall level has significantly improved. Combined with the upward smooth dotted line in the graph, it confirms FinTech's continuous growth trend over the past decade. In contrast, the TFEE violin pattern is relatively narrow overall and its position changes little. The dotted line only rises slightly, reflecting that although TFEE has improved slightly, progress is stable. Overall, the FinTech sector exhibits distinct expansion and dynamic development characteristics, while TFEE maintains a relatively stable evolution pace. Both reflect the differentiated trajectories between technology-driven and energy efficiency management in economic and social development from different dimensions.

Table 2. Descriptive statistics of each variable.

Variable	Indicator	Symbol	N	Mean	Std. dev.
Dependent variable	Total Factor Energy Efficiency	TFEE	2948	0.341	0.134
Independent variable	Financial Technology	FinTech	2948	3.365	1.509
Control variables	Economic Growth	EG	2948	4.878	4.455
	Environmental Regulation	ER	2948	0.003	0.001
	Population Density	PD	2948	443.947	342.410
	Economic Agglomeration	EA	2948	0.359	0.844
	Opening Up	OU	2948	0.017	0.019
	Urbanization Level	UL	2948	0.568	0.149
	Government Intervention	GI	2948	0.199	0.101
	Education Expenditure	EX	2948	0.176	0.039
	Technology Expenditure	TX	2948	0.017	0.018
	Digital Economy	DE	2948	219.123	83.157
Mediating variables	Green Finance	GF	2948	0.336	0.104
	Industrial Structure	IS	2948	1.064	0.587
	Green Technology	GT	2948	816.960	2293.960

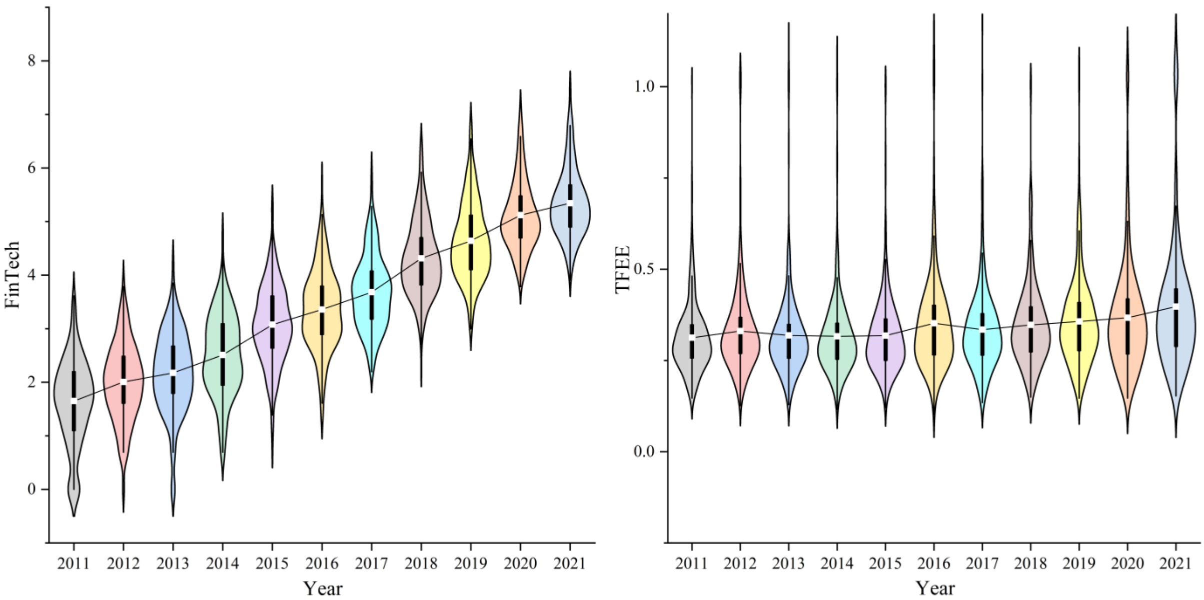

Figure 3. Violin diagrams of FinTech and TFEE.

4. Results and analysis

4.1. Baseline regression

Figure 4 compares TFEE distribution characteristics corresponding to cities with different FinTech levels through the kernel density estimation curve. In the figure, both groups show a single-peak distribution pattern, but there are obvious differences. From the overall trend, the high FinTech level group curve has shifted right overall, indicating that its TFEE distribution is moving towards a higher level, suggesting that FinTech may promote TFEE improvement through optimizing energy allocation, enhancing management accuracy, and other means. The peak pattern concentrated on the low FinTech level group's left side reflects that TFEE is prone to remain in a low-level equilibrium state when lacking FinTech support. In short, the two groups' distribution differences indicate that FinTech development may promote overall TFEE improvement. However, the relationship between the two variables needs further empirical analysis.

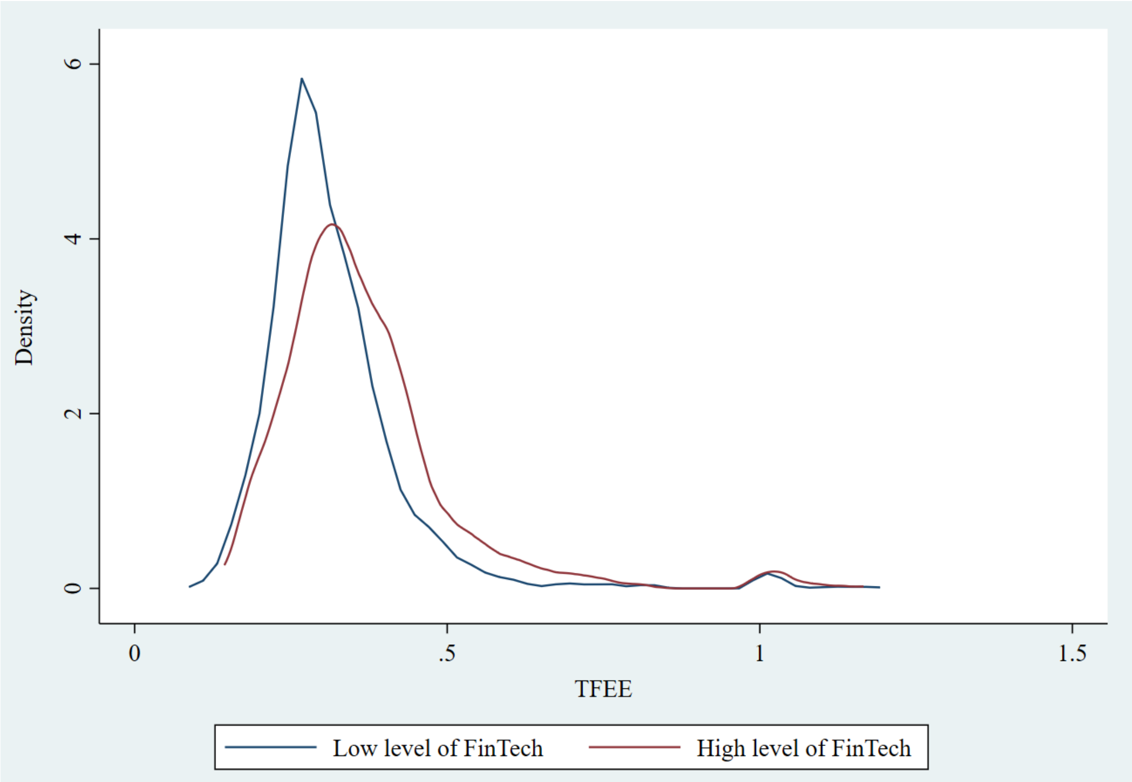

Figure 4. Kernel density distribution of TFEE.

The direct impact of FinTech on TFEE is shown in Table 3. Column (1) shows the random effects estimation results after controlling for other variables, Column (2) shows the estimation results under individual fixed effects, Column (3) shows the estimation results under time fixed effects, and Column (4) includes other variable controls and individual and time fixed effects. The four columns show that FinTech has a significant positive impact on TFEE, indicating that FinTech development plays a positive role in promoting urban green development, that is, Hypothesis 1 has been verified.

Table 3. Baseline regression results.

Variable	(1)	(2)	(3)	(4)
FinTech	0.008***	0.007***	0.008***	0.006**
	(0.003)	(0.002)	(0.003)	(0.002)
Control variables	Yes	Yes	Yes	Yes
Individual fixed effects	No	Yes	No	Yes
Time fixed effects	No	No	Yes	Yes
ML model	RF	RF	RF	RF
N	2948	2948	2948	2948

Notes: Robust standard errors in parentheses, * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

4.2. Robustness tests

We implement a comprehensive robustness testing strategy to assess the reliability and consistency of our major findings. This multi-faceted approach examines whether the results withstand alternative model specifications, measurement approaches, and sample compositions.

First, excessive control variables might cause the model to overfit sample data, adversely affecting estimation results. Therefore, we adopt the RF model to evaluate 10 control variables' importance and eliminate the two least important variables. According to calculations (Figure 5), the two variables with the lowest importance are TE and ER. These two control variables are excluded, and the remaining data are re-analyzed.

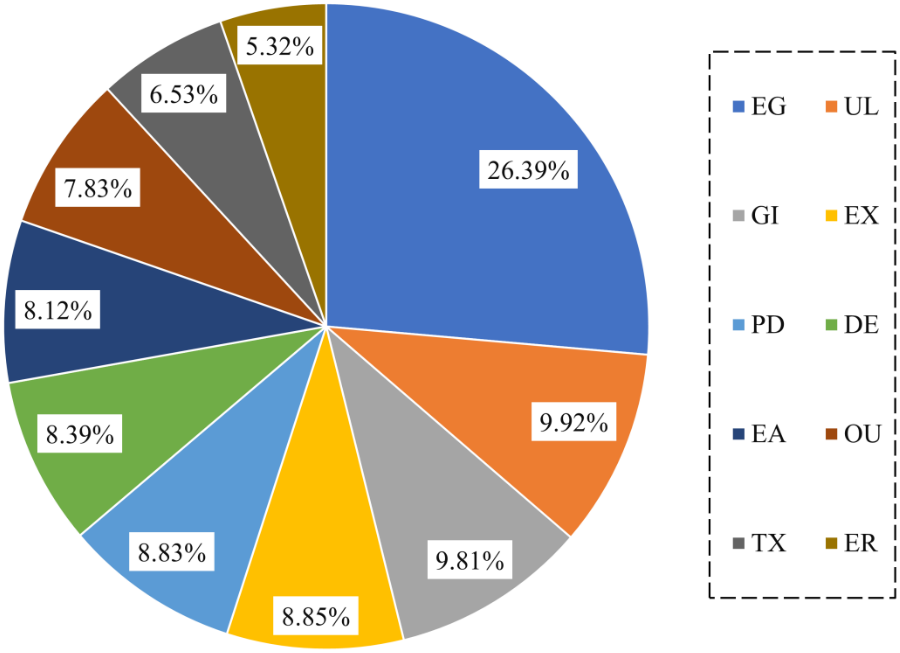

Figure 5. Feature importance proportion and ranking.

The second robustness test method adopted in this paper is replacing the core explanatory variables. Referring to relevant literature [65], we use the information platform "Tianyancha" to comprehensively search for keywords such as "FinTech", "big data", "blockchain", and "artificial intelligence" to collect all related company registration information. After completing screening, the number of FinTech companies in each city per year is counted, and this count is used as a new indicator to measure the FinTech development level in different regions. This alternative measure, based on enterprise registrations, reflects the tangible presence of FinTech entities and mitigates potential media bias.

Given that cities with higher economic development levels tend to have higher FinTech development and TFEE levels, and these cities may have advantages in accessing financial resources and policy support, which could potentially bias estimation results. Additionally, as mentioned earlier, per capita GDP has the greatest impact on FinTech among all control variables. Therefore, we exclude the four municipalities and the top 10 cities ranked by per capita GDP before re-testing.

Since extreme values in the data sample do not represent the majority but are caused by occasional measurement errors or atypical events, they can increase standard errors and affect model stability and accuracy. In this study, FinTech application and TFEE measurement may be influenced by complex factors. To reduce outliers' potential distortion effects, all variables are winsorized at the 1% level on both tails.

To avoid potential biases in conclusions due to DML model setup, we adjust the machine learning model and re-estimates the results. First, the DML model sample split ratio is changed from 1:4 to 1:7

to explore whether sample split ratio differences affect results. Second, the prediction algorithm is changed from the previously used RF model to a Gradient Boosting model to examine whether different prediction algorithms affect conclusions.

The above robustness tests results are presented in columns (1) to (6) of Table 4 in sequence. It can be seen that FinTech coefficients on TFEE displayed in each column all remain significantly positive at the 5% level, indicating that FinTech's positive impact on TFEE is highly robust.

Table 4. Robustness tests results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
FinTech	0.005**	0.141***	0.005**	0.005**	0.006***	0.010***
	(0.002)	0.028	(0.002)	(0.002)	(0.002)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
ML model	RF	RF	RF	RF	RF	GB
N	2948	2948	2794	2948	2948	2948

Notes: Robust standard errors in parentheses, * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

In addition, we select two instrumental variables to address potential endogeneity issues. The first instrumental variable is the lagged level of FinTech, which is highly correlated with the explanatory variable but uncorrelated with the disturbance term, satisfying the relevance and exogeneity conditions required for an instrumental variable [66]. Additionally, Hangzhou is at the forefront of digital finance, and geographical proximity between cities may facilitate FinTech knowledge dissemination and innovative resource sharing. Therefore, cities closer to Hangzhou tend to have higher FinTech levels. However, this distance does not directly translate into TFEE increase, satisfying the relevance and exogeneity conditions for an instrumental variable. Since spatial distance does not change over time, we use the spherical distance between each city and Hangzhou, multiplied by a time dummy variable, as another instrumental variable [67]. The regression results in Table 5 show that instrumental variables yield significantly positive results, indicating that the above conclusions are robust. Specifically, FinTech development indeed significantly promotes TFEE enhancement.

Table 5. Endogeneity treatment results.

Variable	(1)	(2)
FinTech	0.013***	0.057**
	(0.005)	(0.026)
Control variables	Yes	Yes
Individual fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
ML model	RF	RF
N	2680	2948

Notes: Robust standard errors in parentheses, * $P < 0.05$, **$P < 0.01$, *** $P < 0.001$.

4.3. Heterogeneity analysis

(1) Due to significant differences among regions in China in terms of economic development level, industrial structure, resource endowment and policy environment, we divide the research samples into three groups: Eastern, central, and western regions. It can be seen from Table 6 that FinTech regression coefficient is significantly positive only in eastern and central regions. Considering coefficient values' size, FinTech impact on TFEE decreases successively from east to west. The eastern region has a solid economic foundation, complete infrastructure, and relatively high informatization level. These conditions provide fertile ground for FinTech rapid development and wide application, thereby effectively promoting TFEE growth in the eastern region. Although the central region's economic development level is slightly lower than the eastern region, in recent years, with national strategy for central region rise implementation, FinTech positive impact on TFEE has been gradually emerging. However, due to infrastructure and market maturity limitations, its influence may be less significant than the eastern region. In contrast, due to constraints such as natural conditions, economic development levels, human capital, and historical accumulation, FinTech development in the western region lags behind relatively [68], thereby limiting FinTech promoting effect on TFEE.

(2) Old industrial base cities, characterized by a historical legacy of heavy industry, frequently confront intertwined challenges of transitioning their industrial structures and managing environmental stewardship. This makes them exhibit different needs and paths in developing FinTech and promoting green transformation compared to non-old industrial base cities. Therefore, based on the "National Old Industrial Base Adjustment and Transformation Plan (2013-2022)", we further divide the sample into old industrial base cities and non-old industrial base cities to more deeply reveal the mechanisms through which FinTech affects TFEE in different urban development stages and industrial contexts. The results in Table 6 indicate that FinTech has a significant positive impact only on non-old industrial base cities. This can be attributed to complex transformation challenges faced by old industrial base cities, where the economy is often overly dependent on traditional heavy industries [69]. FinTech may have limited potential in promoting green upgrades in these industries. Additionally, old industrial base cities may have more structural obstacles, such as less open policy environments, outdated infrastructure, and talent outflows, which may prevent FinTech potential full realization [13]. In contrast, non-old industrial base cities typically have more dynamic economic structures and higher technology acceptance, enabling FinTech applications to quickly penetrate and promote local economic green transformation, thereby effectively enhancing local TFEE.

(3) City size leads to significant differences in economic development levels, industrial structures, innovation capabilities, and infrastructure construction, all of which can affect FinTech penetration and application to varying degrees. Therefore, we, referring to relevant research [70], define cities with a total population at year-end of more than 5 million as large cities, and the rest as small-medium-sized cities, to more accurately identify specific needs and potential barriers for different sized cities in FinTech development and TFEE enhancement. Table 6 results indicate that FinTech positive impact on TFEE is significant only in the large cities sample. This is because large cities have more mature financial markets and well-developed information infrastructure, providing strong support for FinTech widespread application and penetration [71], enabling capital to flow more efficiently into green projects. Additionally, innovation capabilities and talent agglomeration effects in large cities provide rich intellectual resources and innovative momentum for FinTech and green industries deep integration [72]. Moreover, policy environment and regulatory systems in large cities are generally more complete, providing favorable external conditions for FinTech development and green investments. In contrast, small and medium-sized cities may be limited by insufficient infrastructure,

human resources, and innovation capabilities, as well as less mature policy support and regulatory environments, leading to less significant FinTech effects on TFEE enhancement in these areas.

Table 6. Heterogeneity analysis results.

Variable	(1) East	(2) Central	(3) West	(4) Old industrial base	(5) Non-old industrial base	(6) Large city	(7) Small-medium city
FinTech	0.012**	0.007**	-0.005	0.005	0.007**	0.018***	-0.002
	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ML model	RF	RF	RF	RF	RF	RF	RF
N	1078	1034	836	1001	1947	1100	1848

Notes: Robust standard errors in parentheses, * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

Table 7. Mediating mechanism analysis results.

Variable	(1) GF	(2) TFEE	(3) IS	(4) TFEE	(5) GT	(6) TFEE
FinTech	0.005***		0.068***		0.259***	
	(0.002)		(0.008)		(0.020)	
GF		0.118***				
		(0.029)				
IS				0.017***		
				(0.006)		
GT						0.005**
						(0.002)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
ML model	RF	RF	RF	RF	RF	RF
N	2948	2948	2948	2948	2948	2948

Notes: Robust standard errors in parentheses, * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

4.4. Mediating mechanism analysis

As detailed earlier, FinTech can enhance TFEE by promoting green finance development. To test whether this mechanism holds, we first examine FinTech impact on GF and then GF impact on TFEE. Columns (1)-(2) of Table 7 show the results for FinTech impact on GF and GF impact on TFEE, respectively. The regression coefficients in both columns are significantly positive, indicating that FinTech can indeed promote TFEE enhancement through green finance development. Similarly, we investigate FinTech impact on IS and IS impact on TFEE. The regression results are shown in Columns (3)-(4) of Table 7. The results show that FinTech development significantly promotes IS upgrading, which in turn significantly enhances TFEE. This result confirms IS mediating role between FinTech and TFEE. Specifically, FinTech development indirectly improves TFEE by promoting IS optimization and upgrading. In addition, we empirically examine how FinTech affects TFEE by promoting GT. The mediating analysis results for green patent applications are shown in Columns (5)-(6) of Table 7. The results confirm that FinTech development level is significantly positively related to green patent applications increase, indicating that FinTech development significantly promotes green technological innovation activities. This suggests that FinTech development indirectly improves TFEE by promoting green technological innovation. So far, Hypotheses 2-4 have been verified, that is, FinTech indirectly enhances TFEE by promoting green finance development, industrial structure optimization, and green technology innovation via three mediating pathways.

4.5. Nonlinear effect

The nonlinear impact analysis of FinTech on TFEE, as interpreted through SHAP value derived from the RF model, is presented in Figure 6. A positive SHAP value indicates that the feature exerts a positive influence on the predicted TFEE, whereas a negative value suggests an inhibitory effect. The overall trend reveals that as the FinTech feature value increases, its corresponding SHAP value also rises, indicating a strengthening positive contribution to TFEE. The threshold effect is discernible at the point where the smoothed SHAP value curve intersects the horizontal zero line. Overall, under the condition that other influencing factors remain unchanged, as FinTech characteristic values gradually increase, its SHAP value rises simultaneously. When FinTech development level is lower than around 4.2, its SHAP value is negative, indicating that FinTech has an inhibitory effect on TFEE at this time. However, when FinTech development level exceeds this threshold, its SHAP value turns from negative to positive, and FinTech enhancing effect on TFEE begins to emerge. This phenomenon indicates that FinTech impact on TFEE has nonlinear and threshold effects.

Early-stage FinTech platforms may focus on traditional fields with high returns and short cycles. Algorithm-driven credit models tend to rely more on historical financial data and tangible asset collateral, which may facilitate financing in resource-intensive or highly polluting industries [73], while excluding green projects with long investment return cycles and difficult-to-quantify environmental benefits. Moreover, FinTech infrastructure itself is a high-energy-consuming unit in early construction stages [74]. If its operation relies on traditional fossil energy and energy efficiency optimization is insufficient, its own carbon footprint will directly offset some potential environmental benefits. However, once FinTech development breaks through the key threshold, its powerful enabling effect on TFEE begins to systematically emerge. Financial technology application initial research and development and platform construction costs are extremely high. Only when the user base breaks through the critical point, data network effect forms, and marginal operation cost drops significantly, can the service cover more small and medium-sized green innovative enterprises and individual low-carbon consumption scenarios. Moreover, with FinTech in-depth development and application, supporting policies such as green credit interest subsidies, mandatory environmental information disclosure regulations, and unified green classification directory have been implemented simultaneously [75], systematically releasing carbon reduction efficiency brought about by resource allocation optimization and green innovation acceleration.

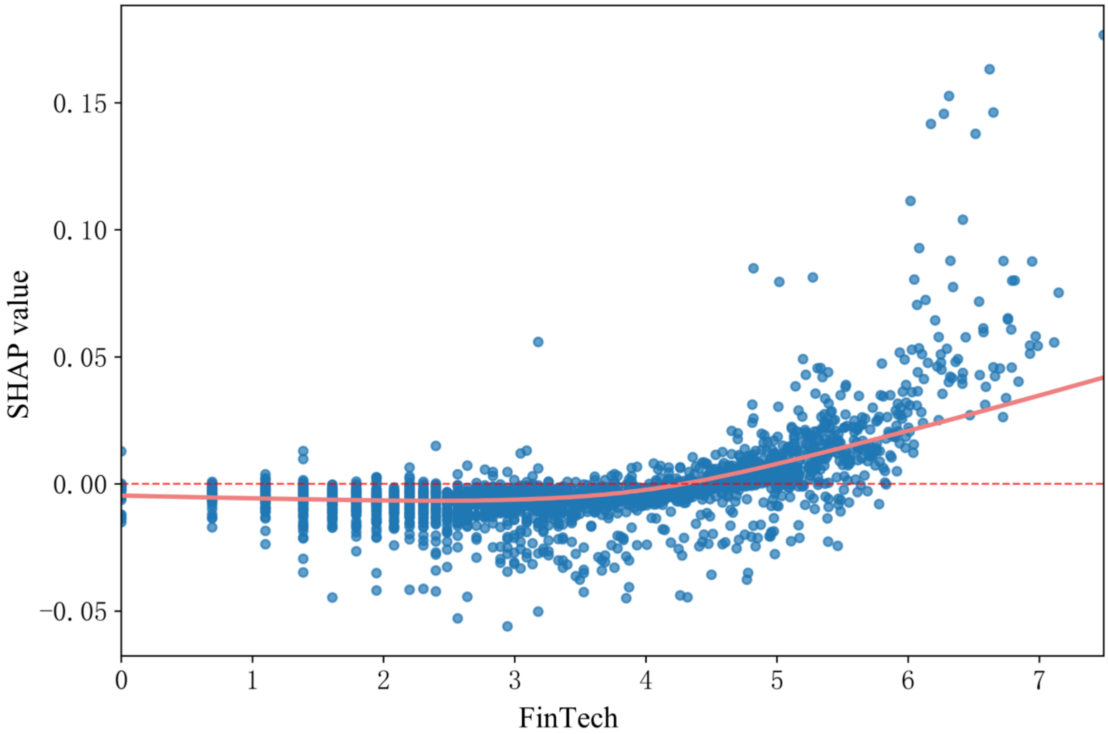

Figure 6. SHAP value trend of FinTech.

5. Discussion

Our findings, which establish a significant positive relationship between FinTech development and TFEE in Chinese cities, resonate with an evolving body of international evidence. Research conducted in other major emerging economies suggests a parallel narrative, where digital financial technologies contribute to environmental improvement by enhancing capital allocation efficiency towards sustainable projects [76]. This pattern observed in China aligns with findings from BRICS nations, where FinTech development has been empirically linked to carbon emissions reductions through similar mechanisms of financial inclusion and resource optimization [18]. The global discourse, however, presents a more nuanced picture when considering economies at different developmental stages. Analyses from developed countries (G7) occasionally document a contrasting relationship, where FinTech proliferation correlates with increased energy consumption [19], particularly in contexts characterized by mature financial systems and consumption-led economic models. This divergence underscores the critical role of national economic structures and policy frameworks in mediating financial innovation environmental outcomes. The identified mediation mechanisms---green finance development, industrial structure optimization, and green technological innovation---resonate with international studies. For instance, research in OECD countries reveals that FinTech drives energy efficiency primarily through technological innovation channels and financial market transformations [77].

While we focus on Chinese cities, the identified mechanisms have broader implications. International evidence suggests that FinTech's energy efficiency benefits operate through similar channels globally. Research across developing countries shows that digital finance improves resource allocation efficiency and promotes cleaner production technologies [78]. However, specific threshold values and implementation pathways may vary based on local institutional contexts and regulatory frameworks. The findings contribute to understanding how digital financial technologies can support sustainable development goals. For instance, FinTech innovations can address market gaps and regulatory constraints that traditionally hindered energy efficiency investments [79]. In this study, we add empirical evidence from China's unique context while reinforcing global patterns of FinTech-enabled sustainability transitions.

6. Conclusions and policy recommendations

6.1. Research conclusions

Based on panel data of 268 Chinese cities from 2011 to 2021, we employ a DML method to deeply explore FinTech potential impact on TFEE, and the nonlinear effect is tested using SHAP value algorithm. The research results show that there is a significant positive correlation between FinTech and TFEE, which remains reliable after various robustness tests. To address potential endogeneity issues, we employ the instrumental variable method for estimation, and the results further verify the research conclusions robustness. Heterogeneity analysis further indicates that FinTech promoting effect is more obvious in eastern China, non-old industrial bases and large cities. This suggests that local economic context, industrial legacy, and urban scale significantly shape FinTech efficacy in enhancing TFEE. Furthermore, our results reveal, through mediating mechanism analysis, that FinTech has a positive impact on TFEE by promoting green finance development, industrial structure optimization, and green technological innovation. Each of these pathways represents a critical transmission mechanism through which FinTech contributes to improved energy and environmental performance. In addition, FinTech impact on TFEE shows obvious nonlinearity and threshold effects. Only when FinTech development level exceeds a specific threshold does its role in enhancing TFEE begin to emerge. This highlights the importance of achieving a mature FinTech development stage for its energy and environmental benefits to be fully realized.

6.2. Policy recommendations

Based on the above research conclusions, the following policy recommendations are proposed to further promote FinTech and urban green transition deep integration, and achieve coordinated and sustainable development of the economy, society, and environment.

First, policymakers should design precise fiscal instruments to accelerate FinTech and green finance synergy. This includes implementing tiered tax incentives for financial institutions that achieve predefined portfolio targets in green asset allocation. Governments could establish dedicated guarantee funds to de-risk early-stage green FinTech lending, particularly for small and medium-sized enterprises in renewable energy and circular economy sectors. Concurrently, regulatory bodies must develop granular green finance taxonomies and mandatory environmental performance disclosure standards, enhancing market transparency and directing capital flows towards verified sustainable projects.

Second, industrial policy should leverage FinTech capabilities for structural transformation. Governments can facilitate specialized digital platforms creation that use artificial intelligence to match green industries with suitable FinTech financing solutions. Specific support should be provided for developing blockchain-based supply chain finance solutions that improve green manufacturing and agriculture transparency. Furthermore, targeted FinTech innovation zones could be established to pilot IoT-enabled asset monitoring for energy efficiency projects, reducing perceived risks and attracting private investment into industrial upgrading.

Third, accelerating green technological innovation requires strategically channeling FinTech resources. Public sector investment should prioritize joint research initiatives between financial institutions and clean technology firms, focusing on scalable solutions like carbon capture and smart grid management. Innovation vouchers could be allocated for green patent commercialization, while regulatory sandboxes would allow testing novel FinTech applications for environmental impact bonds. Performance-based grants should reward financial institutions that demonstrate measurable success in funding green technology adoption and diffusion.

Fourth, region-specific FinTech deployment strategies must address distinct developmental needs. In eastern China, policy should foster deep integration between existing financial hubs and emerging green technology clusters. Central regions would benefit from FinTech applications tailored to traditional manufacturing sectors modernization. Western regions require prioritized digital payment infrastructure investment and financial literacy programs to build foundational capacity. Old industrial base cities need comprehensive transformation packages combining FinTech-enabled asset restructuring with workforce retraining programs. Young industrial bases should receive support for developing niche FinTech applications in their competitive green sectors. Large cities can be encouraged to establish FinTech innovation centers that catalyze development across broader metropolitan areas, while specialized FinTech lending facilities should be created to address specific financing gaps faced by small and medium-sized cities.

Finally, policy interventions must be dynamically calibrated to local FinTech ecosystems maturity. In early development stages, public investment should focus on building core digital infrastructure and establishing interoperable green data standards. Temporary subsidy schemes can lower initial adoption costs for proven green technologies in small businesses. Regulatory guidance should encourage financial institutions to refine credit algorithms to better recognize green projects long-term value, preventing their exclusion due to short-term risk metrics. Once FinTech penetration crosses the identified effectiveness threshold, policy should shift toward scaling incentives, leveraging blockchain for asset provenance tracking and artificial intelligence for dynamic risk pricing, thereby systematically channeling capital into advanced decarbonization technologies and deep emission reduction initiatives.

6.3. Research limitations and prospects

Despite the valuable insights provided by this study, several limitations merit attention, offering avenues for future research to further advance FinTech role understanding in promoting TFEE. First, while green finance, industrial upgrading, and green innovation mechanisms were empirically validated, other potentially significant pathways remain unexplored. For instance, FinTech may influence TFEE through channels like corporate governance improvements, consumer behavior shifts, or cross-regional capital reallocation. In the future, researchers should adopt granular firm-level data to uncover these latent mechanisms and quantify their relative contributions. Second, FinTech index construction based on Baidu search data, while widely used and spatially consistent, may not fully capture FinTech activities depth such as transaction volumes, user adoption rates, or capital flows. Future research could develop more granular and multidimensional indicators, such as those derived from fintech platform penetration, mobile payment usage, or green fintech loan volumes, should such data become accessible at the city level. Third, data limitations include interpolation use for missing values, which relies on specific assumptions, and potential inconsistencies in statistical reporting across cities. While we utilized the most authoritative sources available and applied careful data processing, these factors could potentially introduce measurement error. Future research could benefit from more direct data collection efforts or more sophisticated imputation techniques development that account for spatial and temporal dependencies.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflict of interest.

References

1. Yin K, Miao Y, Huang C (2024) Environmental regulation, technological innovation, and industrial structure upgrading. *Energy Environ* 35: 207–227. https://doi.org/10.1177/0958305x221125645
2. He Y, Zhang Y, Deng J (2024) Path to sustainable development: The effect of China's innovative industrial clusters pilot policy on prefecture-level cities' green total factor productivity. *J Clean Prod* 478: 143988. https://doi.org/10.1016/j.jclepro.2024.143988
3. Colmer J, Martin R, Muûls M, et al. (2025) Does pricing carbon mitigate climate change? Firm-level evidence from the european union emissions trading system. *Rev Econ Stud* 92: 1625–1660. https://doi.org/10.1093/restud/rdae055
4. Ali Y, Khalid H (2025) Green banking policies and sustainable performance: unraveling the mediating role of GC and EP. *AIMS Environ Sci* 12: 744–769. https://doi.org/10.3934/environsci.2025033
5. Zhang Y, Xing C, Guo X (2023) The shielding effect of access to finance on small and medium-sized enterprises during the COVID-19 crisis: Comparing FinTech and traditional finance. Emerging *Mark Financ Trade* 59: 2383–2397. https://doi.org/10.1080/1540496x.2022.2072201
6. Palmié M, Wincent J, Parida V, et al. (2020) The evolution of the financial technology ecosystem: An introduction and agenda for future research on disruptive innovations in ecosystems. *Technol Forecast Soc Change* 151: 119779. https://doi.org/10.1016/j.techfore.2019.119779
7. Liu C, Li Q, Zhang S et al. (2022) How Does Financial Technology Affect Enterprise Innovation? Evidence from Chinese Listed Companies. *Econ Rev* 30-47. https://doi.org/10.19361/j.er.2022.01.03
8. Liao K, Ma C, Zhang J, et al. (2024) Does big data infrastructure development facilitate bank fintech innovation? Evidence from China. *Finance Res Lett* 65: 105540. https://doi.org/10.1016/j.frl.2024.105540
9. Baber H (2020) Financial inclusion and FinTech: A comparative study of countries following Islamic finance and conventional finance. *Qual Res Financ Mark* 12: 24–42. https://doi.org/10.12785/jifs/040203

10. Ren F, Yu X (2021) Coupling analysis of urbanization and ecological total factor energy efficiency: a case study from Hebei province in China. *Sustain Cities Soc* 74: 103183. https://doi.org/10.1016/j.scs.2021.103183
11. Gao D, Li G, Yu J (2022) Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. *Energy* 247: 123395. https://doi.org/10.1016/j.energy.2022.123395
12. Xu J, Li J, Liu C (2022) How does foreign trade affect green total factor energy efficiency? Evidence from China. *Front Environ Sci* 10: 979177. https://doi.org/10.3389/fenvs.2022.979177
13. Zhou C, Qi S (2022) Has the pilot carbon trading policy improved China's green total factor energy efficiency? *Energy Econ* 114: 106268. https://doi.org/10.1016/j.eneco.2022.106268
14. Cheng Z, Zhang Q, Li X (2025) Can environmental information disclosure improve total-factor energy efficiency? *J Environ Plan Manag* 68: 104–131. https://doi.org/10.1080/09640568.2023.2238893
15. Li G, Gao D, Li Y (2023) Impacts of market-based environmental regulation on green total factor energy efficiency in China. *China World Econ* 31: 92–114. https://doi.org/10.1111/cwe.12485
16. Ranabahu N (2024) Financial technology to address the liability of poorness? A typology of FinTech organisations. *Eur J Innov Manag* 27: 1249–1269. https://doi.org/10.1108/ejim-07-2022-0359
17. Yang RX, Liu Z (2025) FinTech and urban entrepreneurial activity. *Finance Res Lett* 75: 106661. https://doi.org/10.1016/j.frl.2024.106661
18. Udeagha MC, Muchapondwa E (2023) Green finance, FinTech, and environmental sustainability: fresh policy insights from the BRICS nations. *Int J Sustain Dev World Ecol* 30: 633–649. https://doi.org/10.1080/13504509.2023.2183526
19. Wang L, Vo XV, Shahbaz M, et al. (2020) Globalization and carbon emissions: is there any role of agriculture value-added, financial development, and natural resource rent in the aftermath of COP21? *J Environ Manag* 268: 110712. https://doi.org/10.1016/j.jenvman.2020.110712
20. Yu H, Wang R, Zhang A (2024) Unraveling the impact of environmental provisions in preferential trade agreements on green total factor energy efficiency. *J Environ Manag* 362: 121205. https://doi.org/10.1016/j.jenvman.2024.121205
21. Zhong K, Lei Y, Zhao J, et al. (2025) How to enhance China's total-factor energy efficiency via digital-real economy integration: New evidence from dynamic QCA analysis. *Energy Econ* 148: 108689. https://doi.org/10.1016/j.eneco.2025.108689
22. Liu C, Song Y, Zhang M, et al. (2025) Enterprise carbon emission reduction effects of the green loan interest subsidy policy: Evidence of city-level spatial spillovers. *Environ Impact Assess Rev* 114: 107954. https://doi.org/10.1016/j.eiar.2025.107954
23. Bansal P, Quan SJ (2024) Examining temporally varying nonlinear effects of urban form on urban heat island using explainable machine learning: A case of Seoul. *Build Environ* 247: 110957. https://doi.org/10.1016/j.buildenv.2023.110957
24. Mol AP, Spaargaren G (2000) Ecological modernisation theory in debate: A review. *Environ Polit* 9: 17-49. https://doi.org/10.1080/09644010008414511
25. Muganyi T, Yan L, Sun HP (2021) Green finance, fintech and environmental protection: Evidence from China. *Environ Sci Ecotechnol* 7: 100107. https://doi.org/10.1016/j.ese.2021.100107
26. Elkington J (1997) Cannibals with Forks: The Triple Bottom Line of 21st Century Business. Capstone Publishing.

27. Ibrahim A, Almasria NA, Al Maqtari FA, et al (2024). The impact of green finance, fintech and digital economy on environmental sustainability: evidence from advanced panel techniques. *Int J Energy Econ Policy* 14: 621-627. https://doi.org/10.32479/ijeep.17180
28. Wang Y, Xiuping S, Zhang Q (2021) Can FinTech improve the efficiency of commercial banks? An analysis based on big data. *Res Int Bus Finance* 55: 101338. https://doi.org/10.1016/j.ribaf.2020.101338
29. Wang H, Li Y, Lin W, et al. (2023) How does digital technology promote carbon emission reduction? Empirical evidence based on e-commerce pilot city policy in China. *J Environ Manag* 325: 116524. https://doi.org/10.1016/j.jenvman.2022.116524
30. Tan C, Wang Z, Zhou P (2023) Fintech "Enabling" and Enterprise Green Innovation: From the Perspectives of Credit Allocation and Credit Supervision. *J Financ Econ* 49: 34-48. https://doi.org/10.16538/j.cnki.jfe.20220519.101
31. Hasan M, Hoque A, Abedin MZ, et al. (2024) FinTech and sustainable development: A systematic thematic analysis using human- and machine-generated processing. *Int Rev Financ Anal* 95: 103473. https://doi.org/10.1016/j.irfa.2024.103473
32. Li X, Cui S, Lai X (2020) Can Digital Finance Increase the Value of Listed Companies?:Theoretical Mechanism Analysis and Empirical Test. *Mod Financ Econ* 40: 83-95. https://doi.org/10.19559/j.cnki.12-1387.2020.09.006
33. Jiang C, Ma X (2019) The impact of financial development on carbon emissions: a global perspective. *Sustainability* 11: 5241. https://doi.org/10.3390/su11195241
34. Cai Q, Chen W, Wang M, et al. (2025) Drivers of green finance development: a nonlinear fsQCA-ANN analysis. *Int J Glob Warm* 36: 86–105. https://doi.org/10.1504/ijgw.2025.10069279
35. He Y, Wang K, Zhang Y et al. (2024) Research on the Effect and Mechanism of Fintech on Enterprise Innovation Investment. *Theory Pract Financ Econ* 45: 25-32. https://doi.org/10.16339/j.cnki.hdxbcjb.2024.02.004
36. Xu J, Li T, Chen F, et al. (2025) Does Fintech Foster the Development of Green Finance? *Emerg Mark Finance Trade* 61: 1771–1781. https://doi.org/10.1080/1540496x.2024.2430500
37. Yu CH, Wu X, Zhang D, et al. (2021) Demand for green finance: Resolving financing constraints on green innovation in China. *Energy Policy* 153: 112255. https://doi.org/10.1016/j.enpol.2021.112255
38. Wang W, Ge P (2024) The Mechanism and Development Path of Industrial Digital Finance Supporting the New Development Pattern of "Dual Circulation". *World Econ Stud* 93-104. https://doi.org/10.13516/j.cnki.wes.2024.02.001
39. Lv P, Xiong H (2022) Can FinTech improve corporate investment efficiency? Evidence from China. *Res Int Bus Finance* 60: 101571. https://doi.org/10.1016/j.ribaf.2021.101571
40. Li L, Yin F (2024) Digital Inclusive Finance, Financing Constraints and Investment Efficiency of Small and Medium-sized Enterprises. *Sci Manag Res* 42: 106-114. https://doi.org/10.19445/j.cnki.15-1103/g3.2024.01.012
41. Li F, Li J, Wang D (2024) Policy instruments and green innovation: Evidence and implications for corporate performance. *J Clean Prod* 471: 143443. https://doi.org/10.1016/j.jclepro.2024.143443
42. Wang D, Liang YF, Dou W (2025) How does urban industrial structure upgrading affect green productivity? The moderating role of smart city development. *Struct Change Econ Dyn* 72: 133–149. https://doi.org/10.1016/j.strueco.2024.09.017

43. Dangelico RM (2017) What drives green product development and how do different antecedents affect market performance? A survey of Italian companies with eco-labels. *Bus Strategy Environ* 26: 1144–1161. https://doi.org/10.1002/bse.1975
44. Zheng S, Liu J, Yao T (2024) Research on the Effect and Mechanism of Digital Finance Promoting Green Technology Innovation. *Econ Probl* 41-47. https://doi.org/10.16011/j.cnki.jjwt.2024.02.016
45. Zameer H, Yasmeen H (2022) Green innovation and environmental awareness driven green purchase intentions. *Mark Intell Plan* 40: 624–638. https://doi.org/10.1108/mip-12-2021-0457
46. Qin L, Aziz G, Hussan MW, et al. (2024) Empirical evidence of fintech and green environment: Using the green finance as a mediating variable. *Int Rev Econ Finance* 89: 33–49. https://doi.org/10.1016/j.iref.2023.07.056
47. Shen N, Zhou J, Zhang G, et al. (2025) How does data factor marketization influence urban carbon emission efficiency? A new method based on double machine learning. *Sustain Cities Soc* 119: 106106. https://doi.org/10.1016/j.scs.2024.106106
48. Chernozhukov V, Chetverikov D, Demirer M, et al. (2018) Double/debiased machine learning for treatment and structural parameters. *Econom J* 21: C1–C68. https://doi.org/10.1111/ectj.12097
49. Borup D, Christensen BJ, Mühlbach NS, et al. (2023) Targeting predictors in random forest regression. *Int J Forecast* 39: 841 – 868. https://doi.org/10.1016/j.ijforecast.2022.02.010
50. Breiman L (2001) Random forests. *Mach Learn* 45: 5-32. https://doi.org/10.1023/A:1010933404324
51. Athey S, Imbens GW (2019) Machine learning methods that economists should know about. *Annu Rev Econ* 11: 685-725. https://doi.org/10.1146/annurev-economics-080217-053433
52. Atzmueller M, Fürnkranz J, Kliegr T, et al. (2024) Explainable and interpretable machine learning and data mining. *Data Min Knowl Discov* 38: 2571–2595. https://doi.org/10.1007/s10618-024-01041-y
53. Aas K, Jullum M, Løland A (2021) Explaining individual predictions when features are dependent: More accurate approximations to Shapley values. *Artif Intell* 298: 103502. https://doi.org/10.1016/j.artint.2021.103502
54. Su X, Zhou W, Nakagami KI, et al. (2012) Capital stock-labor-energy substitution and production efficiency study for China. *Energy Econ* 34: 1208–1213. https://doi.org/10.1016/j.eneco.2011.11.002
55. Yang L, Yang Y, Zhang X, et al. (2018) Whether China's industrial sectors make efforts to reduce CO2 emissions from production? A decomposed decoupling analysis. *Energy* 160: 796–809. https://doi.org/10.1016/j.energy.2018.06.186
56. Ge W, Yang P, Pan X, et al. (2024) Sustainable utilization of mining resources: Exploring the impact of FinTech on green development from the perspective of mining enterprises. *Resour Policy* 97: 105239. https://doi.org/10.1016/j.resourpol.2024.105239
57. Fungáčová Z, Weill L, Zhou M (2017) Bank capital, liquidity creation and deposit insurance. *J Financ Serv Res* 51: 97-123. https://doi.org/10.1007/s10693-016-0240-7
58. Li J, Li J, Zhu X, et al (2020) Risk spillovers between FinTech and traditional financial institutions: Evidence from the US. *Int Rev Financ Anal* 71: 101544. https://doi.org/10.1016/j.irfa.2020.101544
59. Gomber P, Koch JA, Siering M (2017) Digital Finance and FinTech: current research and future research directions. *J Bus Econ* 87: 537-580. https://doi.org/10.1007/s11573-017-0852-x

60. Chen Z, Kahn ME, Liu Y, et al. (2018) The consequences of spatially differentiated water pollution regulation in China. *J Environ Econ Manag* 88: 468–485. https://doi.org/10.1016/j.jeem.2018.01.010
61. Shahbaz M, Li J, Dong X, et al. (2022) How financial inclusion affects the collaborative reduction of pollutant and carbon emissions: The case of China. *Energy Econ* 107: 105847. https://doi.org/10.1016/j.eneco.2022.105847
62. Zhang Y, Bawuerjiang R, Lu M, et al. (2024) Green finance and environmental pollution: Evidence from China. *Econ Anal Policy* 84: 98–110. https://doi.org/10.1016/j.eap.2024.08.022
63. Zhao J, Jiang Q, Dong X, et al. (2022) How does industrial structure adjustment reduce CO2 emissions? Spatial and mediation effects analysis for China. *Energy Econ* 105: 105704. https://doi.org/10.1016/j.eneco.2021.105704
64. Zhai X, An Y, Shi X, et al. (2023) Emissions trading scheme and green development in China: Impact of city heterogeneity. *Sustain Dev* 31: 2583–2597. https://doi.org/10.1002/sd.2533
65. Teng M, Shen M (2023) The impact of FinTech on carbon efficiency: Evidence from Chinese cities. *J Clean Prod* 425: 138984. https://doi.org/10.1016/j.jclepro.2023.138984
66. Qi Y, Ouyang L, Yu Y (2024) The impact of FinTech adoption on corporate investment: Evidence from China. *Finance Res Lett* 67: 105929. https://doi.org/10.1016/j.frl.2024.105929
67. Huang Z, Tan Y, Yang Z, et al. (2023) FinTech adoption and the effects of economic uncertainty on household consumption. *China Econ Rev* 80: 102011. https://doi.org/10.1016/j.chieco.2023.102011
68. Wang X, Zhou H, Cheng L (2023) Fintech Development in China: Index Compilation, Overall Trend and Spatiotemporal Characteristics. *Mod Econ Sci* 45: 46-60. https://doi.org/10.20069/j.cnki.DJKX.202301004
69. Li L, Zhang P, Lo K, et al. (2020) The evolution of regional economic resilience in the old industrial bases in China: A case study of Liaoning Province, China. *Chin Geogr Sci* 30: 340–351. https://doi.org/10.1007/s11769-020-1105-4
70. Yu L, Wang Y, Wei X (2023) Towards low-carbon development: The role of industrial robots in decarbonization in Chinese cities. *J Environ Manage* 330: 117216. https://doi.org/10.1016/j.jenvman.2023.117216
71. Dong H, Zheng Y, Tang Y (2024) Impact of FinTech on the industrial structural transformation: Evidence from China's resource-based cities. *Resour Policy* 91: 104833. https://doi.org/10.1016/j.resourpol.2024.104833
72. Guo M, Luo D, Liu C (2024) City civilization, employment creation and talent agglomeration: Empirical evidence from "National Civilized City" policy in China. *China Econ Rev* 87: 102215. https://doi.org/10.1016/j.chieco.2024.102215
73. Bu Y, Yu X, Li H (2023) The nonlinear impact of FinTech on the real economic growth: evidence from China. *Econ Innov New Technol* 32: 1138–1155. https://doi.org/10.1080/10438599.2022.2095512
74. Luo Y, Andresen J, Clarke H, et al. (2019) A decision support system for waste heat recovery and energy efficiency improvement in data centres. *Appl Energy* 250: 1217–1224. https://doi.org/10.1016/j.apenergy.2019.05.029
75. Dunbar K, Sarkis J, Treku DN (2024) FinTech for environmental sustainability: Promises and pitfalls. *One Earth* 7: 23–30. https://doi.org/10.1016/j.oneear.2023.12.012

76. Arner DW, Barberis J, Buckley RP (2017) FinTech and RegTech in a Nutshell, and the Future in a Sandbox. CFA Institute Research Foundation.
77. Teng M, Shen M (2023) Fintech and energy efficiency: Evidence from OECD countries. *Resour Policy* 82: 103550. https://doi.org/10.1016/j.resourpol.2023.103550
78. Fowlie M, Meeks R (2021) The economics of energy efficiency in developing countries. *Rev Environ Econ Policy* 15: 238-260. https://doi.org/10.1086/715606
79. Buchak G, Matvos G, Piskorski T, et al (2018) Fintech, regulatory arbitrage, and the rise of shadow banks. *J Financ Econ* 130: 453-483. https://doi.org/10.1016/j.jfineco.2018.03.011

AIMS Press

© 2025 the Author(s), licensee AIMS Press. This is an open access article distributed under the terms of the Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0)