Traffic & Transportation

The Impact of Digital Economy on the Green Development Efficiency of the Logistics Industry – A Case from China Based on the Mediation Mechanism and Threshold Effect

Zhiqiang ZHAO[1], Lei ZHANG[2]

Review
Submitted: 16 Jun 2024
Accepted: 20 Sep 2024

[1] zhaozq@sjzpc.edu.cn, Shijiazhuang Posts and Telecommunications Technical College, Faculty of Finance
[2] Corresponding author, zhanglei@sjzpc.edu.cn, Shijiazhuang Posts and Telecommunications Technical College, Faculty of Modern Posts

Publisher:
Faculty of Transport and Traffic Sciences, University of Zagreb

ABSTRACT

The logistics industry is full of expectations for 'quality and efficiency' due to the rapid development of the digital economy (DE). It is worth paying attention to whether the DE can reverse the rough development of the logistics industry and effectively promote the green development efficiency of the logistics industry (GLE). This paper empirically explores the impact of the DE on the GLE using mediation mechanisms and threshold effects, based on China's inter-provincial panel data from 2011–2021. The empirical results indicate that the development of DE plays a significant role in promoting the GLE and can enhance the GLE through industrial structure upgrading. However, there is a masking effect of the labour productivity of the logistics industry on the impact of the DE on the GLE. The threshold test reveals that there is a threshold effect based on the scale of the logistics industry and the level of scientific and technological innovation in the impact of the DE on the GLE.

KEYWORDS

digital economy; green development efficiency of logistics industry; industrial structure; labour productivity; industry scale; scientific and technological innovation.

1. INTRODUCTION

The logistics industry is a basic, strategic and pioneering industry supporting the development of the national economy, and plays an important role in facilitating the flow of industrial factors and promoting the high-quality development of the modern service industry as a bridge between the various links of production, distribution, circulation and consumption in social production [1]. According to the China Logistics Information Centre in 2023, the total social logistics of the country was 352.4 trillion yuan, an increase of 5.2% year-on-year at comparable prices. However, the rapid development of this sector has resulted in a considerable consumption of energy. In 2023, total social logistics costs reached 18.2 trillion-yuan, equivalent to 14.4% of GDP. The crude growth path, which has long been at the expense of resource consumption and environmental pollution, has reached its conclusion [2]. In 2017, the Chinese government proposed the new concept of high-quality development for the first time, indicating that the objective is to "establish and improve the economic system of green, low-carbon and recycling development". The logistics industry, as a traditional source of carbon emissions, has a particular role to play in China's pursuit of high-quality economic growth. The efficiency of green development in the logistics industry (GLE) is therefore a matter of significant interest to the government, academic institutions and the wider public [3].

Since its inclusion in the Chinese government's work report in 2017, the digital economy (DE) based on digital technologies such as the Internet of Things, big data and artificial intelligence, has experienced unprecedented growth. According to the China Digital Economy Development Report (2022) released by the

China Academy of Information and Communication Research, the scale of China's digital economy was already valued at CNY 45.5 trillion in 2021, accounting for 39.8% of the country's GDP. The DE has accelerated the dissemination of knowledge and information , reshaped manufacturing processes and promoted regional innovation [4]. Its impact on the green efficiency of cities [5] and high-quality economic development [6] is becoming increasingly influential. Indeed, the DE is becoming an important force for driving economic transformation and leading the future economy [7].

The development of the DE has created opportunities for the logistics industry to achieve quality and efficiency, intelligent transformation and green development [8]. The profound interpenetration of the DE with the logistics industry facilitates the enhancement of energy and resource utilisation efficiency within the logistics industry, thereby facilitating the green transformation of the logistics industry [9]. The high permeability of the DE, in turn, reinforces the upstream and downstream industrial collaboration of the logistics industry, facilitates the efficient coordination of transport modes and enhances transport efficiency [10]. However, this transformation is not easy to achieve [11]. From the perspective of operational reality, the influence of the DE on the real economy is still in a state of transition and requires observation over an extended period of time. Furthermore, the manner of integration exhibits a discernible 'priority order'. Some scholars have indicated that capital-intensive industries demonstrate a more accelerated rate of integration than labour-intensive industries [12], with the logistics industry representing a notable example of a labour-intensive industry.

As a novel economic paradigm, the DE offers a fresh perspective on the GLE. However, it remains unclear whether the DE can effectively challenge the prevailing crude development model of the logistics industry, and how the logistics industry can take advantage of the opportunities presented by the DE to achieve sustainable and environmentally friendly growth are issues that deserve to be explored in depth. Based on this, it is imperative to ascertain the precise impact of the DE on the GLE and to elucidate the mechanism of the impact of the DE on the GLE. Furthermore, it would be beneficial for both practitioners and managers to ascertain whether this impact of the DE is consistent and whether it displays non-linear behaviour at varying stages of the logistics industry's evolution.

In order to ascertain the influence of the DE on the GLE and respond to the aforementioned queries, China serves as an excellent case study for our research. As the largest developing country and the second largest economy, China's logistics industry and digital economy are both experiencing rapid growth, with both sectors reaching considerable proportions. Secondly, China attaches significant importance to environmental improvement. In the past decades, the country has experienced the painful cost of sacrificing the environment for economic growth. In the context of high-quality development in the new period, accelerating digital transformation and upgrading is an inevitable choice that will promote green and sustainable development. Accordingly, this paper constructs DE and GLE indices based on China's inter-provincial panel data, and conducts a comprehensive examination of the impact of the DE on the GLM and its transmission mechanism through the utilisation of a two-way fixed-effects model and a mediated-effects model. Furthermore, a threshold model is established to investigate the non-linear impact of different indicators on this relationship.

The paper has the potential to make several marginal contributions in the following areas.

Firstly, it develops an analytical framework for the impact of the DE on the GLE. This framework allows for the analysis of the internal mechanism of the impact of the DE on the GLE in terms of both direct and mediated effects. This not only expands the scope and depth of existing research in this field, but also enriches the research dimension for the theory of sustainable development in logistics.

Secondly, this paper applies a variety of econometric models to investigate the influence of the DE on the GLE. This approach enables a comprehensive and detailed understanding of the impact of DE on the logistics industry and, by extension, the tertiary industry. The objective is to enhance the effective support of DE to the real economy. Thirdly, the results of the study can provide a basis for decision-making for practitioners and scholars in the field of DE and logistics, which is of great practical value for transforming the DE into a driving force for promoting the GLE in the new period and promoting the coordinated development of the DE and the logistics industry.

This paper consists of six sections. Section 2 deals with the literature review. Section 3 contains theoretical hypotheses. Section 4 explains the evaluation and analysis methods. Section 5 displays empirical results and discussions. Finally, conclusions are drawn in section 6.

2. LITERATURE REVIEW

The logistics industry is a service sector that encompasses transportation, warehousing and information services. It is linked to both production and consumption and is considered a crucial basic service industry in the national economic system. Accordingly, its operational efficiency has emerged as a pivotal research topic, garnering considerable interest among scholars [3, 13, 14]. Nevertheless, the assessment of logistics efficiency is a challenging undertaking, given the multitude of variables and domains that influence the logistics system [15, 16]. In order to meet the research needs of multi-level logistics efficiency, the measurement methods of logistics efficiency have been diversified in recent years. However, they can be summarised in two main categories: parametric and non-parametric methods. The parametric method most commonly used is frontier efficiency analysis, which is employed as a measurement model. Some scholars have chosen stochastic frontier analysis (SFA) to measure logistics efficiency [16, 17].The non-parametric method of the Data Envelopment Analysis (DEA) is advantageous in situations where a specific production function is not applicable, as it allows for the measurement of logistics efficiency with multiple inputs and outputs. An increasing number of scholars are utilising this method to address such scenarios [18–20]. To date, studies employing conventional DEA techniques to assess logistics efficiency have reached a relatively advanced stage of development [21, 22]. In order to enhance the precision and applicability of the resulting measurements, an increasing number of scholars have adopted enhanced DEA models, such as multi-stage DEA model [3, 22], slacks-based measure (SBM) model [23, 24], Super SBM model [13, 14], epsilon-based measure (EBM) model [25], etc. In recent years, the concept of green development has gained significant traction among the general public and has become a prominent area of interest for academics. There has been a notable shift in the emphasis placed on green sustainability within the logistics industry, with an increasing focus on the incorporation of green and environmental factors into the analytical framework used for the assessment of logistics efficiency [26]. At present, there is no consensus among scholars regarding a definitive definition of the green development efficiency of the logistics industry (GLE). In essence, it can be defined as the pursuit of economic effects in the field of logistics, with due consideration for the constraints imposed by the surrounding ecological environment. This approach is essential in the context of green, sustainable development. Scholars have employed a variety of indicators and methods for the assessment of GLE. In their study, Cao et al. [14] include energy consumption as an input indicator and carbon emission as a non-desired output, employing the Super-SBM model to measure the logistics efficiency of China's Yangtze River Economic Zone. Ye et al. [27] consider both economic and social service outputs in the output indicators, incorporate carbon emissions into the non-expected output indicators and introduce the Super-SBM method to measure the efficiency of China's provincial logistics industry under low carbon constraints. This allows them to explore the driving mechanism of GLE of China, economic development, information technology, government logistics regulation and environmental regulation, which can markedly enhance the efficiency of the regional logistics industry. In 1953, Malmquist proposed the Malmquist model for the study of changes in consumption patterns across different time periods. Subsequently, Fare et al. integrated the Malmquist and DEA approaches to develop the DEA-Malmquist model. This model, along with its subsequent iterations, has since been extensively employed for analysing the dynamic evolution of decision-making units. Zeng [28] employed the DEA-Malmquist index method to assess the productivity of China's logistics industry and highlighted that the level of informatisation can stimulate the growth of total factor productivity in the logistics industry in the region. Chen et al. [13] measured China's GLE using the Super SBM model, and explained the reasons for changes in green logistics efficiency using the Global Malmquist-Luenberger (GML) index model. They imply that green technology advancement is an inherent key factor for green logistics efficiency to achieve growth. The diversification of the logistics efficiency assessment methods, as evidenced in the literature, from the traditional DEA to more complex models that take into account poor outputs and green dimensions, reflects both the interest of academia in the evolving operational efficiency of the logistics industry and the direction of the development of the logistics industry.

The term 'digital economy' was first coined by Tapscott (1996) in his book "The Digital Economy: Promise and Peril in the Age of Networked Intelligence". The reference to the digital economy (DE) gained popularity with the publication of The Emerging Digital Economy (1998) by the US Department of Commerce [29]. Over the past 20 years, the DE has rapidly developed due to advances in information and communication technology. It has become one of the most dynamic, innovative and thriving economic forms, following the agricultural and industrial economies. Scholars and governments are now focusing on effectively measuring the scale of the DE. The US Bureau of Economic Analysis (BEA) estimates the value added of the DE within the supply-use framework, which Xu and Zhang applied to calculate the value added of China's digital economy from

2007 to 2017 [30]. Barefoot et al.[31] describe estimation work undertaken by the BEA to construct a new satellite account of the digital economy (DESA). These two methods facilitate horizontal comparisons of the scale of the DE. However, inconsistencies in statistical quality across regions and challenges in data collection have prompted some scholars to indirectly assess DE indices through the construction of an evaluation index system, especially when studying the DE in different economic agents or regions. Some researchers have employed the indirect measurement of China's digital economy through the construction of a DE index [32, 33]. A number of domestic institutions, including the China Academy of Information and Communications Technology, Tencent Technology (Shenzhen) Co.Ltd, Ali Research, and Institute of Digital Finance Peking University, have also developed indices related to the DE with the objective of examining the varying degrees of digital economic advancement across different regions. This endeavour indirectly provides crucial support for academic research. Jiang et al.[34] measured the DE with reference to the "China Internet + Digital Economy Index" report constructed by Tencent Technology (Shenzhen) Co.Ltd, and found that the DE exerts a significant negative impact on the real economy. Zhao et al. [35] and Ma et al. [4] included the "Peking University Digital Inclusive Finance Index" as an important part of the DE index system. The former posits that the DE can facilitate high-quality development, whereas the latter identifies spatial heterogeneity in the impact of digitalisation on urban greening. The construction of these DE indices provides the basis for the subsequent analysis presented in this paper.

The extant literature on the DE and logistics efficiency is extensive. As the penetration rate of the DE continues to increase, scholars have verified the significant impact of the DE on urban innovation [36], urban green efficiency [4] and High-Quality Development [6]. However, it is challenging to identify direct research on the impact of the DE on the GLE, closer to the results of two categories. One is based on the industrial integration perspective of the study of the coordinated development of the DE and the logistics industry. In the context of the integration of the DE and the real economy, the necessity for the integration of the logistics industry with the core industries of the DE is self-evident [8]. It is therefore evident that an understanding of the temporal evolution and spatial correlation of the integration of the logistics industry and the DE will facilitate the digital transformation of the logistics industry and guarantee the high-quality development of the logistics industry [37]. The other is the study of the digital economy, digital technology impact on the logistics industry, which revealed that the characteristics of digitalisation in logistics exert a considerable influence on the process of logistics network development. The utilisation of digital technology has the potential to enhance the efficiency of logistics network operations [38]. The DE accelerates the dissemination of knowledge and information, which in turn can facilitate the advancement of logistics technology innovation [39]. Furthermore, the interconnectedness of the DE serves to diminish the financial burden associated with market transactions, thereby indirectly enhancing the efficiency of logistics operations [40]. The influence of the DE on carbon emissions in the logistics industry is complex and multifaceted. It can be argued that the application of digital technology and digital platforms is premised on the consumption of a certain amount of energy, which will consequently impact the carbon emissions of the logistics industry [41]. Conversely, the DE is expected to exert a positive influence on the logistics industry through the network and innovation effects, thereby contributing to a reduction in carbon emissions. Li et al. [42] have posited that the DE exerts a non-linear impact on the carbon emissions of the logistics industry, with the current DE in China being in the initial phase of its U-shaped trajectory. This suggests that the DE has a considerable inhibitory impact on the carbon emissions of China's logistics industry. Wang et al. [43] observe that the DE offers the logistics industry a novel opportunity for transformation and upgrading, thereby facilitating the high-quality development of logistics through a range of factors, including basic support, industrial integration, governance and security. The aforementioned studies have concentrated on the evolution of the logistics industry in the context of the DE. They have also illuminated the impact of the DE on the logistics industry from the perspectives of digital technology, energy efficiency and emission reduction. These insights serve to inform the conceptual framework of this paper.

In general, the research conducted in the independent field of DE and logistics industry has yielded significant findings, offering invaluable insights for a comprehensive examination of the influence of the DE on the GLE. Nevertheless, the extant research is not without limitations. Firstly, as the concept of green and high-quality development is relatively novel, research into its integration with the DE is still in its infancy. While studies have been conducted on the impact of the DE on the digital transformation and the carbon emissions of the logistics industry, there is still a relative lack of research on the internal mechanisms of how the DE specifically contributes to the GLE. Secondly, despite the rapid development of China's digital economy and logistics industry, existing research has predominantly concentrated on theoretical investigations of policy orientation or realisation pathways, with a notable scarcity of empirical studies. Theoretical studies on occasion place undue emphasis on the integrative role of the DE, whilst simultaneously failing to adequately consider the intrinsic characteristics and developmental stages of the logistics industry. This highlights the necessity for a more comprehensive and nuanced empirical investigation.

Consequently, the objective of this study is to elucidate the impact of the DE on the GLE and its mechanism of action. This study could be innovative in two ways. Firstly, this study examines the influence of the DE on the efficiency of the GLE, and the mechanisms through which this occurs, from both theoretical and empirical perspectives. This contributes to a more profound comprehension of the intrinsic interconnection between the two. Secondly, in addition to assessing the impact of DE on GLE using two-way fixed effects, the empirical analysis includes industrial upgrading and labour efficiency in the mechanism test, the threshold effect test considering the development stage of the logistics industry, as well as a decomposition of the GLE from the perspective of efficiency change and technological progress are also designed. The conclusions presented are not only empirically sound but also contribute to a deeper understanding of the relationship between the DE and the GLE. Furthermore, these conclusions have significant practical implications for the promotion of a DE that facilitates the green and high-quality development of the logistics industry.

3. THEORETICAL HYPOTHESES

3.1 The direct impact of the DE on the GLE

The DE represents a novel economic paradigm, predicated on digital technology and based on data resources. Its impact on the logistics industry is considerable, affecting total factor productivity [28], industrial structure [44], as well as energy saving and emission reduction [42]. From the perspective of production reshaping, the DE brings about an abundance of knowledge and guides the intelligent transformation of the real economy and industrial upgrading, thereby making the logistics industry profitable. Big data, cloud computing and artificial intelligence are being applied to promote the digital upgrading of the logistics industry, which improves its digitalisation and modernisation levels. This, in turn, increases total factor productivity [45] and paves the way for the sustainable development of traditional logistics. From the perspective of resource allocation, the DE facilitates the transcendence of temporal and spatial constraints, thereby optimising the allocation of resources. The DE is known for its high innovation, strong permeability and wide coverage, allowing it to break down industry, enterprise, geographical and other restrictions. This promotes the integration of information and factor flow. This, in turn, has the effect of enhancing market activity, reducing transaction thresholds and transaction costs [40]. This facilitates the cross-border integration of the logistics industry, enhances logistics efficiency and elevates the value of services [46]. Finally, from the perspective of processes, the DE can facilitate process optimisation [42] and energy monitoring [47] by collecting and analysing logistics data, which in turn has a beneficial impact on the GLE. The logistics industry is a productive service industry, which generates a substantial quantity of data and information in its interactions with related industries. The digitalisation of logistics allows the collection of data and information related to logistics activities in real time, facilitating the optimisation and reorganisation of logistics processes [48]. This approach can manage logistics activities flexibly, efficiently and accurately, while reducing energy consumption at source [49], improving operational efficiency. Therefore, we put forward a fundamental hypothesis 1 (H1). The DE has a contributing effect on improving the GLE.

The GLE can be further decomposed into two distinct elements: efficiency change and technological progress [50]. Efficiency change represents a producer's capacity to maximise output for a given set of factors, typically reflecting the efficiency of the utilisation and allocation of available resources. Technical progress can be defined as the additional rate of growth of output achieved when the input mix remains constant. It implies technological improvements that serve to expand the frontier of production [51]. The combined effect of the network, innovation and efficiency of the DE will facilitate the acceleration and optimisation of the utilisation and open sharing of logistics data resources [42]. This will, in turn, promote the systematic integration of the internal links of logistics as well as the upstream and downstream external links of the relevant industries, thereby accelerating the agglomeration and diffusion of logistics resources, promoting the free flow of logistics factors and enhancing the efficiency of the utilisation of logistics resources [51]. Accordingly, its main advantage is that it can effectively alleviate factor mismatch and improve factor allocation efficiency through integration with the real economy [52]. Therefore, the DE is more likely to directly improve the efficiency of resource allocation and the output efficiency of the logistics industry under established inputs. The relationship between the DE and technological progress is intricate and closely linked to economic development, industrialisation, scientific and technological innovation, and infrastructure [11]. Furthermore, its transformative effect is somewhat delayed [53]. The advancement of technology necessitates a considerable influx of skilled professionals. The labour-intensive nature of China's current logistics industry results in a misalignment between the supply of less-qualified workers and the demand for highly skilled talent for cross-border integration in the DE. This ultimately impedes the potential for significant technological breakthroughs. Therefore, fully realising the potential of the DE in promoting technological progress is challenging. Considering the above discussion the following hypotheses are proposed:

H2a. The DE has a contributory effect on the improvement of efficiency change.

H2b. The DE does not contribute to technological progress.

3.2 The indirect impact of the DE on the GLE

The ‘structural dividend hypothesis’ theory suggests that optimising industrial structure can facilitate the transfer of production factors to industries and sectors with higher productivity, thereby enhancing the total factor productivity of society as a whole [54]. The penetration and application of the DE facilitates cross-industry and cross-field resource sharing, optimises the production methods, supply chains and value chains of traditional industries, raises the level of industrial structure, and forces low-end backward industries to upgrade in order to improve the operational efficiency of industrial organisations [55]. Some scholars have conducted empirical analyses that indicate that the DE is beneficial for China’s regional industrial structure. They have also determined that the upgrading of industrial structures is a key pathway for the digital economy to enhance the green total factor productivity of industries [56] and urban areas [57]. The logistics industry as the ‘meridian’ of the economy, on the one hand, benefits from the efficient circulation of goods and resource elements, and constantly improves the logistics efficiency and service quality; on the other hand, through the optimisation of production methods and organisation of the logistics industry, improving the efficiency of resource utilisation and management efficiency [45], and seeking digitalisation in the process of upgrading the integration of industrial structure, intelligent transformation, to service-oriented, high-end development, the GLE can be effectively enhanced. This paper puts forward hypothesis 3: The DE promotes the improvement of the GLE by promoting the upgrading of industrial structure.

The transformation of the logistics industry into a networked and intelligent industry is reaping the benefits of the DE. However, as a labour-intensive industry, it is also facing significant challenges in improving labour efficiency. Some scholars [58] have highlighted that the time lag and substitution effect of the DE will cause the ‘productivity paradox’, which may indirectly affect the GLE. Firstly, the logistics industry is distinguished by a considerable degree of labour intensity, accompanied by a notable dependence on infrastructure. The introduction of digital technology necessitates not only a considerable investment in equipment renewal and software upgrading, but also in staff training and business restructuring. These costs may act as a deterrent for enterprises. Furthermore, it will necessitate a significant investment of time for workers to gain proficiency in digital technologies and to promote their application [59]. These factors will hinder labour efficiency improvement, which in turn diminishes the role of the DE in promoting the GLE. Secondly, the booming development of the DE has accelerated the transfer of labour and created new demands for skilled personnel in R&D, operations and other areas, while technology-intensive and capital-intensive industries have a stronger attraction for highly skilled personnel, pushing up the cost of labour [60]. Meanwhile, the substitution effect of the DE on programmed labour may force low-skilled workers to turn to physically-intensive work. The logistics industry become an important destination for the absorption of laid-off and unemployed workers. This may increase the total amount of employment in the logistics industry and could lead to the polarisation of the industry, inhibiting the improvement of labour productivity, which will then have a negative impact on the GLE. In light of the above, hypothesis 4 is proposed: The labour productivity of logistics masks the positive impact of the DE on the GLE.

3.3 The non-linear impact of the DE on the GLE

The GLE is not only affected by the DE, but also related to its own scale of development. Marshall’s scale effect theory shows that the scale effect will go through different stages with the expansion of production scale, such as increasing scale effect, constant scale effect and decreasing scale effect. From the point of view of scale effect, when the logistics industry scale is small, the logistics industry will expand with the scale based on the full and effective use of enterprise resources, organisational and operational efficiency to improve the formation of internal economies of scale, through the reasonable division of labour, common and regional layout to achieve the external economies of scale [14]. The DE as a kind of convergence of the economy, through the data elements of the optimisation of the logistics industry's internal management model and organisational form, through the promotion of the factor flow rational resource allocation to promote cross-regional and cross-industry cooperation in the logistics industry, will enhance the promotion of such economies of scale and accelerate the GLE. Some scholars [61] have identified a threshold effect in the logistics industry, whereby the internal operating efficiency of an enterprise declines as it approaches a certain size. This is accompanied by a series of challenges, including external resource constraints, rising factor prices and increasing output exceeding demand, as well as the emergence of vicious competition. A range of internal and external factors will offset the facilitating effect of the DE. Therefore, hypothesis 5 is proposed: The impact of the DE on the GLE has a threshold effect of industry scale.

The rapid development of the DE can create conditions for cross-border integration and technological progress in the logistics industry, but the labour-intensive characteristics of the logistics industry lead to its own slow technological change, superimposed on digital technology as a general-purpose technology with a lag, the role of the DE will be limited by the level of scientific and technological innovation. Investments in science and technology often need to reach a certain scale to become cost-effective, so some scholars [62] have pointed out that the role of the DE in promoting productivity will only appear when the accumulation of information capital exceeds a certain critical value. When the level of scientific and technological innovation is low, the DE can rely on fewer technological resources, the innovation effect and scale effect is not yet obvious and the logistics industry chain is hindered by the efficient serial connection, resulting in the promotion of the efficiency of green development of the logistics industry, the kinetic energy of the relative lack of power. The logistics industry requires an extended period for the assimilation and adaptation of new technologies. Furthermore, the integration of science and technology with other systems is of paramount importance for their effective implementation, which may be constrained [58]. When the level of scientific and technological innovation is high, scientific and technological innovation lays a good innovation foundation for the DE, and the DE helps the logistics industry break through the technological bottleneck, effectively connects the internal links of the logistics industry and the external related industries. In this way, the transformation and upgrading of the logistics industry in the form of intellectualisation and data can be promoted, the dependence on production factors such as labour and capital can be reduced, and at the same time, the energy consumption can be reduced, the operational efficiency can be improved, and a more positive impact of the GLE can be realised [63, 64]. Therefore, hypothesis 6 is proposed: The impact of the DE on the GLE has a threshold effect of scientific and technological innovation.

4. RESEARCH DESIGN

4.1 Model settings

In order to investigate the impact of the DE on the GLE, this paper employs a two-way fixed effects model [6, 65] to construct the benchmark regression, as illustrated in *Equation 1*:

$$GLE_{it} = \alpha_0 + \alpha_1 DE_{it} + \alpha_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

where GLE_{it} is the explained variable, the green development efficiency of logistics industry; DE_{it} is the core explanatory variable; α_1 represents the coefficient of DE impacting on GLE; X_{it} denotes a series of control variables, including economic development, government intervention, openness as well as technological innovation; taking into account that there are still some unobservable factors accompanying the change of time and province in reality, the model has added the individual fixed effect μ_i and the time fixed effect δ_t , ε_{it} is the random error term, i and t denote province and year, respectively.

Moreover, industrial structure (Str) and labour productivity (Lab-Pro) are introduced as mediating variables to analyse the indirect impact of the DE on the GLE. The following mediating effect model, proposed by Yan et al. [6] and Sun et al. [66], is constructed:

$$media_{it} = \gamma_0 + \gamma_1 DE_{it} + \gamma_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

$$GLE_{it} = \beta_0 + \beta_1 DE_{it} + \beta_2 media_{it} + \beta_3 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

where $media_{it}$ denotes the mediating variable, taken as Str and Lab-Pro respectively; $\gamma_1, \gamma_2, \beta_1, \beta_2, \beta_3$ are the regression coefficients and the other parameter values and symbols are consistent with *Equation 1*.

Furthermore, the impact of the DE on the GLE may exist in the threshold effect of logistics scale (LS) and scientific and technological innovation (STI), so the following panel threshold model [6] is set up as an example of a single-threshold scenario:

$$GLE_{it} = \alpha_0 + \alpha_1 DE_{it} I(q \leq \gamma) + \alpha_2 DE_{it} I(q > \gamma) + \alpha_3 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{4}$$

where q is the threshold variable, $I(\cdot)$ represents the indicator function with the value of 1 or 0, γ is the specific threshold value, and the other parameter values and symbols are consistent with *Equation 1*.

4.2 Variables and data

Variabless

The explained variable in this paper is the green development efficiency of the logistics industry (GLE). At present, there is no unified method to measure the GLE. Based on the results of previous studies [14, 47, 50], the Super SBM model which considers non-expected outputs combined with Malmquist index is selected to measure the GLE, and at the same time, with reference to the studies of Zhao et al.[45] and Sun et al. [66], the GLE are further decomposed into two parts: efficiency change (EC) and technical progress change (TC). In the measurement process, the input indicators are capital, labour, infrastructure and energy, where capital input is expressed by fixed investment in logistics, which is treated using the provincial GDP deflator due to the removal of fixed investment prices by the National Bureau of Statistics; labour input is measured by the number of persons employed in the logistics industry in urban units in each province; infrastructure input is expressed as the sum of the distance travelled by the three main modes of transport, namely rail, road and inland waterways; energy input is based on the nine energy sources with the highest share of energy consumption in logistics (hard coal, petrol, paraffin, diesel fuel, fuel oil, natural gas, liquefied natural gas, heat and electricity) and energy consumption is obtained by calculating energy consumption using a scaling factor. The output indicators are desired and undesired outputs. Desired outputs include freight volume, freight turnover and logistics industry value added, where logistics industry value added is processed by deflating the GDP of the base period of the province; undesired outputs are characterised by CO2 emissions from the logistics industry, following Zhang [67], and is calculated based on China's Guidelines for the Preparation of Provincial-Level Greenhouse Gas Inventories (NDRC Climate (2011)) and Guidelines for Calculation Tools for Greenhouse Gas Emissions from Energy Consumption (2011).

The explanatory variable is the digital economy (DE), according to the principles of timeliness, comparability and data availability, referring to the results of Zhao et al. [35] and Luo et al.[64], we take the Internet penetration rate, information industry-related employees, digital industry-related output, mobile phone penetration rate and digital financial inclusion index as the basic indexes of the DE, and use the entropy method to obtain the final index. The specific index composition is shown in *Table 1*.

Table 1 – The evaluation index system of China's digital economy

Target layer	System layer	Indicator layer
Digital economy	Internet penetration rate	Hundreds of Internet broadband access users
	Industry related practitioners	Proportion of software and information technology services practitioners
	Digital industry-related output	Per capita total telecommunications business
	Mobile phone penetration rate	Mobile phone users per 100 people
	Digital inclusive finance index	Digital inclusive finance index (Peking University)

Two mechanism variables were introduced, namely industrial structure upgrading (Str) and labour productivity in the logistics industry (Lab-Pro). Industrial structure upgrading is measured by the ratio of the value added of the tertiary industry to the value added of the secondary industry [6], and labour productivity in the logistics industry [66] is expressed as the total value of the logistics industry per unit of logistics employees.

The control variables are economic development, government intervention, openness and technological innovation. There are more factors affecting the GLE, and in order to avoid possible multicollinearity between the explanatory variables and the control variables, this paper refers to the results of previous research [6, 14, 68, 69], but the control variables do not include the input and output indicators of the GLE. The level of economic development is taken as GDP per capita (RGDP) [68, 69]; the level of government intervention (GOV) is measured by the ratio of general government expenditure to GDP [6, 14]; the level of openness (OPEN) is taken as the total amount of imports and exports of each province [14]; and the level of scientific and technological innovation (STI) is taken as the number of patent applications received by each province [68, 69].

Data source

The regional scope of this study is 30 provinces in China (excluding Hong Kong, Macau, Taiwan and Tibet) and the time frame is 2011–2021. Due to the imperfect statistical system of China's logistics industry, data from the transport, storage and postal sectors are used for analysis instead of logistics data. The data are taken from China Statistical Yearbook, China Energy Statistical Yearbook, Provincial Statistical Yearbook and Peking University Digital Financial Inclusion Index, where RGDP, OPEN and STI are logarithmised, and the descriptive statistics are shown in the *Table 2* below.

Table 2 – Variable descriptive statistics

Variable	Observation	Mean	SD	Min	Max
GLE	300	1.023	0.166	0.513	2.486
EC	300	1.038	0.187	0.556	2.166
TC	300	0.998	0.143	0.483	1.74
DE	300	0.338	0.157	0.069	0.885
Str	300	1.374	0.738	0.611	5.244
Lab-Pro	300	42.105	18.356	10.686	112.966
GOV	300	0.263	0.113	0.105	0.758
Ln (RGDP)	300	10.871	0.435	9.849	12.142
Ln (OPEN)	300	19.576	1.575	14.523	22.664
Ln (STI)	300	10.864	1.356	6.738	13.796

5. EMPIRICAL RESULTS

5.1 Benchmark regression results

To ensure robustness, this paper employs the stepwise regression method [49] and reports the benchmark regression results in *Table 3*. Column (1) displays the estimated coefficient of 0.838, which is significant at the 10% level when only the DE is included and the two-way fixed effects are controlled. This suggests that the development of the DE contributes to the improvement of the GLE. When including control variables and control two-way fixed effects sequentially, the estimated coefficient of the core explanatory variables remains significantly positive at the 10% level. The coefficient size, significance and other characteristics of the control variables did not change substantially, thus confirming hypothesis 1 of this paper. The results of the control variables are consistent with those of other scholars and viewpoints [19, 68, 70], and will not be reiterated here.

This study presents empirical evidence that the DE has a positive impact on the GLE, which is consistent with the findings of previous scholars in this field [28, 42, 43]. The advancement of information technology facilitates an enhancement in the total factor productivity of the logistics industry [28], and the DE is conducive to the promotion of carbon emission reduction in the logistics industry [42], which emphasises the positive effect of the DE on the GLE. Indeed, the DE is of pivotal importance in the promotion of industrial integration [9], urban innovation [36], energy conservation and emission reduction [48]. It is becoming an important driving force for the real economy, including the logistics industry, to achieve industrial transformation and upgrading, and to improve quality and efficiency. This is also consistent with the current Chinese government's objective of actively promoting the transformation of traditional logistics into digitalisation, networking and intelligence, with the aim of promoting the green and sustainable development of the logistics industry through the DE [46]. It is thus imperative to undertake a comprehensive and detailed investigation into the impact of the DE on the GLE, in order to provide the government with the requisite evidence to inform the formulation of accurate policies.

Table 3 – Benchmark regression results

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
DE	0.838*	0.828*	0.995*	1.010**	1.111*
	(0.458)	(0.480)	(0.489)	(0.496)	(0.632)
GOV		-0.044	-0.423	-0.482	-0.499
		(0.322)	(0.360)	(0.371)	(0.388)
Ln (RGDP)			-0.381***	-0.415***	-0.499**
			(0.130)	(0.143)	(0.234)
Ln (OPEN)				0.015	0.025
				(0.035)	(0.047)
Ln (STI)					0.056
					(0.129)
Two-way fixed	yes	yes	yes	yes	yes
N	300	300	300	300	300
R^2	0.313	0.313	0.321	0.321	0.325

*Robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1*

5.2 Robustness tests and heterogeneity analysis

Robustness tests

In order to ensure the credibility of the conclusions of the benchmark regression, this paper conducts robustness tests in several ways. One is to select the DE variable, lagged by one period, as an instrumental variable for the explanatory variables and apply two-stage least squares (2SLS) to mitigate the endogeneity problem. Second, to replace the explanatory variables and re-measure the DE using principal component analysis [5] (PCA) as a substitute variable for the explanatory variables. Third, given that the green development efficiency value of the logistics industry is a non-negative truncated data, which is a restricted dependent variable, we chose to use a right-subsumed Tobit panel model [69] to conduct a robustness test. From the results *(Table 4)*, consistent with the benchmark regression, the DE has a significant positive impact on the GLE.

Table 4 – Robustness test regression results

Variable	2SLS	PCA	Tobit
DE	2.574***	0.169*	1.111*
	(0.897)	(0.095)	(0.585)
Control variable	yes	yes	yes
Two-way fixed	yes	yes	yes
N	300	300	300
R^2	0.128	0.207	Prob >chi2=0.000

*Robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1*

Heterogeneity analysis

Due to the unbalanced regional development in China, there are large differences in both the development status of the DE and the GLE, resulting in the possible heterogeneity of the impact of the DE. This paper discusses the heterogeneous impact of the DE on the GLE from three aspects: the period of development of the DE, regional differences and the level of the GLE.

Heterogeneity of the development period of the DE. The development of the DE has obvious time characteristics – after the early stage of website as king and traffic competition for differentiated services, the DE jumped out of the category of big data, with data resources as the key elements, fully penetrated into social and economic activities, with 2019 being the first year of society's comprehensive entry into the era of DE in China. In this paper, the sample is divided into two periods of 2011–2018 and 2019–2021 to construct the digital economic development dummy variable XN_year, which takes the value of 0 in the early period and the value of 1 in the late period, and the interaction term between the core explanatory variables and the digital economic development dummy variable ($DE \times XN\_year$) is included in the baseline regression for estimation. The estimated coefficient of the interaction term in column (1) of *Table 5* is significantly positive at the 5% level, indicating that the DE plays a greater role on the GLE in the later stage, which is consistent with the characteristics of the DE governed by "Metcalfe's Law", and the share of GDP in the DE jumps from 21.6% in 2012 to 39.8% in 2021, and its impact on the GLE is even greater.

Regional heterogeneity. China's eastern and western regions are different in terms of economic base, natural endowment, transportation, science and technology, so the impact of the DE may also vary across regions. This paper distinguishes between the eastern region and the central and western regions (central and western region location = 0, eastern region location = 1), and includes the interaction term between region and digital economy (DE×location) in the baseline model. Column (2) of *Table 5* shows an interaction effect coefficient of 0.377, which is significant at the 10% level, suggesting a greater role for the eastern region. These findings align with those of Wang et al. [37], who observed that the integration of China's logistics industry and digital economy exhibits a distinct 'east high, west low' pattern. The eastern region is a relatively developed region of China's economy, exhibiting advanced infrastructure, rapid economic growth and a high level of integration between the DE and the service industry. This integration confers a competitive advantage in the development of data elements during industrial digitalisation, which is more pronounced in the eastern region than in the central and western regions. The role of data elements in the process of industrial digitisation is more pronounced, and the promotion of the efficiency of green logistics development is also more effective than that of the central and western regions. Wang et al.'s empirical analysis based on the evaluation index system for high-quality logistics development reaches a similar conclusion [43].

Table 5 – Heterogeneous regression results

Variable	(1)	(2)
DE	0.718	0.781
	(0.607)	(0.561)
$DE \times XN\_year$	0.446**	
	(0.178)	
DE×location		0.377*
		(0.204)
Control variable	yes	yes
Two-way fixed	yes	yes
N	300	300
R^2	0.336	0.344

*Robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1*

Heterogeneity of the GLE. The benchmark regression model focuses on the conditional expected mean of the core explanatory variables on the explanatory variables, considering that the impact of the DE may be different when the GLE is at different levels, while the quantile regression can exclude the interference of the extreme values and has the advantage of presenting the full picture of the conditional distribution. In this paper, we use the panel quantile regression model [42] to test the difference in the impact of the DE at different quantiles of the GLE. The coefficient value of the DE in Figure 1 shows a decreasing trend in each level from 0.1 to 0.9 of GLE, indicating that the promoting effect of the DE on the GLE is characterised by diminishing marginal utility, which is basically in line with some of the results of Bai et al. [71]. The possible explanation for this is that the overall view of the DE is still in the early stages of development, mainly through the efficiency index to achieve the GLE, the role of technological progress has not yet been reflected, and it is difficult to achieve technological progress brought about by the efficiency of the leap, showing the law of diminishing marginal effect. It should be noted that the estimated coefficients of the DE only passed the 10% significance test at the 30% to 50% quantile, probably due to the small sample size, and the robustness of the trend needs further verification.

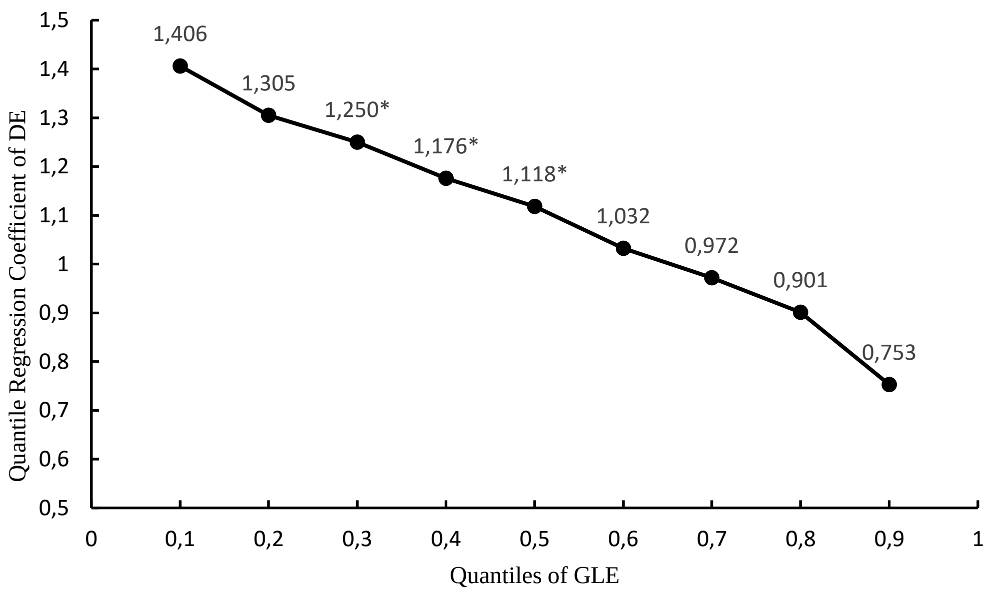

Figure 1 – Trend plot of panel quantile regression coefficients for digital economy
*Note: *** p < 0.01, ** p < 0.05, * p < 0.1*

5.3 Influence mechanism test

By examining the underlying mechanisms behind the impact of the DE on the GLE, this study contributes to a more comprehensive understanding of the relationship between the DE and the GLE. It also provides insights for policymakers to design more effective policies to better utilise the positive effects of the DE on the GLE. Through the previous theoretical analysis, this paper conducts the mediation effect regression model test on industrial structure (Str) and labour productivity of the logistics industry (Lab-Pro). To enhance the reliability of the mediation effect analysis, the bootstrap test [29] is also selected to verify the robustness of the mediation effect.

In *Table 6,* Model (1) is used to test whether the DE has an effect on the industrial structure, the coefficient of the DE is positive and significant at 10% level, indicating that the DE promotes the upgrading of the industrial structure. Model (2) verifies whether the industrial structure plays a mediating role between the DE and the GLE. The coefficient of the industrial structure is positive and significant, indicating that the mediating effect exists, and the confidence level of the indirect effect is [0.032, 0.903], which does not contain 0, confirming the significance of the mediating effect and indicating that the DE can promote the upgrading of the industrial structure to promote the GLE, confirming the research hypothesis 3.

This conclusion is related to the findings of Liu et al. [29], who determined that the industrial structure upgrading serves as a mediating transmission mechanism for the impact of the DE on urban total factor productivity. Given that the industrial structure represents the nexus between resources and the urban economy, and that logistics represents the vital pulse of urban economic activity, it follows that the intermediary transmission mechanism of industrial structure upgrading is also reflected in the impact of the DE on the GLE. A number of potential explanations for this can be put forward. Firstly, the DE, which is based on Internet technology, has the potential to transcend traditional industrial boundaries, promote multidisciplinary integration and innovation. Concurrently, the DE is enhanced by data-driven intelligence, which facilitates the intelligent and automated transformation of decision-making in the real economy and, in turn, drives the upgrading of industrial structures. As a foundational service industry, the logistics sector stands to benefit from the DE to enhance the sector's intrinsic capabilities. Secondly, the logistics industry plays a pivotal role in extending the industrial chain, upgrading the value chain and constructing the supply chain. In the context of the DE, which is promoting the upgrading of the industrial structure, the logistics industry is positioned between various industries. This further enriches the application scenarios of the logistics industry, accelerates the cross-industry and cross-region linkage of the logistics industry and allows it to benefit from the optimal allocation of external resources.

In *Table 6,* the coefficient of the DE on Lab-Pro in model (3) is significantly negative, indicating that the DE is not conducive to the improvement of labour productivity in the logistics industry. Considering the mediating variable of the Lab-Pro in model (4), the coefficient of DE is significantly positive, i.e. the direct effect is positive. The coefficient of the Lab-Pro on the GLE is positive, and the multiplication with the coefficient of the DE on the Lab-Pro gets the negative indirect effect. The signs of the direct effect and the indirect effect are opposite, which is judged to be a masking effect, and the 95% confidence interval of the confidence level of the indirect effect is [-0.431,-0.025], which does not include 0, and the result is robust. Labour productivity masks the contribution of the DE to the efficiency of green development in the logistics industry, confirming hypothesis 4.

This conclusion is related to Yang et al.'s [59] findings, who observed heterogeneity in the impact of the DE on labour productivity. The time lag of the DE and the substitution effect of the DE on labour may, in certain instances, give rise to a phenomenon known as the 'productivity paradox'. Furthermore, Jin et al. [62] emphasised that the DE does not enhance labour productivity in industries that are labour-intensive. This paper offers support for their view. Additionally, China's logistics industry is experiencing a discrepancy between supply and demand due to shifts in the labour force structure. The modernisation of the logistics industry will lead to an increased demand for highly skilled professionals. However, the traditional labour-intensive approach of many enterprises may persist due to cost considerations. Additionally, people who have become unemployed in other sectors in China tend to take up relatively low-skilled logistics jobs, such as truck drivers, couriers or takeaway delivery staff. This can be attributed to the relative ease with which these positions can be obtained, but it also reflects an alteration in the structure of the labour force brought about by the DE. While the DE has undoubtedly enhanced the GLE at the macro level, at the micro level, labour productivity in the logistics industry has overshadowed the contribution of the DE on the GLE. This masking effect requires attention and action.

Table 6 – Influence mechanism test

Variable	Str (1)	GLE (2)	Lab-Pro (3)	GLE (4)
DE	1.401*	0.584	-53.776**	1.333**
	(0.798)	(0.491)	(25.791)	(0.639)
Str		0.376*		
		(0.214)		
Lab-Pro				0.004***
				(0.001)
Control variable	yes	yes	yes	yes
Two-way fixed	yes	yes	yes	yes
N	300	300	300	300
R^2	0.980	0.381	0.948	0.336
Bootstrap test confidence interval (500 times)	[0.032–0.903]		[-0.431 – -0.025]	

*Robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1*

5.4 Threshold effect test

The previous paper employed an empirical methodology to investigate the positive impact of the DE on the GLE. This raises the question of whether this impact is non-linear. To what extent will this be constrained by external conditions, and to what extent is it related to the development of the logistics industry itself? This paper examines the existence and threshold amount of the threshold effect of science and technology innovation (STI) and logistics scale (LS) in the role of the DE on the GLE by adopting a self-sampling (Bootstrap) method [6]. This study offers a more detailed insight into the non-linear characteristics of the relationship between the DE and the GLE by exploring the effects of the STI and the LS as threshold variables.

The precondition of the threshold test is that there must be a threshold effect. Therefore, this paper first tests the significance of the threshold effect. Secondly, the specific threshold value is estimated. In this paper, through the bootstrap (300 times) method, single threshold, double threshold and triple threshold tests are carried out sequentially, and the results show that the LS significantly passes the double threshold, fails to pass the triple threshold and that the STI passes the single threshold, fails to pass the double threshold and triple threshold. The results of the threshold tests are shown in *Table 7*.

Table 7 – Threshold effect test of each variable

Variable	Threshold number	F-value	P-value	Critical value			Threshold value
				10%	5%	1%	
LS	Single	23.690**	0.010	14.573	16.989	23.546	213.842
	Double	42.700***	0.000	11.960	14.841	20.657	377.374
	Triple	10.900	0.400	43.163	58.935	88.715	-
STI	Single	19.650**	0.030	12.813	16.628	23.728	6451
	Double	12.930	0.200	18.591	24.598	38.197	-

*Robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1*

Based on the results of the threshold effect existence test, the double-threshold model is selected for the regression with the LS as the threshold variable, and the single-threshold model is selected for the regression with the STI as the threshold variable.

As shown in *Table 8(1)*, we can see that the impact of the DE on the GLE is non-linear due to the different size of the logistics industry. When the LS is smaller than the first threshold (213.842), the coefficient estimate of the DE is 0.787 and insignificant, indicating that the DE does not contribute to the GLE at this time. When the LS is larger than the first threshold (213.842) and smaller than the second threshold (377.374), the coefficient estimate jumps to 2.723 and is significant at the 1% level. As the size of the logistics industry increases, the promotional effect of the DE on the GLE becomes markedly more pronounced. When the LS is higher than the second threshold (377.374), the positive effect of the DE drops to 0.9329, which is significant at the 10% level. This result confirms Hypothesis 5.

These findings align with those of Huang et al. [72], who demonstrated that the logistics industry's development level has a significant double threshold effect on the environmental regulations affecting the logistics industry's total factor energy efficiency. This paper identifies a notable double-threshold effect of logistics scale on the impact of the DE on the GLE.

One potential explanation for this is that Marshall's theory of economies of scale remains a valuable framework for understanding the role of the DE in enhancing the GLE. Firstly, when the logistics scale is small, it is often compelled to adopt extensive development methods in response to investment pressure or limited experience and conceptual understanding. In 2021, the Chinese logistics market will comprise nearly 8,000 A-class logistics enterprises and only 400 5A-class enterprises with total assets exceeding 500 million yuan. The digital divide and the necessity for digital transformation present significant challenges for small and medium-sized enterprises. These organisations often lack the resources and expertise to navigate these issues effectively, hindering their ability to fully leverage the advantages offered by the DE, including resource integration and accurate decision-making. Secondly, as the scale of logistics increases, the DE will accelerate the integration of the logistics industry. This will enable the traditional logistics industry to form a new core competitiveness through the use of advanced technology, thereby effectively reducing costs and significantly improving efficiency. The logistics industry has recently undergone a period of accelerated expansion, deriving benefits from economies of scale and digitisation. This is evidenced by the fact that China's cross-border e-commerce market has reached CNY16.85 trillion in 2023. Thirdly, the continuous expansion of the logistics business has resulted in constraints on management systems and resource efficiency, which may give rise to congestion effects that offset the promotion effects of the DE. This also serves to diminish the capacity of the DE to facilitate the GLE, a perspective that is similarly espoused by Li et al. [73].

As shown in *Table 8(2)*, there is a non-linear relationship between the DE and the GLE with the STI as the threshold, when the STI is lower than the threshold value of 6451, the coefficient estimate of DE is 0.315 but insignificant; when the level of STI is higher than the threshold value of 6451, the coefficient estimate of DE is 1.001 and significant at the 10% level. That is, as the level of scientific and technological innovation increases, the DE plays a significant role in promoting the GLE, and this result proves the correctness of hypothesis 6.

The present study corroborates the threshold effect of the STI. The STI attributes of the DE have consistently constituted a subject of interest among academics. Xie et al [49] have demonstrated that the degree of digitalisation within the logistics industry will exert an influence on the reduction of carbon emissions through the advancement of technology. Chen et al [13] identified the advancement of green technology as an intrinsic factor in achieving growth in green logistics efficiency. In contrast with the findings of previous studies, this study did not confirm the impact of STI on the GLE. The selection of the STI indicators may prove to be a limiting factor in this regard. The current China Statistical Yearbook does not include any indicators for logistics technology. The indicators employed in this study are of a provincial general category, therefore it is not feasible to focus on the specific impact of logistics technology. However, this serves to corroborate the technology-intensive character of the DE, which requires the accumulation of the STI. Therefore, the findings support the proposition put forth by Jin et al [62] that the beneficial impact of the DE is only evident when the accumulation of the IT investments attains a critical threshold. The digitisation of the traditional logistics industry necessitates a greater investment in technology facilities, which may also contribute to the lag in the DE. A comparable phenomenon can be observed in the development of China's JD Logistics business group. The company has consistently prioritised asset investment as a strategic objective, allocating funds to the development of logistics warehousing and supply chain infrastructure. Following a period of sustained losses, the company finally achieved profitability in 2023. The company currently operates in excess of 1,500 warehouses and a network of smart logistics parks, thereby establishing a competitive core.

Table 8 – Regression results statistics of the threshold effect of each variable

LS (1)		STI (2)	
DE(LS<213.842)	0.787	DE (STI< 6451)	0.315
	(0.515)		(0.461)
DE(1.6799≤LS≤377.374)	2.723***	DE (STI ≥ 6451)	1.001*
	(0.845)		(0.558)
DE(LS>377.374)	0.926*		
	(0.473)		
Control variable	yes	Control variable	yes
Two-way fixed	yes	Two-way fixed	yes
N	300	N	300
R^2	0.419	R^2	0.310

*Robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1*

5.5 Efficiency change or technological progress

Prior research has focused on the comprehensive impact of the DE on the reduction of carbon emissions in the logistics sector and the enhancement of logistics efficiency. Given the considerable scale of China's logistics industry and its labour-intensive nature, further investigation is required to ascertain whether the DE is driving efficiency changes (EC) or technological progress change (TC). This study provides a more detailed theoretical framework for understanding the impact of the DE on traditional industries and identifies the specific mechanisms through which the DE affects the logistics industry in the current context. Furthermore, it seeks to gain a deeper understanding of the core aspects and trajectory of digital transformation within the logistics industry.

Theoretical analysis points out that the promoting effect of the DE on the GLE is mainly realised through technical efficiency. This paper decomposes the GLE into EC and TC, and estimates the impact of DE on EC and TC respectively, and the results are shown in *Table 9*. The coefficient of the DE in model (1) is significantly positive, and the coefficient of the DE in model (2) is negative but not significantly, which indicates that there is a significant positive effect of the DE on the EC, whereas it is not significant for the TC, i.e. the facilitating effect of DE on the GLE is mainly in the aspect of the EC, which verifies hypothesis 2.Therefore, we only perform a robustness test for the EC, which is the same as in the previous article, and it remains the two-stage least squares method with the DE lagged by one period as instrumental variables; the core explanatory variables are replaced by the principal component method; the right-integrated Tobit panel model is tested in three ways, and the results are shown in model (3), (4) and (5), which show that the DE has a significant positive impact on the EC , the results have a robustness.

The findings of this study indicate that the facilitating effect of the DE on the GLE is primarily evident in the EC. This lends support to the perspective of Guo et al. [51] on the real economy, namely that the DE promotes efficiency. However, at this juncture, the deficiencies in the core technology links in China and the diversion of talent and capital towards the digital industry have resulted in the DE failing to advance technology or, conversely, impeding the DE's potential.

China currently has a substantial logistics sector, yet it remains a labour-intensive industry. The industry's data-oriented scale effect and integration into the DE have enabled it to benefit from optimal resource allocation, a phenomenon that aligns with the previous analysis. The DE has facilitated the upgrading of China's industrial structure, the free flow of factors and the optimal allocation of resources. Consequently, the efficiency change of the logistics industry, which is characterised by the optimisation of outputs on a given set of factors, is more readily achievable. The structural imbalance between labour supply and demand, the weak capacity for independent innovation in the logistics industry and the persistent challenges encountered by core technology public relations in the context of capital and talent constraints collectively impede technological progress within the logistics industry. Consequently, new logistics technologies and industry advances have yet to be realised, and the attainment of technological progress aimed at expanding production boundaries is a challenging endeavour. Similarly, Lei et al. [74] posited that a degree of skill bias is inherent to the technological advancement of China's logistics industry. It is imperative that those responsible for formulating policy pay heed to the discrepancies that have emerged as a consequence of technological advancement within the logistics sector. Furthermore, they must address the challenges associated with achieving technological breakthroughs.

Table 9 – Regression results of the impact of DE on EC, TC

Variable	EC (1)	TC (2)	EC		
			2SLS (3)	**PCA (4)**	**Tobit (5)**
DE	1.460**	-0.191	2.747***	0.203*	1.460**
	(0.686)	(0.361)	(1.003)	(0.108)	(0.611)
Control variable	yes	yes	yes	yes	yes
Two-way fixed	yes	yes	yes	yes	yes
N	300	300	300	300	300
R^2	0.176	0.369	0.096	0.167	Prob >chi2=0.000

*Robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1*

This paper investigates the non-linear relationship between DE on EC and TC. Taking the EC as the explanatory variable, the logistics scale passes the single threshold test. When the LS crosses the threshold, the promotional effect of the DE decreases rapidly and becomes insignificant, as shown in *Table 10(1)*. Scientific and technological innovation passes the double threshold test. When the STI is low, the promotion effect of the DE is insignificant; when the first threshold is crossed, the promotion effect increases rapidly; when the STI crosses the second threshold, the promotion effect decreases, as shown in *Table 10(2)*. This is basically consistent with the change law of the GLE. TC has not passed the threshold test. This further verifies hypothesis 2. The current sample is mainly based on the efficiency change to promote the GLE, where efficiency changes that describe the output of a given combination of factors vary with the scale of logistics and the level of technology, while technological progress that represents a leap in the production frontier has not been observed. The calculation process is the same as in 5.4, and only the threshold effect regression results are shown here.

Table 10 – Regression results statistics of the threshold effect of each variable-based on the EC

LS (1)		STI (2)	
DE(LS<273.194)	1.899***	DE (STI< 8575)	0.454
	(0.543)		(0.427)
DE (LS ≥ 273.194)	0.815	DE (8575≤STI≤9275)	2.242***
	(0.519)		(0.501)
		DE(STI>9275)	1.058*
			(0.591)
Control variable	yes	Control variable	yes
Two-way fixed	yes	Two-way fixed	yes
N	300	N	300
R^2	0.148	R^2	0.195

*Robust standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.1*

6. CONCLUSIONS

Using panel data from 30 provinces in China between 2011 and 2021, this paper constructs a measurement index for the DE and the GLE. The paper then empirically analyses the impact of the DE on the GLE.

The results indicate that the DE has a significant positive impact on the GLE. This effect is mainly reflected in the technical efficiency level, where the DE promotes the maximum output capacity of the logistics industry under given factors. (2) The impact of the DE on the GLE is heterogeneous. China's DE has experienced rapid growth in recent years. After the DE gradually matures, its promotion effect on the GLE is more significant. From a logistics perspective, the promotion of the DE has diminishing marginal utility for the GLE. Furthermore, the DE plays a stronger role in the eastern region compared to the central and western regions in China. (3) The industrial structure and labour productivity serve as the transmission mechanism of the DE to the GLE. On one hand, the development of the DE can strengthen industrial linkages, accelerate industrial integration and promote industrial structure upgrading, which can improve the synergy between logistics industry elements and enhance the GLE. On the other hand, the time lag and substitution effect of the DE can have an impact on the traditional service industry, leading to labour mismatch, the 'productivity paradox' phenomenon and the masking effect. (4) The impact of the DE on the GLE is non-linear when industry scale and science and technology innovation are considered as threshold variables. It can be observed that when science and technology innovation reaches a certain threshold, the DE is able to promote the GLE more effectively. Additionally, the role of the DE on the GLE is largely dependent on the scale of the logistics industry. When logistics operations fall within a certain scale, the DE can significantly enhance the GLE. However, beyond this scale, the promotion of the DE will be considerably hindered.

To improve the GLE, it is important to fully utilise the potential of the DE. This can be achieved by integrating and implementing digital technology, promoting the digital transformation of traditional logistics and leveraging the benefits of the DE. Furthermore, policy-makers would be well advised to attach great importance to the exploration of breakthrough in technological progress within the DE for the logistics industry. This should be based on the comprehensive and effective utilisation of technical efficiency, which is a key driver of the DE's ability to enhance the GLE. Secondly, we should formulate a coordinated development plan for the DE and logistics industry based on local conditions. This plan should promote cross-industry and cross-regional cooperation and exchanges in the application of digital technology, digital economy and logistics industry, as well as the tertiary industry in the eastern region and high digital economy areas, so as to form and play a leading and exemplary role. Thirdly, we should adhere to the development law of the DE and effectively utilise its potential to optimise the industrial structure. We must promote the coordinated development of data and talent elements, improve the quality of the workforce, reduce structural imbalances and enhance the positive impact of the DE on the GLE. Fourthly, we should strengthen infrastructure construction, talent training and scientific innovation achievement output. This will lay a solid foundation for the DE to improve the GLE. From an industrial perspective, it is important to avoid the negative consequences of blindly expanding the logistics industry. Instead, we should focus on transforming the DE into a powerful tool to improve the GLE, while adhering to the principle of adaptation.

The limitations of this study provide a foundation for further research. (1) The use of Chinese provincial panel data to examine the influence of the DE on the GLE is a valuable undertaking. However, it is limited in its ability to account for the heterogeneous characteristics of cities and countries. Consequently, future research will encompass the incorporation of additional cities and countries. (2) The GLE may be spatially dependent, and the development of the DE may have spatial spillover effects. The spatial dynamics of the DE and the GLE, as well as the spatial spillover effect, will be the subject of further in-depth exploration in future studies. (3) This paper primarily examines the influence of the DE on the GLE from a macro perspective. However, micro-level data may elucidate disparate mechanisms and pathways through which the DE affects the GLE. Consequently, future investigations into the impact of the DE on the GLE can be conducted at the micro level, contingent on the acquisition of pertinent data at the enterprise level.

ACKNOWLEDGEMENTS

This research was supported by the Research Project on Humanities and Social Sciences in Higher Education Institutions of Hebei Province: SZ2024035 "Research on the Measurement and Impact of Green Total Factor Productivity of Productive Service Industry in Hebei Province under Low Carbon Perspective".

REFERENCES

[1] Qin W, Qi X. Evaluation of green logistics efficiency in Northwest China. *Sustainability.* 2022;14(11):6848. DOI: 10.3390/su14116848.

[2] Ouyang X, Li Q, Du K. How does environmental regulation promote technological innovations in the industrial sector? Evidence from Chinese provincial panel data. *Energy Policy.* 2020;139:111310. DOI: 10.1016/j.enpol.2020.111310.

[3] Gan W, Yao W, Huang S. Evaluation of green logistics efficiency in Jiangxi Province based on Three-Stage DEA from the perspective of high-quality development. *Sustainability.* 2022;14(2):797. DOI: 10.3390/su14020797.

[4] Ma L, et al. Does digitalization make urban development greener? A case from 276 cities in China. *Frontiers in Ecology and Evolution.* 2023;11:1074827. DOI: 10.3389/fevo.2023.1074827.

[5] Wang X, et al. Digital economy development and urban green innovation ca-pability: Based on Panel data of 274 prefecture-level cities in China. *Sustainability.* 2022;14(5):2921. DOI: 10.3390/su14052921.

[6] Yan T, Chen Y. The impact of digital economy on high-quality development: Verification based on intermediary model and threshold model. *Journal of Economics and Management.* 2022.

[7] Wu T, Shao W. How does digital economy drive industrial structure upgrading: An empirical study based on 249 prefecture-level cities in China. *PLoS One.* 2022;17(11):e0277787. DOI: 10.1371/journal.pone.0277787.

[8] Guo Y, et al. Data-driven coordinated development of the digital economy and logistics industry. *Sustainability.* 2022;14(14):8963. DOI: 10.3390/su14148963.

[9] Zhang W, et al. A study measuring the degree of integration between the digital economy and logistics industry in China. *PLoS One.* 2022;17(9):e0274006. DOI: 10.1371/journal.pone.0274006.

[10] Wang L, Wang Q. Eco-efficiency evaluation of integrated transportation hub using super-efficiency EBM model and Tobit regressive analysis–Case study in China. *Promet-Traffic&Transportation.* 2024;36(2):307-325. DOI: 10.7307/ptt.v36i2.411.

[11] Huang Y. China-Africa joint endeavor on the digital silk road: Opportunities, challenges and approaches. *China International Studies.* 2019(05):13-28+2.

[12] Lu C. Toward a new era of digital economy. *Telecommunications Science.* 2018;34(07):1-6. DOI: 10.11959/j.issn.1000–0801.2018220

[13] Chen B, et al. Spatial and temporal evolution of green logistics efficiency in China and analysis of its motivation. *Environment, Development and Sustainability.* 2024;26(2):2743-2774. DOI: 10.1007/s10668-022-02833-2.

[14] Cao B, Deng L. Influencing factors of logistics industry growth efficiency in Yangtze river economic belt. *Economic Geography.* 2019;39(7):148-157. DOI: 10.15957/j.cnki.jjdl.2019.07.017.

[15] Lan S, Tseng ML. Coordinated development of metropolitan logistics and economy toward sustainability. *Computational Economics.* 2018;52(4):1113-1138. DOI: 10.1007/s10614-017-9788-z.

[16] Zhang Y, Wang Y. Logistics industry efficiency evaluation and influencing factors analysis. *Statistics and Decision Making.* 2018;34(08):109-112. DOI: 10.13546/j.cnki.tjyjc.2018.08.026.

[17] Wang H, et al. Stochastic frontier analysis of logistics efficiency and its influencing factors in provinces along the “belt and road”. *Journal of Highway and Transportation Research and Development.* 2020;37(10):151-158. DOI: 10. 3969 /j. issn. 1002-0268. 2020. 10. 017.

[18] Liang W, Xu L. Influence of new-type urbanization on the logistics total factor productivity an empirical analysis based on China's provincial capital cities. *Journal of North China Electric Power University (Social Science Edition).* 2018 (02):57-64+94. DOI: 10.14092/j.cnki.cn11-3956/c.2018.02.008.

[19] Zheng W, Xu X, Wang H. Regional logistics efficiency and performance in China along the Belt and Road Initiative: The analysis of integrated DEA and hierarchical regression with carbon constraint. *Journal of Cleaner Production.* 2020;276:123649. DOI: 10.1016/j.jclepro.2020.123649.

[20] Gong X. Regional logistics efficiency measurement and influencing factors analysis. *Statistics and Decision Making.* 2022;38(12):112-116. DOI: 10.13546/j.cnki.tjyjc.2022.12.022.

[21] lo Storto C, Evangelista P. Infrastructure efficiency, logistics quality and environmental impact of land logistics systems in the EU: A DEA-based dynamic mapping. *Research in Transportation Business & Management.* 2023;46:100814. DOI: 10.1016/j.rtbm.2022.100814.

[22] Gong R, Xue J, Liu R. China 's regional logistics efficiency measurement and its spatial and temporal characteristics analysis. *Statistics and Decision Making.* 2022;38(10):141-145. DOI: 10.13546/j.cnki.tjyjc.2022.10.028.

[23] Momeni E, et al. A new fuzzy network slacks-based DEA model for evaluating performance of supply chains with reverse logistics. *Journal of Intelligent & Fuzzy Systems.* 2014;27:793-804. DOI: 10.3233/IFS-131037.

[24] Bajec P, Tuljak-Suban D. An integrated analytic hierarchy process—Slack based measure-data envelopment analysis model for evaluating the efficiency of logistics service providers considering undesirable performance criteria. *Sustainability.* 2019;11(8):2330. DOI: 10.3390/su11082330.

[25] Liu H, et al. Spatial-Temporal pattern and dynamic evolution of logistics efficiency in China's. *Quantity Economy, Technology and Economics Research.* 2021;38(05):57-74. DOI: 10.13653/j.cnki.jqte.2021.05.005.

[26] Li M, Wang J. Spatial-temporal evolution and influencing factors of total factor productivity in China's logistics industry under low-carbon constraints. *Environmental Science and Pollution Research.* 2022;29(1):883-900. DOI: 10.1007/s11356-021-15614-7.

[27] Ye C, et al. Spatial-temporal evolutionary characteristics and its driving mechanisms of China's logistics industry efficiency under low carbon constraints. *Polish Journal of Environmental Studies.* 2022;31(6):5405-5417. DOI: 10.15244/pjoes/151602.

[28] Zeng Q. The spatial spillover effect of informatization development on the productivity of logistics industry. *China 's circulation economy.* 2016;30(09):38-48. DOI: 10.14089/j.cnki.cn11-3664/f.2016.09.006.

[29] Liu Y, et al. Digital Economy development, industrial structure upgrading and green total factor productivity: empirical evidence from China's cities. *International Journal of Environmental Research and Public Health.* 2022;19(4):2414. DOI: 10.3390/ijerph19042414

[30] Xu X, Zhang M. Research on the scale measurement of China's digital economy—Based on the perspective of international comparison. *China Ind. Econ.* 2020;5:23-41. DOI: 10.19581/j.cnki.ciejournal.2020.05.013.

[31] Barefoot K, et al. Defining and measuring the digital economy. *US Department of Commerce Bureau of Economic Analysis, Washington, DC.* 2018;15:210. https://www.bea.gov/sites/default/files/papers/defining-and-measuring-the-digital-economy.pdf.

[32] Wang J, Zhu J, Luo X. Research on the measurement of China's digital economy development and the characteristics. *Journal of Quantitative & Technological Economics.* 2021;38(07):26-42. DOI: 10.13653/j.cnki.jqte.2021.07.002.

[33] Xu Y, Li T. Measuring digital economy in China. *National Accounting Review.* 2022;4(3):251-272. DOI: 10.3934/NAR.2022015.

[34] Song J, YuXin S. An empirical study on the effect of digital economy on real economy. *Science Research Management.* 2020;41(5):32. DOI: 10.19571/j.cnki.1000-2995.2020.05.004.

[35] Zhao T, Zhang Z, Liang S. Digital economy, entrepreneurship, and high-quality economic development: Empirical evidence from urban China. *Journal of Management World.* 2022;36(10):65-76. DOI: 10.19744/j.cnki.11-1235/f.2020.0154.

[36] Zhang C, Liu B, Yang Y. Digital economy and urban innovation level: A quasi-natural experiment from the strategy of "Digital China". *Humanities and Social Sciences Communications.* 2024;11(1):574. DOI: 10.1057/s41599-024-03122-1.

[37] Xie X, Wang J. Study on the regional differences and dynamic evolution of the digitalization level of China's logistics industry. *The World of Survey and Research.* 2023(02):33-46. DOI: 10.13778/j.cnki.11-3705/c.2023.02.004.

[38] Korchagina E, et al. Main logistics digitalization features for business, *E3S Web of Conferences*. 2020. p. 10023. DOI: 10.1051/e3sconf/202016410023.

[39] Zhang Y. Digital economy, industrial structure upgrading and logistics technology innovation. *Logistics Engineering and Management.* 2020;42(12):61-64. DOI: 10.3969 /j.issn.1674 -4993. 2020. 012.020.

[40] Lu Y. The impact of digital economy development on logistics efficiency improvement-analysis based on transaction costs. *Business Economic Research.* 2021(16):99-103.

[41] Salahuddin M, Alam K. Internet usage, electricity consumption and economic growth in Australia: A time series evidence. *Telematics and Informatics.* 2015;32(4):862-878. DOI: 10.1016/j.tele.2015.04.011.

[42] Li J, Wang Q. Impact of the digital economy on the carbon emissions of China's logistics industry. *Sustainability.* 2022;14(14):8641. DOI: 10.3390/su14148641.

[43] Wang C, Guo K. The effect of digital economy empowering high-quality development of green logistics. *East China Economic Management.* 2024;38(02):53-63. DOI: 10.19629/j.cnki.34-1014/f.230917004.

[44] Lin C, Cui L. Digital economy development, technological innovation and circulation industrial structure upgrading. *Business Economic Research.* 2023(04):119-122.

[45] Zhao W. The impact of technological innovation on the high-quality development of circulation industry-the mediating effect of logistics efficiency and the moderating effect of environmental regulation. *Business Economic Research.* 2023(19):29-32.

[46] Yu T, Chen F. The intelligent transformation of circulation in the era of digital economy : characteristics, driving force and realization path. *China 's circulation economy.* 2020;34(11):33-43. DOI: 10.14089/j.cnki.cn11-3664/f.2020.11.003.

[47] Ding J, Liu B, Shao X. Spatial effects of industrial synergistic agglomeration and regional green development efficiency: Evidence from China. *Energy Economics.* 2022;112:106156. DOI: 10.1016/j.eneco.2022.106156.

[48] Yu W, et al. Does the digital economy drive low-carbon urban development? The role of transition to sustainability. *Frontiers in Ecology and Evolution.* 2023;11:1248515. DOI: 10.3389/fevo.2023.1248515.

[49] Xie X, Wang J. Study on the impact of industrial digitization on carbon emissions: evidence from China's Logistics Industry. *Environmental Research Communications.* 2023;5(10):105008. DOI: 10.1088/2515-7620/acf918.

[50] Xu C, Qi Y. Measurement and spatial analysis of green development efficiency of regional logistics industry in China. *Ecological Economy.* 2023;39(04):81-88.

[51] Guo J, Liang S. The impact mechanism of the digital economy on China 's total factor productivity : An uplifting effect or a restraining effect ? *Southern economy.* 2021(10):9-27. DOI: 10.19592/j.cnki.scje.390281.

[52] Dai K, Huang Z, Wang S. Does the digital economy promote the structural upgrading of the Chinese service industry. *Journal of Quantitative & Technological Economics.* 2023;40:90-112. DOI: 10.13653/j.cnki.jqte.2023.02.002.

[53] Yang W, Zeng H. Effect evaluation of digital economy promoting total factor productivity. *Journal of Technology Economics.* 2022;41:1-9.

[54] Zhong K. Does the digital finance revolution validate the Environmental Kuznets Curve? Empirical findings from China. *PLoS ONE.* 2022;17. DOI: 10.1371/journal.pone.0257498.

[55] Han J, Jiang T. Does the development of the digital economy improve carbon emission efficiency? *Frontiers in Ecology and Evolution.* 2022;10. DOI: 10.3389/fevo.2022.1031722.

[56] Lyu Y, Gu B, Zhang J. Does digital finance enhance industrial green total factor productivity? Theoretical mechanism and empirical test. *Environmental Science and Pollution Research.* 2023;30(18):52858-52871. DOI: 10.1007/s11356-023-26057-7.

[57] Guo Q, Ma X. Research on the impact of digital economy on urban green total factor productivity. *Modern Management Science.* 2022(05):156-166.

[58] Brynjolfsson E, Rock D, Syverson C. Artificial intelligence and the modern productivity paradox. *The economics of artificial intelligence: An agenda.* 2019;23:23-57. DOI: 10.7208/9780226613475-003.

[59] Yang J, Fu D. The impact of digital economy on labor productivity - An Empirical study based on provincial panel data. *Statistics and Decision Making.* 2023;39(01):5-10. DOI: 10.13546/j.cnki.tjyjc.2023.01.001.

[60] Hu Y, Guan L. Research on employment creation effect and employment substitution effect of digital economy. *Reform.* 2022(04):42-54. DOI: 50.1012.F.20220422.1357.004.

[61] Leng J, Liu Y. Research on the threshold effect of industrial agglomeration on logistics efficiency. *Prices Monthly.* 2019;12:47-54. DOI: 10.14076/j.issn.1006-2025.2019.12.08.

[62] Jin H, Yang J. Can the development of the digital economy unravel the new "Solow paradox"? *Industrial Economic Research.* 2023(05):101-114. DOI: 10.13269/j.cnki.ier.2023.05.010.

[63] Su Y, Liu Z. Logistics efficiency, technological innovation and the development of modern service industry-Analysis from provincial panel data. *Macroeconomic Research.* 2022(07):149-162. DOI: 10.16304/j.cnki.11-3952/f.2022.07.010.

[64] Luo R, Wang Q. The impact of China 's urban digital economy on the high-quality development of the logistics industry. *city problem.* 2022(06):35-46. DOI: 10.13239/j.bjsshkxy.cswt.220604.

[65] Han D, et al. The impact of digital economy on total factor carbon productivity: The threshold effect of technology accumulation. *Environmental Science and Pollution Research.* 2022;29(37):55691-55706. DOI: 10.1007/s11356-022-19721-x.

[66] Sun G, Li T, Mo Y. The impact of digital economy on China's agricultural total factor productivity. *Economic and Management Review.* 2023;39(01):92-103. DOI: 10.13962/j.cnki.37-1486/f.2023.01.008.

[67] Zhang L. Research progress on the energy consumption and carbon emission of China 's logistics industry. *Technical Economy and Management Research.* 2016(01):119-123.

[68] He J, Wang S, Xu L. Research on the efficiency and influencing factors of green logistics in three bay-area city clusters under the constraint of carbon emissions. *Railw. Transp. Econ.* 2021;43:30-36. DOI: 10.16668/j.cnki.issn.1003-1421.2021.08.06.

[69] Guo M, Li H, Lin W. The impact of economic growth, FDI, and innovation on environmental efficiency of the logistics industry in provinces along the belt and road in China: An empirical study based on the panel Tobit model. *Science Progress.* 2021;104(2):00368504211018054. DOI: 10.1177/00368504211018054.

[70] Dai Q. Study on the influence of heterogeneous environmental regulation on green total factor productivity in the logistics industry. *Journal of Chongqing University of Arts and Sciences (Social Science Edition).* 2020;39(06):63-74. DOI: 10.19493/j.cnki.issn1673-8004.2020.06.007.

[71] Bai W, Sun R, Bai G. Does the development of digital economy improve the total factor productivity of enterprises?-Based on the analysis of A-share listed companies. *Economic and Management Review.* 2022;38(05):5-19. DOI: 10.13962/j.cnki.37-1486/f.2022.05.001.

[72] Huang K, Wang J. Research on the impact of environmental regulation on total factor energy effect of logistics industry from the perspective of green development. *Mathematical Problems in Engineering.* 2022;2022:3793093. DOI: 10.1155/2022/3793093.

[73] Li M, Wang J. Spatial-temporal distribution characteristics and driving mechanism of green total factor productivity in China's logistics industry. *Polish Journal of Environmental Studies.* 2021;30(1):201-213. DOI: 10.15244/pjoes/121046.

[74] Lei X-q, Yang J-j, Zou J-b *et al.* Research on the impact of logistics technology progress on employment structure based on DEA-Malmquist method. *Mathematical Problems in Engineering.* 2020;2020(1):7064897. DOI: 10.1155/2020/7064897.

赵志强，张蕾（通讯作者）

数字经济对物流业绿色发展效率的影响： 基于中介机制和门槛效应的中国案例

摘要：
随着数字经济的快速发展，物流业对"质量和效率"充满了期待。数字经济能否扭转物流业的粗放式发展，进而有效促进物流业的绿色发展效率值得关注。本文基于2011-2021 年中国省际面板数据，运用中介机制和门槛效应实证研究了数字经济对物流业绿色发展效率的影响。实证结果表明，数字经济对物流业绿色发展效率有显著的正向作用，并通过产业结构升级促进物流业绿色发展效率，而物流业劳动生产率在数字经济对物流业绿色发展效率中存在掩蔽效应。门槛检验发现物流产业规模和科技创新水平在数字经济对物流业绿色发展效率的影响中存在门槛效应。

关键词：
数字经济; 物流业绿色发展效率; 产业结构; 劳动生成率; 产业规模; 科技创新.