The power of technology innovation: can smart transportation technology innovation accelerate green transportation efficiency?

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Abstract

Purpose – The purpose of this study is to explore the causal relationship between smart transportation technology innovation and green transportation efficiency.

Design/methodology/approach – A comprehensive framework is used in this paper to assess the level of green transportation efficiency in China based on the instrumental variable – generalized method of moments model, followed by an examination of the impact of innovation in smart transportation technology on green transportation efficiency. Additionally, their non-linear relationship is explored, as are their important moderating and mediating effects.

Findings – The findings indicate that, first, the efficiency of green transportation is significantly enhanced by innovation in smart transportation technology, which means that investing in such technologies contributes to improving green transportation efficiency. Second, in areas where green transportation efficiency is initially low, smart transportation technology innovation exerts a particularly potent influence in driving green transportation efficiency, which underscores the pivotal role of such innovation in bolstering efficiency when it is lacking. Third, the relationship between smart transportation technology innovation and green transportation efficiency is moderated by information and communication technology, and the influence of smart transportation technology innovation on green transportation efficiency is realized through an increase in energy efficiency and carbon emissions efficiency.

JEL classification – C23, O32, Q16, P25, R41

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Originality/value – Advancing green transportation is essential in establishing a low-carbon trajectory within the transportation sector.

Keywords China, Moderation effect, Mediation effect, Green transportation efficiency, Smart transportation technology innovation

Paper type Research paper

Introduction

The transportation industry, especially in China, where it ranks as the third-highest carbon-emitting sector, is a significant consumer of energy and a notable source of carbon emissions (Xu *et al.*, 2022; Zhao *et al.*, 2022c). According to data from the National Bureau of Statistics of China [1], China's transportation sector consumed 9,916 million tons of coal equivalent (tce) in 2001. By 2021, this consumption had surged to 41,309 tce, marking an increase of over fourfold. As per statistics provided by the China Emission Accounts and Datasets [2], carbon emissions from China's transportation industry totaled 167 million Mt of CO_2 in 1999. This figure experienced a substantial surge to 732 Mt CO_2 in 2019, also indicating a more than fourfold increase in carbon emissions from the transportation sector over the past two decades. Given the transportation sector's substantial contribution to carbon emissions and energy consumption, evaluating and enhancing green transportation efficiency (GTE) becomes imperative (Chen and Wang, 2020; Zhao *et al.*, 2022e). The implications of this assessment are far-reaching, as advancements in transportation efficiency not only drive the sustainable evolution of transportation but also play a pivotal role in achieving broader energy transition goals (Dominković *et al.*, 2018; Wu, 2023; Yuan *et al.*, 2021). Research underscores the critical roles of technological progress and transportation structure in propelling efficiency improvements (Liu *et al.*, 2021; Ma *et al.*, 2021; Song *et al.*, 2022; Xu *et al.*, 2022; Zhao *et al.*, 2022c), emphasizing the need for concerted efforts and innovations in creating a more sustainable transportation future.

Using contemporary information and communication technology (ICT) within transportation, smart transportation technology innovation (STTI) includes the management of real-time traffic, tracking of vehicles, transmission of updates on road conditions, control of intelligent traffic signals, and the implementation of autonomous driving systems (Shah *et al.*, 2021; Wu and Wang, 2022; Yang *et al.*, 2023; Zhao *et al.*, 2022b; Yu *et al.*, 2023). This wide array of advancements is designed to promote efficiency, safety, and sustainability of transportation systems (Du *et al.*, 2022; Qi, 2008; Zhao *et al.*, 2022a). The integration of STTI presents innovative solutions to long-standing challenges in conventional transportation, paving the way for a cleaner and more efficient development path in the sector (Dong *et al.*, 2023a; Mouratidis *et al.*, 2021; Wu *et al.*, 2023; Zhao *et al.*, 2022d). Additionally, shared mobility services reduce car ownership, resulting in fewer emissions and a more streamlined transportation system (Barth *et al.*, 2003). Thus, STTI has the potential to significantly enhance the efficiency of green transportation and realize long-term sustainable transportation development. Nevertheless, while there is currently no direct literature linking STTI to GTE, the potential benefits are substantial and deserve further investigation.

Based on the above analysis, several questions arouse our interest. First, can the development of STTI contribute to higher levels of GTE? Second, is the relationship between STTI and GTE nonlinear? And can STTI have an asymmetric impact on GTE? Third, what factors play a mediatory role in the nexus between STTI and GTE? Therefore, this paper uses the dynamic econometric model to investigate the causal relationship between STTI and GTE. This paper also checks their non-linear nexus. Further, this paper delves into the factors that affect their relationship, as well as the channels through which STTI affects GTE.

The contributions of this study are threefold. First, this study uses a well-structured framework that takes into account both input and output factors of GTE, and these indicators are comprehensive and thoughtfully chosen to capture various dimensions of green transportation, with both expected and unexpected outputs allowing for a nuanced evaluation of the impacts of transportation development. Then, for the first time, to the best of the authors' knowledge, we investigate the causal relationship between STTI and GTE and find a promoting effect of STTI on GTE by using the dynamic econometric model, which helps to circumvent issues related to endogenous interference and reverse causality between variables. Second, beyond their linear relationship, we also consider the non-linear STTI-GTE nexus and check the asymmetric impact of STTI on GTE. We find that STTI is more effective in enhancing GTE when the initial level of GTE is low, and this impact shrinks as the level of GTE increases. Third, we analyze the logical transmission mechanism in-depth and examine the moderating role of ICT development. The findings show that STTI indirectly affects GTE by stimulating energy efficiency and carbon emission efficiency; at the same time, ICT development synergistically enhances the positive impact of STTI on GTE. This contribution enables us to peer into the inner workings of how STTI influences GTE, providing us with additional empirical insights.

The remainder of the study is structured as follows. Section 2 reviews the current literature. Section 3 proposes empirical methods and data. Section 4 analyzes baseline results, robustness checks and asymmetric results. Section 5 further discusses the moderating and the mediating effects. Section 6 concludes this paper.

Review of literature

Empirical studies on smart transportation technology innovation

The importance of STTI is constantly emphasized by scholars, and its positive economic and environmental effects have also been confirmed (Yang *et al.*, 2023). For example, the significance of autonomous vehicles is stressed by Mouratidis *et al.* (2021), who reckon that they contribute to a more streamlined and environmentally friendly transportation system. Also, the role of bike-sharing and car-sharing in reducing emissions is advocated. The shared vehicle is also highly advocated by Barth *et al.* (2003), who think that shared-use vehicle systems are thought to offer superior economic and environmental benefits compared to public transportation. Moreover, the alternative fuel vehicle is stressed by Nordlund *et al.* (2016), who reckon that cutting-edge technologies are crucial for the transportation transition. Moreover, they also mention the positive environmental effects of electric vehicles. Likewise, Qi (2008) also stresses the importance of wireless communications and sensors in constructing a smart transportation system. Additionally, Singh *et al.* (2022) explore how blockchain and artificial intelligence (AI) can be effectively used in intelligent transportation, including autonomous trains, to bring about a revolution in the transportation sector. Shah *et al.* (2021) believe that smart transportation systems are urgently needed in major urban cities because of urban congestion and pollution. Moreover, focusing on green transportation and sustainable transportation, they propose some barriers to the enhancement of transportation system efficiency.

Empirical studies on green transportation efficiency and its influencing factors

Recently, many scholars have paid attention to transportation efficiency and have evaluated it from different aspects, such as environmental efficiency (Liu *et al.*, 2020; Wei *et al.*, 2021), eco-efficiency (Song *et al.*, 2022), growth-adjusted energy-emission efficiency (Du *et al.*, 2021;

Xu *et al.*, 2022; Zhao *et al.*, 2022c; Zhang *et al.*, 2020), total-factor energy efficiency (Liu *et al.*, 2021), safety-adjusted transportation efficiency (Wang, 2021), green logistics efficiency (Du and Li, 2022) and green efficiency (Ma *et al.*, 2021). Notably, most of these papers use the data envelopment analysis model to measure efficiency. Aiming to assess the transportation efficiency in China, Liu *et al.* (2020) and Zhang *et al.* (2020) both find that the efficiency of green transportation in eastern China outperforms that in central and western China, and the uneven development situation is also verified by Wei *et al.* (2021).

Among these studies, the influencing factors of transportation efficiency are also highlighted. For example, focusing on three kinds of efficiency in transportation (i.e. economic, environmental and green efficiency), Ma *et al.* (2021) point out that technological efficiency and innovation are two important means for increasing efficiency, especially in eastern and central China, while the role of technological and economic scale development in promoting total-factor energy efficiency in transportation systems is mentioned by Liu *et al.* (2021). In addition, Du *et al.* (2021) find that the income level of countries along the Belt and Road is highly and positively connected with their transportation carbon efficiency. In the study of Van *et al.* (2022), urban housing development is believed to be an influencing factor in transportation system efficiency. Xu *et al.* (2022) conclude that transportation energy utilization is a contributing factor to transportation efficiency. Moreover, transportation structure, infrastructure level, and technological progress are positive and indispensable factors of transportation efficiency, according to Zhao *et al.* (2022c). Du and Li (2022) examine the impact of innovative city policy on green logistics efficiency, and mention that the level of cities' innovation has a positive impact on green logistics efficiency, especially in western China. Song *et al.* (2022) examine the eco-efficiency of China's transportation and indicate that industrial structure and technology are positively correlated to the efficient development of transport.

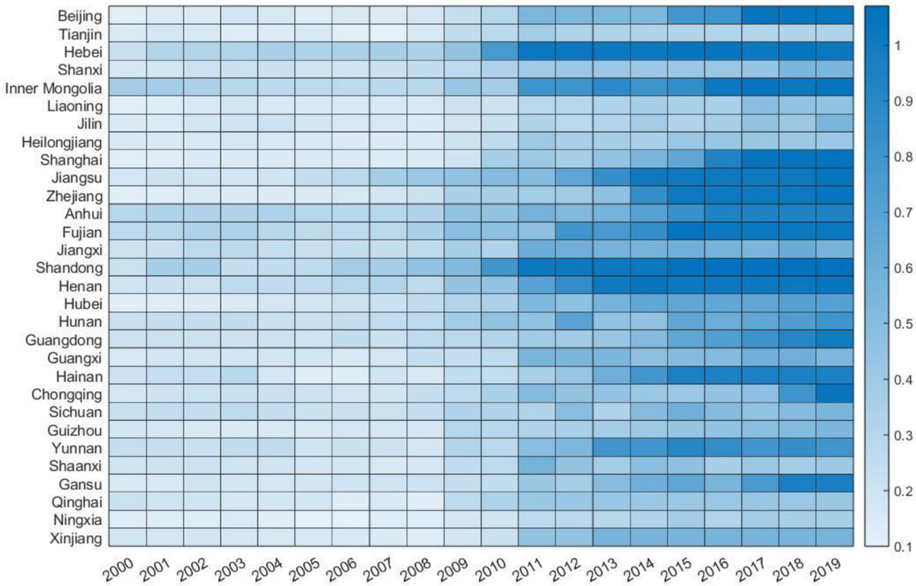
Literature gaps

We outline several existing research deficiencies. First, although some papers discuss the importance of STTI, there is a scarcity of papers exploring its economic, environmental, and transportation impacts. Most of these studies concentrate on the analysis of specific transportation technologies, neglecting the social effects of STTI. Second, concerning the literature on GTE, although some researchers mention the promoting effect of technology on such efficiency, there is a lack of in-depth discussion regarding the direct impact of STTI. In other words, there currently exists no literature directly linking STTI with GTE, representing a notable research gap. Additionally, many studies mention regional imbalances and unevenness in the development of GTE in China. Hence, it is imperative to investigate the influence of STTI on GTE in regions with varying levels of GTE. Nevertheless, existing literature has scarcely addressed the nonlinear effects of these two factors. Fourth, there is limited research on the impact mechanisms between STTI and GTE.

Empirical design

Variables and data. Green transportation efficiency (GTE) is the dependent variable, which is measured by the Global Malmquist–Luenberger (GML) index based on the SBM-DEA model. This paper measures the level of GTE, considering multiple input and output factors. We select three input indicators: labor input, capital input, and infrastructure input (Du and Li, 2022; Zhang *et al.*, 2020; Zhao, 2023). We use employees in the transportation sector to gauge labor; capital input consists of capital stock and the wage of employees; infrastructure input includes public transport vehicles, passenger volume of public transport, rail transit mileage and urban road lighting. As for output, we have expected output, such as transportation sector added value and government financial expenditure, and unexpected output, including traffic accidents, traffic prices and carbon emissions. Positive effects of transportation development include the transportation sector added value and government financial expenditure (Chang *et al.*, 2013; Liu *et al.*, 2016; Song *et al.*, 2016), while negative effects include property loss in traffic accidents, consumer price index and carbon emissions (Zhang *et al.*, 2015; Zhang and Wei, 2015; Zhou *et al.*, 2013). The GTE index system considers many measurements of green and efficient development, such as labor and capital inputs, public transport development reflected in the number of public transport vehicles and passengers (Liu *et al.*, 2019; Stefaniec *et al.*, 2020; Zhang *et al.*, 2020) and urban road lighting. Public transport development is essential to the formulation of a low-carbon development blueprint for the transport sector. In addition, negative impacts such as traffic accidents, traffic prices and carbon emissions are also considered. Traffic prices can reflect the accessibility of people to basic daily transportation demands, while carbon emissions directly explain the degree of green transportation development. Appendix Table A1 lists the input and output factors.

After contracting the input-output indicator framework, we apply the GML based on the SBM-DEA model to calculate the level of GTE in 30 provinces in China from 2000 to 2019. The score of GTE ranges from 0 to 1, with higher values indicating a greater degree of GTE. Figure 1. illustrates a consistent enhancement in the overall GTE across China throughout the observed period, with notable advancements in most provinces post-2010. However, there are differences in the degree of GTE among provinces. The GTE index of Beijing, Hebei, Fujian, Jiangsu and Shandong is relatively dark blue, indicating that the development of GTE in these provinces is at a leading level in the country. In contrast, although Gansu,



Notes: The horizonal axis represents the year, and the vertical axis represents the 30 provinces in China

Source: Author' own work

Figure 1. Level of green transportation efficiency in each province

Xinjiang, and Guangxi have also experienced some improvement in their GTE index, their transportation sectors still need further efficient and low-carbon development, as their improvement was not significant during the sample period. These findings suggest that while progress has been made in improving GTE across China, there is still room for improvement in some provinces to achieve sustainable and efficient green transportation practices.

STTI is the key independent variable in this paper, which is calculated using the IPC code and is consistent with the paper by Zhao *et al.* (2023). The calculated equation is as follows:

$$STTI_{\mathrm{it}} = \sum_{j=0}^{t} Patent_{\mathrm{it}} \exp[-\delta_1 (t-j)]\{1-\exp[-\delta_2 (t-j)]\} \tag{1}$$

where $Patent_{it}$ is the number of patents we searched from the China Patent Search and Analysis Database [3]. We consider the depreciation rate and diffusion rate, which are denoted by λ_1 and λ_2, and they are set to be 0.36 and 0.03, respectively (Popp, 2002).

We plot the development level of STTI for the years 2000, 2010 and 2019 in Figure 2. During this period, the level of STTI exhibited an upward trend, which was evident in nearly every province. This indicates that STTI has made significant advancements in all

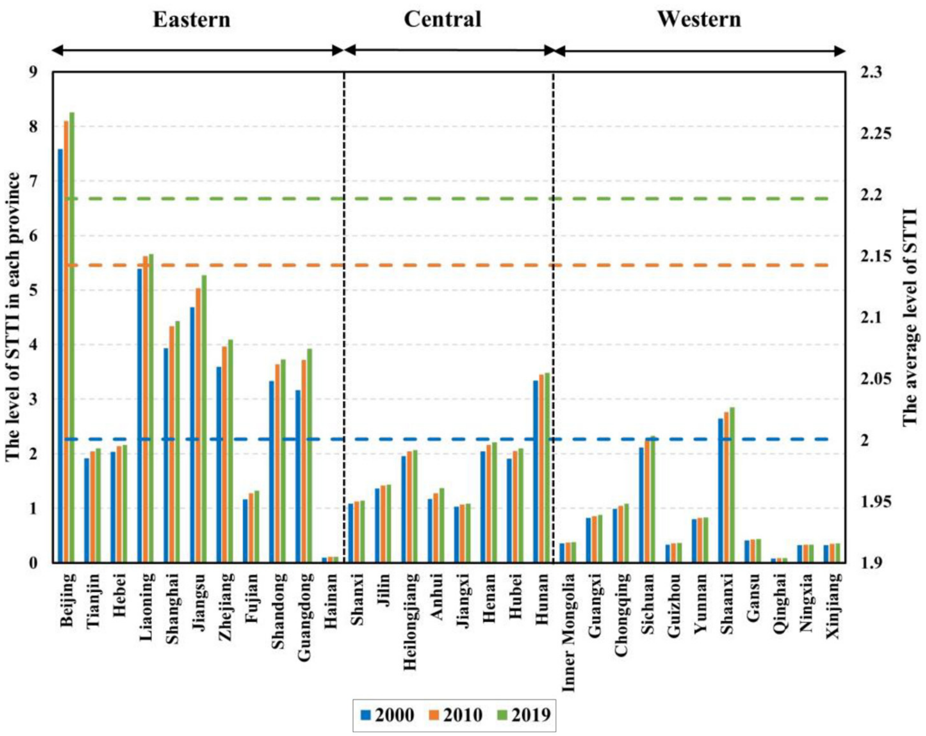


Figure 2.
Level of smart transportation technology innovation in each province

Source: Author' own work

provinces of China over the past two decades. Additionally, we categorized the 30 provinces into eastern, central and western regions, according to their geographical location. The STTI level in the eastern region is notably at the forefront, particularly in provinces such as Beijing, Shanghai, Zhejiang and Jiangsu. In contrast, there remain significant improvement needs for STTI in some provinces in the central and western regions.

We also have another simpler method to calculate the level of STTI:

$$STT_{it} = Patent_{it} + (1-\gamma)STT_{i,t-1} \tag{2}$$

where γ is usually set at 10% (Bottazzi and Peri, 2007). In addition, the second way to gauge the level of STTI will be through robustness checks.

Four control variables at the provincial level are considered in this paper to reduce the omitted variable bias: GDP per capita (e.g. *PGDP*); industrial development (e.g. *IND*); human capital (e.g. *HC*); and energy consumption (e.g. *EC*). The data on the input and output factors of GTE, as well as the control variables, come from various statistical yearbooks, such as Yearbook on energy, science and technology, and labor. We use a balanced panel data set containing 30 provinces in China during 2000–2019 and Table 1 presents the descriptions.

Estimation strategy

A framework containing STTI, GTE, and four control variables is constructed as follows:

$$GTE_{it} = f(STTI_{it}, PGDP_{it}, IND_{it}, HC_{it}, EC_{it}) \tag{3}$$

where GTE_{it} is the efficiency level of green transportation, and $STTI_{it}$ shows the technological innovation level of smart transportation. $PGDP_{it}$, IND_{it}, HC_{it} and EC_{it} are four control variables introduced in Section 3.1.

Based on the above framework, we further use the reduced form for regression, which can be represented as follows:

$$\begin{aligned}\ln GTE_{\mathrm{it}} = {} & \beta_0 + \beta_1 \ln STTI_{it} + \beta_2 \ln PGDP_{it} + \beta_3 \ln IND_{it} + \beta_4 \ln HC_{it} + \beta_5 \ln EC_{it} \\ & + \pi_i + \mu_t + \varepsilon_{it}\end{aligned} \tag{4}$$

All variables have the same meaning as those in equation (4). As we take the logarithm form of these variables, the parameters β_1–β_6 denote the elasticity nexus between variables. Specifically, β_1 is the change of GTE when the level of STTI increases by one percent.

Variable	Mean	SD	Min.	Median	Max.
lnGTE	−12.8933	6.6905	−30.5439	−12.9451	−0.9561
lnSTTI	0.2859	1.1133	−2.4882	0.5035	2.1133
lnPGDP	10.0855	0.8410	7.9226	10.2406	12.0110
lnIND	8.1644	1.2081	4.3932	8.2853	10.6807
lnHC	3.8540	0.9579	0.3001	4.0331	5.4466
lnEC	9.0836	0.7896	6.1737	9.1370	10.6308

Notes: Mean refers to the average value of the variables; SD = standard deviation; Min = median; and Max indicates the minimum, median and maximum values of the variables, respectively
Source: Authors' own work

Table 1.
Descriptive statistics of the variables

By implication, β_1 shows the marginal impact of STTI on STE, which is the most important parameter that we aim to estimate, and we assume it to be positive. In addition, we consider time and individual fixed effects, which are crucial for reducing endogeneity.

Moreover, considering that the level of GTE in the previous period can affect the level of GTE in the current period, we add the lagged term of GTE as an independent variable on the basis of the above static panel model. Thus, the dynamic model for baseline regressions is set as follows:

$$\ln GTE_{it} = \beta_0 + \beta_1 \ln GTE_{i,t-1} + \beta_2 \ln STTI_{it} + \beta_3 \ln PGDP_{it} + \beta_4 \ln IND_{it} + \beta_5 \ln HC_{it} + \beta_6 \ln EC_{it} + \pi_i + \mu_t + \varepsilon_{it} \quad (5)$$

Using a traditional econometric model to estimate the dynamic nexus may have endogeneity issues; thus, we use a specialized dynamic model, namely, the generalized method of moment (GMM) model, to conduct dynamic regressions (Arellano and Bover, 1995). In addition, compared to the difference-GMM (DIF-GMM) model, which uses the difference equation for estimation, the system-GMM (SYS-GMM) model, which uses differential equation and level equation, has higher efficiency, and is preferred in this paper.

Estimation results

Baseline regression result

Table 2 shows the baseline regression result, where we list the results estimated by both the static model (i.e. OLS, FE and FGLS) and the dynamic model (i.e. SYS-GMM) for comparison. The SYS-GMM model requires two preliminary tests: the Arellano–Bond (A-B) test and the Sargan test. The former assesses the autocorrelation of the random disturbance term, while the latter evaluates the validity of the instrumental variables (Che *et al.*, 2013). Examining the final three rows of Table 2, we observe that the p-values for AR (1), AR (2) and Sargan are below 0.1, above 0.1 and above 0.1, respectively. This indicates that the instrumental variables are exogenous, affirming the suitability of using the GMM model.

According to the results in Table 2, the parameters of STTI are consistently significant at the 1% significant level, regardless of using a dynamic or static model, which means that the development of STTI can significantly lead to the increase in GTE. Quantitively, the

Variable	OLS	FE	FGLS	SYS-GMM
L. lnGTE				1.0643*** (75.0712)
lnSTTI	2.0866*** (8.7405)	2.2806*** (4.2090)	2.8789*** (4.9036)	0.4588*** (3.0940)
lnPGDP	−8.5908*** (−23.4265)	−9.0070*** (−14.1998)	−5.6682*** (−21.8367)	0.7241*** (3.1323)
lnIND	5.1456*** (7.5711)	4.3034*** (5.0312)	0.7188*** (3.4193)	1.5415*** (7.3712)
lnHC	−2.0315*** (−3.6102)	−3.8565*** (−4.7470)	−0.7916*** (−9.0576)	0.4166 (1.3366)
lnEC	−4.3699*** (−7.1762)	−2.4078*** (−3.5291)	−3.8519*** (−36.3781)	−2.1155*** (−7.5120)
Constant	66.9834*** (17.1507)	87.0507*** (17.8840)	63.7363*** (37.7846)	−15.9440*** (−8.0058)
AR(1)				0.0012
AR(2)				0.4630
Sargan				0.9999
N	600	600	600	570

Notes: ***indicates statistical significance at the 1, 5 and 10% levels respectively; the values in parentheses represent t-statistics
Source: Authors' own work

Table 2.
Baseline regression result

estimated result implies that when the level of STTI increases by 1%, taking the model of SYSGMM for analysis, the level of GTE can be increased by 0.4588%. Thus, the positive coefficient of STTI signifies that the increase of STTI is conducive to improving GTE.

The main reasons for the promotion effect of STTI on GTE can be analyzed from four aspects. First, STTI, such as intelligent traffic management systems and autonomous vehicles, are designed to optimize traffic flow and reduce congestion (Anthony, 2023; Dong *et al.*, 2023b). This leads to smoother traffic patterns, which in turn can result in reduced fuel consumption and emissions, leading to improved GTE. For example, autonomous vehicles can communicate with each other and traffic infrastructure, allowing for more efficient use of roadways (Duarte and Ratti, 2018). Second, electric and alternative fuel vehicles are also critical components of STTI. By transitioning to greener forms of propulsion, the transportation sector can significantly reduce its environmental impact and increase its green efficiency (Lave and MacLean, 2002). Third, safety is a fundamental aspect of STTI. Advanced driver assistance systems and autonomous vehicles are equipped with sensors, which can lead to fewer accidents and less property loss associated with traffic incidents (Piao and McDonald, 2008; Sun *et al.*, 2021); thus, the efficiency of transportation can be highly enhanced. Fourth, STTI can improve the efficiency and accessibility of public transportation systems. This can lead to increased use of public transit, reducing the number of individual vehicles on the road and lowering overall emissions. All these crucial points of STTI are conducive to greater GTE.

All control variables have significant coefficients except for human capital. Focusing on the result estimated by the SYSGMM model, every increase of 1% in GDP and secondary industrial development promotes GTE to increase by 0.7241% and 1.5415%, respectively. A robust economy provides the financial resources necessary for substantial infrastructure development, which may include the construction of efficient public transportation systems, the expansion of electric vehicle charging networks, and the implementation of intelligent traffic control systems. These infrastructure improvements directly contribute to greener and more efficient transportation. Regarding secondary industrial development, it can lead to higher levels of GTE, probably for the following reasons. Secondary industries often involve manufacturing and processing activities. These industries are well-positioned to develop and implement green technologies, such as advanced materials, energy-efficient manufacturing processes and eco-friendly transportation solutions. On the negative side, the increase in energy consumption leads to a decrease in GTE, which may be because those traditional modes of transportation, such as internal combustion engine vehicles, rely on fossil fuels such as gasoline and diesel, which is not conducive to the transportation energy transition and cannot promote its efficient development (Wang *et al.*, 2014; Zhu *et al.*, 2020).

Robustness tests

We use the instrumental variable – generalized method of moments (IV-GMM) model to conduct a robustness test. Although this paper has controlled for a series of control variables, we may still omit some variables related to GTE, and the endogeneity caused by omitted variable bias may exist. In the IV-GMM model, the IV is used to address endogeneity issues, and it is incorporated into the estimation process through the GMM framework. This allows for consistent and efficient estimation of the parameters, even in the presence of endogeneity. Moreover, we use the lag term of the independent variable, namely, the lag term of STTI, as the IV, which is consistent with the practice of Acheampong *et al.* (2020) and Acheampong *et al.* (2021).

We have mentioned two methods to calculate the level of STTI, and in the baseline regressions, we use the comparatively sophisticated. In the robustness test, we use the comparatively simpler one. Moreover, we also use two methods, namely, the FE and the SYSGMM model for regressions, and the results are listed in the last two columns in Table 3.

The coefficient of STTI is 0.5770, which suggests that for every 1% improvement in STTI, GTE can be increased by 0.5770%. This marginal impact is similar to that in the baseline regression. Thus, the positive relationship between STTI and GTE is robust. From the results in the last two columns in Table 2, the sign and significance level of the alternative proxy variable of STTI remain unchanged, which once again verifies our primary finding.

Asymmetric result

The linear relationship between STTI and GTE has been estimated; however, the STTI-GTE nexus may be heterogeneous and asymmetric because of different development stages of GTE. The panel quantile regression model is used to detect the asymmetric impact of STTI on GTE, which was proposed by Bassett and Koenker (1982). The estimation model is set as follows:

$$Q_{\mathrm{q}}(GTE|x) = \sum \beta_{q_i} X_{q_\mathrm{i}} + \beta_{q_0} \tag{6}$$

where q_i denotes the ith quantile of the variable, and we focus on four quantiles, namely, the 20th, 40th, 60th and 80th quantiles. The estimation result of the asymmetric impact of STTI on GTE is displayed in Table 4. Also, Figure 3 intuitively shows the asymmetric result.

The findings presented in Table 4 indicate that STTI has a positive influence on GTE development across all quantiles, ranging from the 20th to the 80th. Given that the coefficients for STTI are consistently significant and positive across these quantiles, we can conclude that STTI consistently contributes to the enhancement of GTE, regardless of its initial level of development. Moreover, the incremental impact of STTI on GTE varies across different quantiles. Specifically, when GTE is at the 20th percentile, a 1% increase in STTI leads to an acceleration of GTE by approximately 2.1953%. However, this incremental impact decreases to 2.1291%, 2.0628%, and 1.9692% when GTE is at the 40th, 60th, and

Variable	IV-GMM	FE	SYS-GMM
L. lnGTE			1.0198*** (88.1240)
lnSTTI	0.5770* (1.8996)		
lnSTTI_AI		0.1528*** (4.1966)	0.3121*** (4.9521)
lnPGDP	−7.2454*** (−12.4148)	−7.7786*** (−53.4441)	−0.5866** (−2.3620)
lnIND	4.0445*** (3.9059)	2.5172*** (27.9066)	1.6560*** (7.9942)
lnHC	−0.8298 (−0.9685)	−0.8594*** (−10.7723)	1.0818*** (3.1072)
lnEC	−1.9977** (−2.5732)	−3.5905*** (−50.2071)	−2.2962*** (−9.3301)
Constant	41.4246*** (5.8312)	66.9291*** (68.3654)	−11.2070*** (−6.7617)
AR(1)			0.0017
AR(2)			0.2574
Sargan			0.9999
N	600	600	570

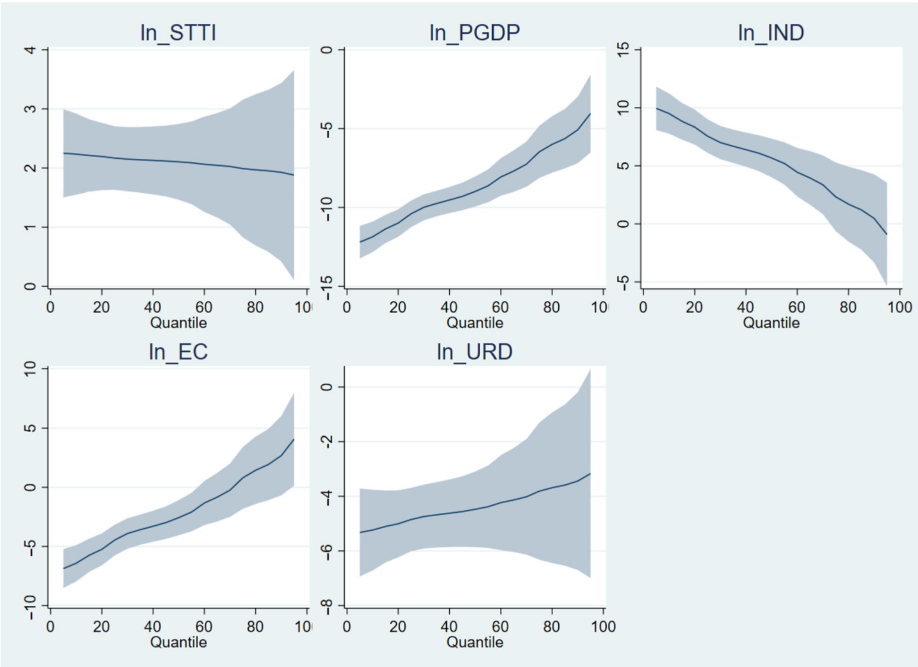
Notes: ***, ** and *indicates statistical significance at the 1, 5 and 10% levels respectively; the values in parentheses represent t-statistics
Source: Authors' own work

Table 3.
Robustness tests

Variable	Quantiles 20th	40th	60th	80th
lnSTTI	2.1953*** (7.5595)	2.1291*** (7.2694)	2.0628*** (5.0165)	1.9692*** (3.0157)
lnPGDP	−10.9864*** (−24.7514)	−9.5271*** (−22.5209)	−8.0665*** (−13.3015)	−6.0018*** (−6.5582)
lnIND	8.3382*** (10.8354)	6.3935*** (8.5105)	4.4469*** (4.1666)	1.6953 (1.0292)
lnHC	−5.2453*** (−7.6027)	−3.2876*** (−4.9302)	−1.3281 (−1.3970)	1.4418 (0.9917)
lnEC	−5.0036*** (−7.9868)	−4.6176*** (−7.3168)	−4.2312*** (−4.7728)	−3.6850*** (−2.6203)
Constant	93.0669*** (19.7323)	77.1784*** (17.2811)	61.2749*** (9.5538)	38.7943*** (4.0333)
N	600	600	600	600

Notes: ***indicates statistical significance at the 1, 5 and 10% levels respectively; the values in parentheses represent *t*-statistics
Source: Authors' own work

Table 4. Asymmetric impact result



Source: Author' own work

Figure 3. Figure of the asymmetric impact

80th percentiles, respectively. Hence, it is evident that as the level of GTE rises, the promoting effect of STTI on GTE shrinks.

The impact of STTI on GTE depends on the initial level of GTE, in that if the transportation system is already relatively efficient and environmentally friendly, the potential for further substantial improvements may be limited. In contrast, a system with lower initial efficiency has more room for significant enhancements through innovation. Regions with lower initial levels of GTE may also have more dependence on fossil fuels, and

STTI can provide crucial resources and support to help these regions transition toward more efficient and sustainable transportation systems. Zhao *et al.* (2023) also find similar asymmetric impacts in the nexus between STTI and green total factor productivity.

Further discussion

Moderating effect analysis

We use the moderation effect model to investigate whether the development of ICT can adjust the nexus between STTI and GTE. To this end, we first estimate the direct impact of ICT on GTE and then add both ICT and STTI to the estimation model. Afterward, we generate an interaction term by interacting ICT with STTI. The interaction term can show the moderating effect of ICT. The detailed model setting is as follows:

$$\ln GTE_{it} = \alpha_0 + \alpha_1 \ln GTE_{i,t-1} + \alpha_2 \ln ICT_{it} + \alpha_3 \ln PGDP_{it} + \alpha_4 \ln IND_{it} + \alpha_5 \ln HC_{it} + \alpha_6 \ln EC_{it} + \pi_i + \mu_t + \varepsilon_{it} \tag{7}$$

$$\ln GTE_{it} = \chi_0 + \chi_1 \ln GTE_{i,t-1} + \chi_2 \ln STTI_{it} + \chi_3 \ln ICT_{it} + \chi_4 \ln PGDP_{it} + \chi_5 \ln IND_{it} + \chi_6 \ln HC_{it} + \chi_7 \ln EC_{it} + \pi_i + \mu_t + \varepsilon_{it} \tag{8}$$

$$\ln GTE_{it} = \delta_0 + \delta_1 \ln GTE_{i,t-1} + \delta_2 \ln STTI_{it} + \delta_3 \ln ICT_{it} \cdot \ln STTI_{it} + \delta_4 \ln PGDP_{it} + \delta_5 \ln IND_{it} + \delta_6 \ln HC_{it} + \delta_7 \ln EC_{it} + \pi_i + \mu_t + \varepsilon_{it} \tag{9}$$

where ICT_{it} is the development level of the ICT sector, which is measured by the output of the ICT industry. Parameter δ_3 is the most important one which denotes the moderating effect. Results are in Table 5.

In the first column, we estimate the simple impact of ICT on GTE by only adding ICT as the core independent variable, and obviously the coefficient of ICT is significantly positive, which

Variable	(1)	(2)	(3)
L. lnGTE	1.0584*** (79.9897)	1.0357*** (74.0510)	1.0244*** (58.0578)
lnSTTI		1.1238*** (5.6232)	1.0979*** (7.5503)
lnICT	0.5500*** (2.7517)	0.7345** (2.3635)	
lnSTTI × ICT			0.5815*** (3.1836)
lnPGDP	0.4451** (2.5355)	0.2896 (1.4388)	0.1825 (0.8123)
lnIND	1.9855*** (10.8053)	1.9003*** (9.1606)	1.8779*** (9.6257)
lnHC	0.2233 (0.7019)	0.3577 (1.1456)	0.4760* (1.7221)
lnEC	−2.3285*** (−17.0807)	−2.4778*** (−8.8430)	−2.5439*** (−11.8912)
Constant	−13.8603*** (−5.8515)	−12.6670*** (−6.7956)	−12.4242*** (−6.9105)
AR(1)	0.0008	0.0008	0.0010
AR(2)	0.2767	0.2545	0.1797
Sargan	0.9510	0.9540	0.9613
N	570	570	570

Notes: ***, ** and *indicate statistical significance at the 1, 5 and 10% levels, respectively; the values in parentheses represent *t*-statistics
Source: Authors' own work

Table 5.
Result of moderation effect

means that ICT can also realize the promoting effect on GTE, similarly to STTI. In Column (2), when both STTI and ICT are included as independent variables, their coefficients remain unchanged, suggesting that both STTI and ICT independently contribute to the promotion of GTE. More importantly, the positive coefficient of the interaction term between STTI and ICT in Column (3) indicates that the combination of STTI and ICT has a synergistic effect on the development of GTE. In other words, their joint presence enhances their impact on GTE beyond what can be attributed to each variable separately. Also, we can conclude that ICT serves as a moderator in the relationship between STTI and GTE, positively adjusting and amplifying the marginal impact of STTI on GTE. That is to say, with the help of ICT, STTI can be more helpful in promoting GTE.

ICT enables real-time data collection, analysis, and communication, allowing for more efficient traffic flow, reduced congestion, and better utilization of transportation resources (Cohen *et al.*, 2002). Additionally, ICT facilitates the integration of various transportation modes and supports shared mobility solutions, reducing individual vehicle usage and emissions (Dong *et al.*, 2022). Moreover, it enables remote monitoring and maintenance of vehicles, ensuring they operate at peak efficiency. By providing tools for precise planning, monitoring, and control of transportation systems, ICT empowers authorities and operators to make informed decisions, ultimately leading to more sustainable and efficient transportation networks (Black and Van Geenhuizen, 2006; Khan *et al.*, 2021). Furthermore, when integrated with STTI, ICT enhances the precision and responsiveness of transportation systems. That is to say, ICT empowers STTI initiatives to achieve even greater strides in promoting GTE (Wang and Guo, 2023). The synergy between STTI and ICT creates a transformative effect that optimizes resource usage, minimizes environmental impact, and ultimately leads to more sustainable transportation systems.

Mediating effect analysis

The mediation effect model can be used to analyze the impact mechanism through which STTI affects GTE. Moreover, as current studies have pointed out, technological innovation can promote the efficiency of carbon emissions and energy utilization. Thus, we consider the mediating role of carbon emissions efficiency and energy efficiency as two potential impact channels. The specific mediation effect model setting is shown as follows:

$$\begin{aligned}\ln CE_{it} = {} & \chi_0 + \chi_1 \ln CE_{i,t-1} + \chi_2 \ln STTI_{it} + \chi_3 \ln PGDP_{it} + \chi_4 \ln IND_{it} + \chi_5 \ln HC_{it} \\ & + \chi_6 \ln EC_{it} + \pi_i + \mu_t + \varepsilon_{it}\end{aligned} \tag{10}$$

$$\begin{aligned}\ln GTE_{it} = {} & \chi_0 + \chi_1 \ln GTE_{i,t-1} + \chi_2 \ln STTI_{it} + \chi_3 \ln CE_{it} + \chi_4 \ln PGDP_{it} + \chi_5 \ln IND_{it} \\ & + \chi_6 \ln HC_{it} + \chi_7 \ln EC_{it} + \pi_i + \mu_t + \varepsilon_{it}\end{aligned} \tag{11}$$

$$\begin{aligned}\ln EE_{it} = {} & \chi_0 + \chi_1 \ln EE_{i,t-1} + \chi_2 \ln STTI_{it} + \chi_3 \ln PGDP_{it} + \chi_4 \ln IND_{it} + \chi_5 \ln HC_{it} \\ & + \chi_6 \ln EC_{it} + \pi_i + \mu_t + \varepsilon_{it}\end{aligned} \tag{12}$$

$$\begin{aligned}\ln GTE_{it} = {} & \chi_0 + \chi_1 \ln GTE_{i,t-1} + \chi_2 \ln STTI_{it} + \chi_3 \ln EE_{it} + \chi_4 \ln PGDP_{it} + \chi_5 \ln IND_{it} \\ & + \chi_6 \ln HC_{it} + \chi_7 \ln EC_{it} + \pi_i + \mu_t + \varepsilon_{it}\end{aligned} \tag{13}$$

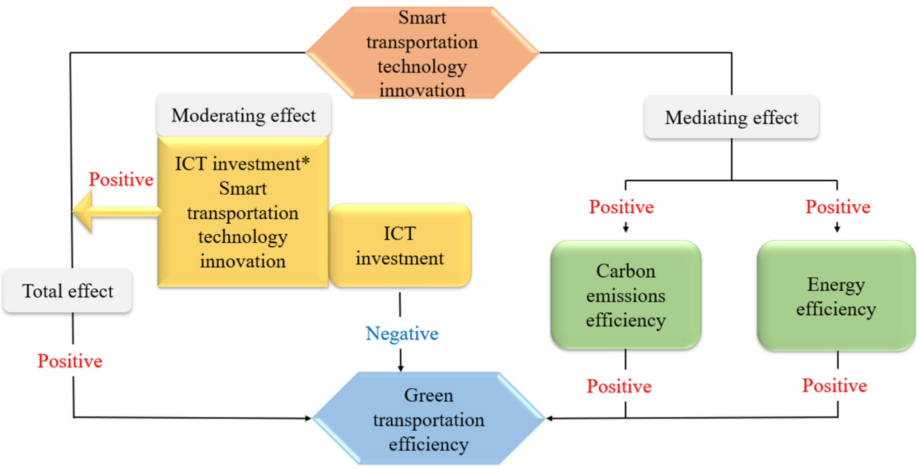
where *CE* and *EE* denote the efficiency of carbon emissions and energy, respectively. Equations (10) and (11) estimate the first channel of carbon emissions efficiency, while equations (12) and (13) estimate the second channel of energy efficiency. Table 6 and Figure 4 show the results.

As for the first effect, the elasticity relationship between STTI and carbon emissions efficiency is 2.0782, and this figure in the nexus between carbon emissions efficiency and GTE is 0.2242, which means that STTI is conducive to the increase of carbon emissions efficiency, and at the same time, the increased carbon emissions efficiency leads to higher levels of GTE.

Variable	(1)	(2)	(3)	(4)
L. lnGTE		1.0515*** (68.3281)		1.0632*** (91.2517)
L. lnCE	0.5266*** (30.2620)			
L. lnEE			0.5783*** (37.2174)	
lnSTTI	2.0782** (2.3651)	0.3473** (2.5031)	0.9308* (1.7295)	0.2781** (2.2233)
lnCE		0.2242*** (3.3044)		
lnEE				1.0832*** (8.9575)
lnPGDP	0.5584*** (8.4746)	0.5064** (2.5033)	−0.0508 (−1.3572)	0.0239 (0.1029)
lnIND	0.1143** (2.2711)	1.3580*** (9.8021)	0.5033*** (11.2546)	0.7272*** (5.2355)
lnHC	−0.9206*** (−16.5861)	0.7707*** (3.0094)	0.3377*** (10.3700)	−0.0296 (−0.1212)
lnEC	−0.0467 (−1.4160)	−2.1232*** (−9.0448)	−0.2334*** (−11.9664)	−1.6059*** (−9.6027)
Constant	2.2130*** (6.1001)	−15.8648*** (−10.7754)	−3.1257*** (−13.3242)	−7.2612*** (−3.8746)
AR(1)	0.0791	0.0011	0.0003	0.0022
AR(2)	0.7862	0.4217	0.8439	0.7462
Sargan	0.9999	0.9923	0.9999	0.9999
N	570	570	570	570

Notes: ***, ** and *indicate statistical significance at the 1, 5 and 10% levels, respectively; the values in parentheses represent *t*-statistics
Source: Authors' own work

Table 6.
Result of mediation effect



Source: Author' own work

Figure 4.
Figure of the impact mechanisms

Thus, the positive relationship between STTI and carbon emissions efficiency, as well as the positive relationship between carbon emissions efficiency and GTE, imply that through the channels of carbon emissions efficiency, STTI can realize the promotion effect on GTE.

From the statistics in Columns (3) and (4), both the coefficient of STTI in Column (3) and the coefficient of energy efficiency in Column (4) are positive and significant. Thus, both the boosting effect of STTI on energy efficiency and the enhancing effect of energy efficiency on GTE exist. Put differently, by facilitating energy efficiency, STTI also contributes to the successful increase of GTE.

STTI helps smart transportation systems to improve by providing information on the most efficient routes for vehicles to take when considering factors such as traffic conditions, road quality and distance; simultaneously, by optimizing traffic flow, STTI reduces congestion and traffic jams, resulting in shorter travel times, which leads to more efficient fuel consumption (Zhao *et al.*, 2023). Moreover, STTI often goes hand in hand with innovations in vehicle design (Shladover, 2018), which include the introduction of more fuel-efficient engines, lighter materials and streamlined aerodynamics. In addition, STTI can be integrated with renewable energy sources such as solar or wind power to charge electric vehicles, further encouraging more energy-efficient driving behaviors, reducing reliance on fossil fuels and increasing carbon emission efficiency (Richardson, 2013; Xiao *et al.*, 2022). Furthermore, increasing energy efficiency means that vehicles and transportation systems can achieve the same level of performance with less energy input, which directly incentives the adoption of green transportation options and accelerates GTE.

Conclusions and policy implications

This paper uses the IPC code to search for patents related to smart transportation and then calculate the level of STTI in current China; simultaneously, we also use the SBM-DEA model to quantify the efficiency of green transportation. Then this paper considers the potential promoting effect of STTI on GTE based on a panel data set covering 30 provinces in China during 2000–2019. The main findings are as follows:

- First, according to the baseline regression result, there is a strong correlation between the increase of STTI and the improvement of GTE. Quantitatively, for every 1% improvement in STTI, the level of GTE gets promoted by 0.4588%.
- Second, we find that the impact of STTI on GTE is asymmetric; when GTE is at the 20th percentile, a 1% rise in STTI results in a GTE acceleration of around 2.1953%. Nevertheless, this incremental effect diminishes to 2.1291%, 2.0628% and 1.9692% when GTE is at the 40th, 60th and 80th percentiles, respectively.
- Third, with the help of the moderating effect model, the moderating role of ICT development is detected, which suggests that ICT can facilitate the accelerating impact of STTI on GTE, leading to the synergic effect.
- Fourth, by using the mediating effect model, two channels are found, namely, the carbon emissions efficiency and the energy efficiency. These two kinds of efficiency are crucial impact mechanisms through which STTI affects GTE. To be more specific, by boosting the efficiency of carbon emissions and energy, STTI contributes to the development of GTE.

The above conclusions inspire us with some clean and practical policy suggestions. First, as we find that developing STTI is helpful for promoting the efficiency of green transportation, it is feasible to increase support for STTI. It is important for the government to provide financial incentives, grants, and technical support for startups and small to medium-sized enterprises working on innovative transportation technologies. Moreover, it is also crucial to foster collaborations between government agencies, private companies, and research institutions. These partnerships can lead to the development and deployment of cutting-edge transportation technologies.

Second, it is vital to note that STTI demonstrates a greater effect in regions where GTE levels are lower. Financial incentives can be extended to companies engaged in the advancement and implementation of STTI in regions with lower levels of GTE. This could encompass incentives such as tax deductions or subsidies for companies committed to the development and utilization of STTI. Furthermore, fostering public-private collaborations in the research and implementation of STTI, coupled with providing comprehensive training and educational resources for transportation professionals and the general public regarding the advantages of this technology, can significantly enhance awareness and facilitate broader adoption.

Third, the mediation effect reveals that energy efficiency and carbon emission efficiency are also important for GTE. Thus, to realize GTE improvement, harnessing energy efficiency and carbon emission efficiency is paramount. A pivotal practice involves prioritizing technological advancements that enhance energy efficiency in transportation, which encompasses extensive research and development efforts aimed at refining propulsion systems, optimizing fuel consumption, and advancing electric and hybrid vehicle technologies. Simultaneously, stringent enforcement of emission standards is imperative to curtail carbon emissions and promote the production of eco-friendly vehicles. Additionally, investing in robust charging and refueling infrastructure for electric and alternative fuel vehicles is crucial to ensuring seamless integration into existing transportation networks.

While this paper provides a comprehensive examination of the impact of STTI on GTE and explores two mechanisms, there are still some research limitations. First, our study is confined to China and does not use global-level data. Future research can investigate the relationship between STTI and GTE in other countries and also make comparisons between developing and developed nations. Second, we analyze the nonlinear relationship between STTI and GTE without considering the threshold effect. Subsequent research could use threshold models to analyze the relationship under different threshold conditions.

Notes

1. For details, see www.stats.gov.cn/sj/ndsj/.
2. For details, see www.ceads.net/.
3. For details, see https://pss-system.cponline.cnipa.gov.cn/conventionalSearch.

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Appendix

Table A1. Indicators for measuring green transportation efficiency

Input and output	Indications	Definition	Unit
Input	Labor input	Number of employees in transportation sector	10,000 people
	Capital input	Capital stock in transportation sector	100m yuan
		Average wage of employees in transportation sector	Yuan
	Infrastructure input	Number of public transport vehicles	Vehicle
		Total passenger volume of public transport	People
		Rail transit mileage	Mileage
		Urban road lighting	Lamp
Expected output	Economic output	Value added of transportation sector	100m yuan
	Fiscal output	Government financial transportation expenditure	100m yuan
Unexpected output	Traffic accidents	Property loss in traffic accidents	10,000 yuan
	Traffic price	Transportation consumer price index	–
	Emissions output	CO_2 emissions in transportation sector	Million tons

Source: Authors' own work

About the author

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