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Measurement and determinants of smart destinations' sustainable performance: a two-stage analysis using DEA-Tobit model

Dongdong Wu, Hui Li, Qing Huang, Chunlin Li and Sai Liang

College of Tourism and Service Management, Nankai University, Tianjin, People's Republic of China

ABSTRACT

With a two-stage analysis framework, this paper investigates how information communication technology can improve the sustainable performance of smart tourism destinations. It analyzes the impact of online attention (in the form of activity on a search engine) and the level of the digital economy on sustainable performance of smart tourism destinations, measured using an advanced data envelopment analysis model. The empirical results from 50 key smart tourism destinations in China show that: (1) the average value of smart destination performance from 2008 to 2019 is 0.74; (2) both online attention and digital economy have significant positive impacts on sustainable performance; (3) digital economy positively moderates the impact of online attention on sustainable performance; (4) undesirable outputs (air pollution) and tourist satisfaction are two factors that can be considered in measuring the sustainable performance of a destination.

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Tourism sustainability and competitiveness; online attention; digital economy; data envelopment analysis; panel Tobit model

1. Introduction

Both the tourism industry and information communication technology (ICT) are important drivers of economic growth in many countries (Errichiello & Micera, 2021; Ivars-Baidal et al., 2019). The digital economy underpins what have been termed smart cities, where it supports industrial transformation and upgrading (Tang, 2023). These two concepts are merged into the term 'smart tourism destinations', because smart cities are tightly linked to smart tourism. That is, smart tourism technologies are employed by urban tourism destinations to strengthen their sustainable competitive advantages and support their sustainable development (Shafiee et al., 2019). Therefore, the ICTs and digital economy are considered to be important supports for sustainable development, which can be defined as efficient, equitable, green development aimed at meeting people's growing needs for a better life (Baggio et al., 2020).

Performance measurement is a well-established research area in tourism economics and a crucial development issue for a smart tourism destination (Miller & Torres-Delgado, 2023). Sustainable tourism destinations have been evaluated according to their social, economic, and environmental sustainability (Kronenberg & Fuchs, 2021). In the context of tourism, despite widespread concern about the sustainable development of destinations, there is little effective way to measure the current development level (i.e. performance) or its distance from a target level (i.e. benchmark). Besides, ICT plays a crucial and increasingly important role in the management and marketing of tourist destinations. It can be used to create strategic tools to promote tourism sustainable

CONTACT Qing Huang huangqing@nankai.edu.cn
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development (Zhao et al., 2020). Despite ongoing research, there are still several gaps in current knowledge about the determinants of a city's performance as a smart tourism destination.

In recent years, the use of data envelopment analysis (DEA) to measure the efficiency and productivity of tourist destinations has attracted the attention of scholars (Niavis, 2020; Wu et al., 2023a). This paper proposes an extended weighted additive DEA model to measure destination performance. Considering the environmental dimension of sustainability, we use the air quality index of smart destinations as a proxy for undesirable output. Similar to research into online customer ratings and customer satisfaction (Mariani & Visani, 2019) using DEA modelling to study efficiency, we test a satisfaction-informed weighted additive DEA model for additional insight. Considering the social dimension of sustainability, this paper embeds tourist satisfaction to represent a desirable output.

We further use a panel Tobit model to analyze the factors that influence sustainable performance of smart destinations. The Baidu index measures the total number of searches for any keywords; as well as the total, the numbers can be obtained separately for searches from PCs and from mobile devices (after 2011) (Zhang & Huang, 2021). We take the Baidu index as a proxy for online attention, and examine its association with destination performance. The Digital Economy Index focuses on important aspects of digital transformation. It is represented by a measure of the local level of the digital economy across China's cities made available by a national research institute (Zhao et al., 2020). We explore its association with destination performance and investigate the moderating effect between online attention on that relationship.

Following the call of 'multiple worldviews and disciplinary perspectives' to advance the sustainable development goals (Nunkoo et al., 2023), this study fills some of these gaps by constructing mathematical models that can be used to measure the sustainable performance (derived from economic, social and environmental dimensions) and the determinates (derived from new factors brought by ICTs) of a smart tourism destination. The main contributions are summarized as follows. Firstly, we propose a two-stage analysis framework using a DEA-Tobit model to investigate the measurement and determinants of destination performance. Secondly, we explore the influence and mechanism of online attention and the Digital Economy Index on destination performance. Thirdly, we show how tourist satisfaction can be incorporated into the modeling of performance.

The paper is structured as follows. Section 2 reviews the related literature and proposes the research hypotheses. The research design and methodology are laid out in Section 3. Section 4 presents the sample selection, data collection and descriptions of the variables. The empirical results and discussion and robustness checks are provided in Section 5. Section 6 presents the conclusion and implications.

2. Literature review and hypothesis development

2.1 Literature review

The use of multidimensional indexes to measure destination performance have attracted the attention of scholars (Wang et al., 2022; Zhang & Huang, 2021). Initially introduced by Charnes et al. (1978), DEA is recognized as a nonparametric linear programming technique. It can be used to analyze the relative efficiency of decision-making units (DMUs), especially there exists multiple outputs and inputs (Wang et al., 2022). As a classical frontier analysis method, several scholars have used DEA to examine efficiency in many domains, including tourism and hospitality (Assaf & Tsionas, 2019), where it has been used to evaluate destination efficiency (Lozano-Ramírez et al., 2023). There is no need to set subjective weights for input-output indicators in DEA. Additionally, it can consider the externality of tourism economic growth, that is, its undesirable outputs (Wu et al., 2023a). In this paper, we focus on efficiency-based differences, and DEA is adopted to measure destinations' sustainable performance.

Speaking of the theoretical foundation of measuring performance, the resource-based view supports the examination of differences in the performance of smart destinations (Barney & Clark, 2007).

This theory seeks to explain how tourism destinations maintain unique and sustainable positions in competitive environments according to their resources. Furthermore, competitive advantage theory expands our knowledge of the relationship between destination performance and competitiveness. Following the latest methodological development of DEA modeling, we extend the weighted additive model with a slack-based measure (SBM) (Tone, 2001) and directional distance function (DDF) (Chung et al., 1997) to measure destination performance. The DDF model assumes the expansion or shrinkage of input and output factors is strictly proportional, which may lead to 'slack bias'. Färe and Grosskopf (2010) introduced the SBM measure based on DDF model (i.e. the SBM-DDF model), which can consider desirable and undesirable outputs, and capture the proportional and 'slack' changes of each factor at the same time.

In this paper, we adjust the SBM-DDF model by setting a more suitable directional vector to implement the measurement of sustainable performance of smart destinations. The range-adjusted measure (RAM) and bounded adjusted measure (BAM) models are based on the weighted additive structure and belong to non-radial DEA model, but with different weights and efficiency or inefficiency measures. Furthermore, we extend those models by modeling undesirable output, as shown in the appendix. As for model specifications, the undesirable output (i.e. air pollution) is modelled by assuming weak disposability and null-jointness (Wang et al., 2023). The assumption of variable return to scale is in line with reality that differences exists among the destinations. This paper extends previous research on the measurement of tourism destination sustainability and competitiveness (Wu et al., 2023a).

The analysis of the determinants of destination performance is crucial, especially in relation to information technology and smart destinations. In this paper, we focus on those new influencing factors brought by ICTs. Digital marketing may arouse consumers' curiosity and often leads to online searches for particular tourism destinations and various points of interest (Almeida-Santana & Moreno-Gil, 2017). Accordingly, tourists' online attention given to a smart tourism destination may impact the sustainable performance. Besides, destination digitalization is a major topic for tourism destination research (Huang et al., 2023). Recently, Tang (2023) verified that digital economy had a driving effect on the UK's tourism with a marginal increasing trend. Therefore, the level of the digital economy as another factor that may impact the sustainable performance of smart tourism destinations.

For the analysis of determinates of smart destinations, two-stage analysis frameworks have proved an effective tool in the study of destination management. Corne and Peypoch (2020) combined DEA and fuzzy-set qualitative comparative analysis to investigate the determinants of tourism performance. Deng et al. (2020) investigated gaming efficiency in casino tourism destinations with DEA model and its determinants with seemingly unrelated regressions. Besides, Tobit regression is widely adopted to explain the performance values in the second stage, especially when advanced DEA performance modeling is done with specific considerations in the first stage. In this paper, Tobit regression is used to analyze the determinates of smart destinations' sustainable performance.

2.2 Hypotheses development

The tourism decision-making model proposed by Mathieson and Wall (1982) consists of six steps: the formation of tourism desire, tourism information search, scheme evaluation, decision-making, the tourism experience itself, and satisfaction evaluation. Information search runs through the decision-making process (Almeida-Santana & Moreno-Gil, 2017). Cognitive psychology regards attention as an internal information processing mechanism, which has the functions of distribution, signal detection, search, and selection. Among them, the selective theory of attention is one of the cores of attention theory. For example, from the perspective of the stock market, it has been shown that the attention of individual investors has a significant positive impact on the performance of restructured tourism firms (Li et al., 2020).

In this paper, we extend the study of attention to smart destinations. Tourists can necessarily consider only those smart destinations that have attracted their attention when making travel decisions. By actively searching the Internet for tourism-related information about smart destinations, tourists can reduce the level of information asymmetry. According to planned behaviour theory (Ajzen, 1991), tourists' attention to the tourism-related elements of smart destinations reflects their behavioural intentions, which may predict their travel plans or indeed their actual behaviours. Therefore, online attention is expected to have a positive impact on destination performance. Drawing on the preceding discussion, we hypothesize:

H1a: The online attention given to a smart destination positively impacts destination performance.

The tourism sector is full of uncertainty due to the intensive information flows brought by ICTs and the complexity and dynamism brought by globalization (Sainaghi & Baggio, 2017). In a complex competitive context, dynamic capabilities theory can assist explain the influence of technological changes on destination performance and competitiveness (Teece et al., 1997; Wu et al., 2023b). For example, digitalization can facilitate information exchange and makes it easier for travelers to perform tasks like searching, buying tickets, booking and communicating. Besides, digital technologies embedded in the environment of smart destinations can enrich the experience of tourists (Pencarelli, 2020). Digital marketing can accelerate digital branding, customer experience design, demand generation and product innovation to enhance the value of smart destinations (Almeida-Santana & Moreno-Gil, 2017; Buonincontri & Micera, 2016).

Online reviews and other types of information play an important role in tourists' decision-making (Pan & Fesenmaier, 2006). However, such information search comes at a cost and depends on adequate ICT infrastructure. An established digital economy can reduce the transaction cost between the multiple agents in the tourism supply chain and promote the digital transformation of the tourism industry (Zhao et al., 2020). Therefore, the digital economy can reduce transaction costs and enhance dynamic capabilities that positively act on destination performance and competitiveness. The level of the digital economy could be another key indicator to measure the competitiveness of smart destinations. Drawing on the preceding discussion, we hypothesize:

H1b: The level of the digital economy positively impacts destination performance.

A highly developed digital economy will meet the needs of tourists for information acquisition (Zhang & Huang, 2021). The construction of digital infrastructure will provide tourists with a convenient platform for information exchange. According to data on search engine use in China from the CNZZ Data Center, Baidu leads in usage and market share. The Baidu index is based on enormous amounts of Internet user behaviour data, specifically in the form of searches for particular keywords (Li et al., 2020). According to the experiential pattern of dual system theory (McCabe et al., 2016), people most often make decisions using simple, easy, nonanalytic, and rapid processes. Although digital technology has brought a variety of information and a wide range of search options, travel decision-making based on keyword searches on a search engine is likely to remain dominant.

From the perspective of cognition, tourism-related information processing underpins attitudes, preferences and purchase intention. The two-process theory (Schneider & Shiffrin, 1977) of human information processing states that the controlled processing requires attention and will consume a large amount of individual cognitive resources. Digital technology promotes the effective integration of information resources and reduces the consumption of individual cognitive resources in the process of tourism information search. Besides, an established digital economy will stimulate the demand of tourists for diversified tourism products or services at smart destinations, which in turn will stimulate online search behaviour (Xiang & Pan, 2011). Therefore, the level of the digital economy may positively moderate the positive impact of online attention on destination performance. Drawing on the preceding discussion, we hypothesize:

H2: The level of the digital economy enhances the positive impact of online attention on destination performance.

3. Research design and methodology

Based on DEA and a Tobit model, this paper proposes a two-stage analysis framework to measure the efficiency values and identify the determinants of destination performance. Figure 1 presents the proposed two-stage analysis framework using a DEA-Tobit model. Stage 1 measures destination performance considering sustainability dimensions and Stage 2 identifies the determinates using regression analysis. As can be seen in Stage 1 of Figure 1, the dependent variable of this paper is destinations' sustainable performance measured by the adjusted SBM-DDF model. Besides, RAM (Cooper et al., 1999) and BAM (Cooper et al., 2011) model with the consideration of undesirable output are provided in the Appendix and adopted for model comparisons and robustness checks.

In this paper, the adjusted SBM-DDF model is used to model the production process, which consumes the inputs of employed labour, energy consumption, capital stock, and tourism resource to yield economical outputs (i.e. tourism revenue and visitor number) and environmental outputs (i.e. air pollution). Efficiency value is be used to proxy sustainable performance of smart tourism destinations. As can be seen in Stage 2 of Figure 1, we test the main effect and moderating effects of the focused independent variables on the dependent variable that defined and measured in Stage 1.

3.1 Weighted additive DEA model

Färe and Grosskopf (2010) combined the additive structure of an SBM model (Tone, 2001) and a DDF model (Chung et al., 1997), and developed an SBM measure on the sum of DDF, which can be deemed as an additive model with weight equal to 1. In this paper, we focus on constructing the adjusted SBM-DDF model as follows. Suppose each $DMU_j (j = 1, 2, \ldots, n)$ uses $x_{ij} (i = 1, 2, \ldots, m)$

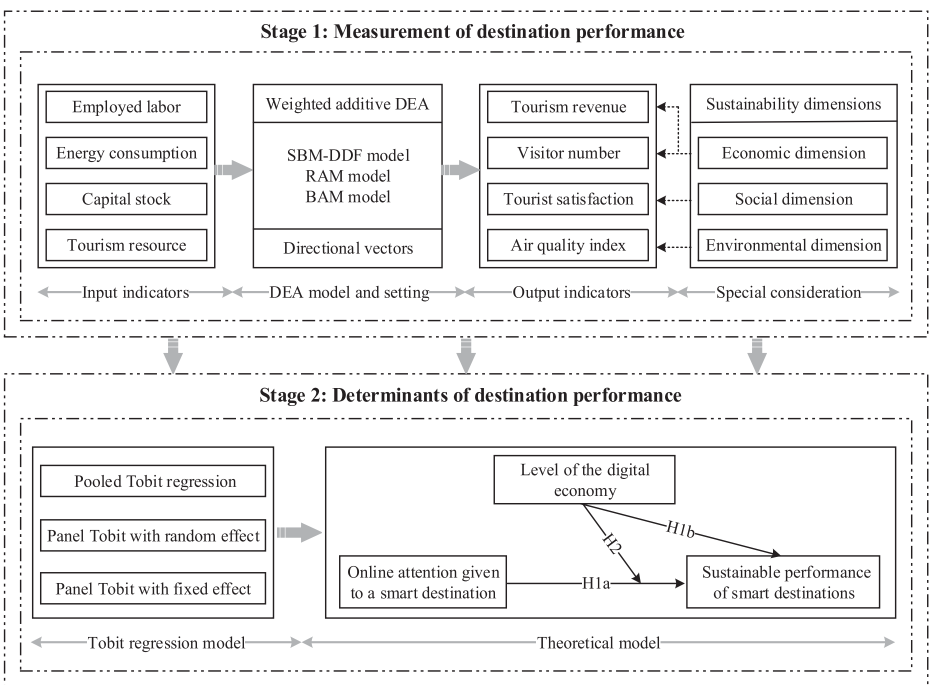

Figure 1. Two-stage analysis framework using a DEA-Tobit model.

inputs to obtain $y_{rj}(r = 1, 2, \ldots, q_1)$ desirable outputs but also $b_{tj}(t = 1, 2, \ldots, q_2)$ undesirable outputs, where vectors y_{rj}, b_{tj} and x_{ij} are the the r-th desirable, the t-th undesirable output, and the i-th input associated with DMU$_j$.

Following Wang et al. (2023), we focus on the assumption of weak disposability and null-jointness of undesirable outputs and the scale return is set as variable return to scale. Therefore, the production possibility set can be denoted as follows:

$$P = \left\{ \begin{array}{l} (x, y, b): \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_r, \forall r; \ \sum_{j=1}^{n} \lambda_j b_{tj} = b_t, \forall t \\ \sum_{j=1}^{n} (\lambda_j + \mu_j) x_{ij} \leq x_i, \forall i; \ \sum_{j=1}^{n} (\lambda_j + \mu_j) = 1; \lambda_j, \mu_j \geq 0, \forall j \end{array} \right\} \tag{1}$$

where λ_j and μ_j are the intensity weights. The directional slack-based inefficiency $\overrightarrow{S}(x, y, b; g)$ of the evaluated DMU$_k$ can be derived by the following adjustment of the SBM-DDF model (Fukuyama & Weber, 2009). Parameters, s_r^{y+}, s_t^{b-}, and s_i^{x-} are the slack vectors of desirable, undesirable outputs and inputs, while g_r^y, g_t^b, and g_i^x are positive directional vectors. The slacks and directional vectors are unit invariant, and thus s_r^{y+}/g_r^y, s_t^{b-}/g_t^b, and s_i^{x-}/g_i^x represent the normalized slacks.

$$\begin{aligned} &\overrightarrow{S}(x, y, b; g) = \max \frac{1}{2}\left[\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^{x-}}{g_i^x} + \frac{1}{q_1 + q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^{y+}}{g_r^y} + \sum_{t=1}^{q_2}\frac{s_t^{b-}}{g_t^b}\right)\right] \\ &s.t. \sum_{j=1}^{n}(\lambda_j + \mu_j)x_{ij} + s_i^{x-} = x_{ik}, i = 1, 2, \ldots, m \\ &\sum_{j=1}^{n}\lambda_j y_{rj} - s_r^{y+} = y_{rk}, r = 1, 2, \ldots, q_1 \\ &\sum_{j=1}^{n}\lambda_j b_{tj} + s_t^{b-} = b_{tk}, t = 1, 2, \ldots, q_2 \\ &\sum_{j=1}^{n}(\lambda_j + \mu_j) = 1; \lambda_j, \mu_j \geq 0 \\ &s_i^{x-}, s_r^{y+}, s_t^{b-} \geq 0; j = 1, 2, \ldots, n \end{aligned} \tag{2}$$

If we set $w^x = \frac{1}{2mg_i^x}$, $w^y = \frac{1}{2(q_1 + q_2)g_r^y}$ and $w^b = \frac{1}{2(q_1 + q_2)g_t^b}$, then the objective function of model (2) can be transformed into $\max \sum_{i=1}^{m} \frac{1}{2mg_i^x} s_i^{x-} + \sum_{r=1}^{q_1} \frac{1}{2(q_1 + q_2)g_r^y} s_r^{y+} + \sum_{t=1}^{q_2} \frac{1}{2(q_1 + q_2)g_t^b} s_t^{b-}$. In fact, the objective function of model (2) equals that of the weighted additive model $\max \sum_{i=1}^{m} w^x s_i^{x-} + \sum_{r=1}^{q_1} w^y s_r^{y+} + \sum_{t=1}^{q_2} w^b s_t^{b-}$.

According to the range directional model (RDM) proposed by Portela et al. (2004), we can define the directional vector considering the range of possible improvement in equation (3). The assumption of variable return to scale and the setting of directional vectors enable the inefficiency value of the adjusted SBM-DDF model, that is $\overrightarrow{S}(x, y, b; g)$, to be bounded in the interval [0, 1]. Accordingly, the efficiency of the adjusted SBM-DDF model can be calculated as $1 - \overrightarrow{S}(x, y, b; g)$. In fact, the proposed adjusted SBM-DDF model with RDM range setting can be deemed as a special case of non-radial DDF (Zhou et al., 2012).

$$\begin{cases} g_i^x = x_{ik} - \min\{x_{ij}\}, i = 1, 2, \ldots, m \\ g_r^y = \max\{y_{rj}\} - y_{rk}, r = 1, 2, \ldots, q_1 \\ g_t^b = b_{tk} - \min\{b_{tj}\}, t = 1, 2, \ldots, q_2 \end{cases} \quad (3)$$

3.2 Panel Tobit model

The pooled Tobit regression, the panel Tobit regression with individual random effects and the panel Tobit regression with two-way fixed effects are constructed as shown in equation (4), equation (5) and equation (6), respectively. Furthermore, we use the regression model with two-sided censoring (Alan et al., 2014) to estimate the panel Tobit regression with fixed effects as a measure of robustness check.

$$y_{i,t} = \alpha + \boldsymbol{x}'_{i,t}\boldsymbol{\beta} + \boldsymbol{z}'_{i,t}\boldsymbol{\delta} + \varepsilon_{i,t} \quad (4)$$

$$y_{i,t} = \alpha + \boldsymbol{x}'_{i,t}\boldsymbol{\beta} + \boldsymbol{z}'_{i,t}\boldsymbol{\delta} + \lambda_i + \varepsilon_{i,t} \quad (5)$$

$$y_{i,t} = \boldsymbol{x}'_{i,t}\boldsymbol{\beta} + \boldsymbol{z}'_{i,t}\boldsymbol{\delta} + \lambda_i + \mu_t + \varepsilon_{i,t} \quad (6)$$

Therein, subscript i and t represent city and year, parameters λ_i and μ_t denote individual and time effects. $y_{i,t}$ is the dependent variable, $\boldsymbol{x}'_{i,t}$ is the independent variable, $\boldsymbol{z}'_{i,t}$ is the control variable, and $\varepsilon_{i,t}$ is a random error or disturbance term. Parameter α represents the intercept term, parameter $\boldsymbol{\beta}$ represents the regression coefficient of independent variables, and parameter $\boldsymbol{\delta}$ represents the regression coefficient of the control variables.

For panel data, it is usually impossible to obtain consistent estimates from nonlinear models with fixed effects, so a panel Tobit model with random effects is often used. Furthermore, the likelihood-ratio test and Hausman test show that the panel Tobit model with random effects is appropriate for the analysis of a moderating effect. Therefore, we estimate equation (7) to test the impact of online attention on destination performance and the moderating effect of the level of the digital economy:

$$\begin{aligned} \text{efficiency}_{it} &= \alpha + \beta_1 \cdot \text{ln\_netatten}_{it} + \beta_2 \cdot \text{ln\_}dige_{it} \\ &+ \xi \cdot \text{ln\_netatten}_{it} \times \text{ln\_}dige_{it} + \boldsymbol{z}'_{i,t}\boldsymbol{\delta} + \lambda_i + \varepsilon_{i,t} \end{aligned} \quad (7)$$

In this equation, β_1 and β_2 represent the main effects of online attention and digital economy, respectively. The variable *efficiency* is defined as the sustainable performance of a smart destination measured by the SBM-DDF model, or RAM and BAM models. The interaction between online attention and digital economy is represented by ξ, while $\boldsymbol{\delta}$ captures the effect of the vector of control variables. To reduce the effect of outliers and heteroscedasticity, the natural logarithms of both independent variables are used. The variables *ln_netatten* and *ln_dige* represent the logarithm of the focused independent variables and then are carried out by the centralized processing.

4. Sample selection and data collection

The sample comprises 50 key tourism cities selected as the focus of a tourism statistical survey by the Ministry of Culture and Tourism of China. The sample cities cover all 31 provinces in mainland China (each province has at least one). Most of the sample cities are listed as smart cities pilots and smart tourism pilot cities. Panel data for the years 2008–2019 is used to evaluate the destination performance of these 50 cities. The city-level data was mainly derived from *China City Statistical Yearbook* and the EPS database (https://www.epsnet.com.cn/), which provides advanced data retrieval, data extraction, data analysis and prediction tools. Table 1 shows the descriptive statistic of the variables.

Table 1. Descriptive statistics of the variables.

Variable	Observation	Min	Max	Mean	Std. Dev.
Input-output variables					
Employed labour	600	4.86	681.08	80.56	105.64
Energy consumption	600	2.00	4067.33	547.72	634.37
Capital stock	600	739.79	103835.84	20406.11	16238.33
Tourism resource	600	40.27	799.13	159.22	118.32
Tourism revenue	600	12.00	4886.88	826.75	851.12
Visitor number	600	134.62	65708.03	7362.49	7948.81
Air quality index	600	21.01	384.00	77.50	27.23
Panel regression variables					
Destination performance	600	0.38	1.00	0.76	0.21
Digital economy development level	150	42.90	89.80	65.64	11.55
Online attention	450	9.09	136.26	33.18	21.95
Urbanization level	600	2.71	8.25	6.15	0.87
Economic development level	600	2.12	6.15	4.16	0.56
Financial decentralization	600	0.05	1.54	0.69	0.21
Financial development level	600	1.07	13.53	3.81	1.59
Foreign direct investment	600	0.00	0.13	0.03	0.02
Industrial structure	600	0.28	0.84	0.52	0.10
Scientific and technological development level	600	0.00	0.13	0.03	0.02
Population growth rate	600	−8.76	25.18	6.11	4.68

4.1 Input-output variables

Input variables. The input variables are labour, energy, capital factor, and the tourism endowment of smart destinations (Wu et al., 2023a). (1) Employed labour (unit: 10,000 persons) is denoted by the number of persons employed at the end of the year. (2) Energy consumption (unit: 10,000 metric tons of standard coal equivalent) is converted into standard coal equivalents (Wang et al., 2023; Du et al., 2023), which is calculated by the reference coefficient method considering the consumption of electricity, coal, natural gas, and liquefied petroleum gas (Zha et al., 2020). (3) Capital stock (unit: 100 million CNY) is measured by transforming fixed asset investment using the perpetual inventory method. (4) Tourism resource (unit: piece) is proxied by the value of entropy weight, which aggregates the number of star-rated hotels, travel agencies and A-level tourist attractions.

Desirable and undesirable output variables. Total number of inbound and domestic visitor numbers (unit: 10,000 persons) and the total revenue from inbound and domestic tourism (unit: 100 million CNY) are used to represent the desirable outputs (Wu et al., 2023a). The annual average CNY exchange rate against the US dollar of the current year is adopted to convert the inbound tourism income into CNY. Previous studies have used tourism carbon emissions as a proxy for undesired output (Zha et al., 2020). However, due to the unavailability of specific city-level data, the calculation of tourism carbon emissions may be limited. In this paper, China's urban Air Quality Index (AQI) is used to represent the undesirable output of tourism economic production. The bigger the value, the worse the air pollution and the greater the harm to human health. Data is collected from Ministry of Ecology and Environment of China and the China air quality online monitoring and analysis platform (http://www.aqistudy.cn/historydata/) using Python 3.10 software.

4.2 Panel regression variables

Dependent and independent variables. The dependent variable of this paper is destination performance measured by the adjusted SBM-DDF model. Additionally, destination performances measured by the RAM and BAM model are used as alternative dependent variables for the subsequent robustness check. Level of the digital economy (*dige*). The China Urban Digital Economy Index is used as the proxy for the level of development of the digital economy for each city. The data is crawled from Digital Economy Research Institute of New H3C Technologies Co., Ltd (http://deindex.h3c.com/), and the time range is from 2017 to 2019. The Digital Economy Index is a comprehensive measure that includes data and information infrastructure, urban services, urban governance and industrial integration. Online attention of smart destination (*netatten*). This variable is the volume of Internet searches for the keywords of smart destinations. The data is crawled from the Baidu index (https://index.baidu.com/), covering the period from 2011 to 2019. The tourism-related keywords we use are: 'food', 'accommodation', 'travel', 'tourism' and 'shopping' for each smart destination (i.e. city). Python 3.10 software is used to collect the original daily data. The index weight of each dimension is obtained by the entropy weight method.

Control variables. In line with Zhao et al. (2020), the analysis incorporates the following control variables that may influence destination performance. (1) Urbanization level (*urban*): the logarithm of population density. (2) Economic development level (*develop*): per capita gross regional product (GRP). (3) Financial decentralization (*finadp*): the ratio of budgetary revenue to budgetary expenditure. (4) Financial development level (*finance*): the ratio of institutional balances of deposits and loans to GRP. (5) Foreign direct investment (*fdi*): the ratio of the actual use of foreign capital and GRP that year. (6) Industrial structure (*industr*): the proportion of the added value of the tertiary industry in GRP. (7) Scientific and technological development level (*stdev*): the proportion of science and technology expenditure in financial expenditure. (8) Population growth rate (*popgrow*): the year-end population growth rate (unit: permillage) of each city.

5. Empirical results and discussion

5.1 Sustainable performance of smart destinations

Table 2 shows the average values over the period 2008–2019 of destination performance for each city. The average values over all cities over the period of the adjusted SBM-DDF, RAM and BAM models are 0.76, 0.94 and 0.74, respectively. The efficiency value of the RAM model is higher than that of the BAM model. Because the SBM-DDF and BAM models have similar direction vector settings, there is not much difference between their efficiency values.

Table 2. The average value of destination performance from 2008 to 2019.

City	SBM-DDF	RAM	BAM	City	SBM-DDF	RAM	BAM
Beijing	1.00	1.00	1.00	Zhengzhou	0.78	0.90	0.77
Tianjin	0.97	0.98	0.97	Luoyang	1.00	1.00	1.00
Shijiazhuang	0.53	0.82	0.50	Wuhan	0.96	0.98	0.96
Qinhuangdao	0.55	0.93	0.51	Yichang	0.64	0.93	0.60
Taiyuan	0.54	0.88	0.50	Changsha	0.68	0.90	0.65
Hohhot	0.50	0.91	0.46	Zhangjiajie	1.00	1.00	1.00
Shenyang	0.67	0.88	0.64	Guangzhou	1.00	1.00	1.00
Dalian	0.65	0.88	0.62	Shenzhen	0.67	0.87	0.64
Changchun	0.69	0.91	0.68	Zhuhai	0.65	0.96	0.62
Harbin	0.60	0.89	0.57	Dongguan	0.78	0.95	0.75
Shanghai	1.00	1.00	1.00	Nanning	1.00	1.00	1.00
Nanjing	0.71	0.86	0.69	Guilin	0.76	0.97	0.74
Wuxi	0.94	0.98	0.94	Haikou	0.60	0.97	0.56
Suzhou	0.91	0.96	0.90	Sanya	1.00	1.00	1.00
Hangzhou	0.95	0.97	0.94	Chongqing	1.00	1.00	1.00
Ningbo	0.74	0.92	0.72	Chengdu	0.84	0.92	0.82
Wenzhou	0.76	0.95	0.74	Guiyang	1.00	1.00	1.00
Hefei	0.63	0.88	0.60	Kunming	0.75	0.95	0.72
Huangshan	1.00	1.00	1.00	Lijiang	1.00	1.00	1.00
Fuzhou	0.69	0.94	0.66	Lasa	1.00	1.00	1.00
Xiamen	0.84	0.98	0.83	Xi'an	0.68	0.87	0.66
Quanzhou	0.86	0.98	0.84	Lanzhou	0.45	0.86	0.40
Nanchang	0.55	0.91	0.51	Xining	0.44	0.89	0.39
Jinan	0.56	0.86	0.53	Yinchuan	0.58	0.94	0.54
Qingdao	0.67	0.88	0.64	Urumqi	0.42	0.84	0.36

We can compare the efficiency values of the different models. Although there are some differences among the three models in measuring efficiency, the DMUs that are evaluated as efficient (i.e. have an efficiency value of 1) are consistent across all three models. In the regression analysis, the efficiency values measured by the adjusted SBM-DDF model were taken as independent variables.

5.2 Destination performance and tourist satisfaction

In the above evaluation of destination performance, we considered the DEA modeling of an economic dimension and an environmental dimension. We provide a comparison analysis using the 2010–2015 period to investigate how tourist satisfaction will influence destination performance, by incorporating this variable into the DEA model or not. Here, we consider a social dimension of sustainability of smart destinations, namely tourist satisfaction. Tourist satisfaction is represented by the Tourist Satisfaction Index (TSI) of smart destinations. The data is collected from the tourism industry research series of CSMAR database (https://www.gtarsc.com/). The original data came from the National Tourist Satisfaction Survey of the China Tourism Academy. This paper takes the mean of the quarterly data over the period to obtain the annual data of the TSI for each smart destination.

Table 3 shows the average value of destination performance with and without consideration of TSI from 2010 to 2015. The average values of destination performance with TSI and without TSI are 0.779 and 0.774, respectively. After considering TSI, the classification of Tianjin, Xiamen, and Chengdu changes inefficient destination performance to efficient. Therefore, this social dimension is an important factor in destination performance. In fact, destination performance provides a comprehensive benchmark for, and acts an important determinant of, competitiveness. We also compare destination performance with and without TSI. With account taken of TSI, the efficiency value of 14 DMUs increases, 21 DMUs decreases, and the other 15 DMUs remains unchanged.

Table 3. The comparison of destination performance with and without TSI.

City	With TSI	Without TSI	City	With TSI	Without TSI
Beijing	1.000	1.000	Zhengzhou	0.824	0.815
Tianjin	0.982	1.000	Luoyang	1.000	1.000
Shijiazhuang	0.535	0.473	Wuhan	1.000	1.000
Qinhuangdao	0.541	0.519	Yichang	0.598	0.584
Taiyuan	0.535	0.494	Changsha	0.688	0.634
Hohhot	0.512	0.515	Zhangjiajie	1.000	1.000
Shenyang	0.692	0.703	Guangzhou	1.000	1.000
Dalian	0.707	0.666	Shenzhen	0.714	0.703
Changchun	0.666	0.614	Zhuhai	0.673	0.822
Harbin	0.620	0.576	Dongguan	0.829	0.895
Shanghai	1.000	1.000	Nanning	1.000	1.000
Nanjing	0.771	0.852	Guilin	0.657	0.636
Wuxi	1.000	1.000	Haikou	0.614	0.754
Suzhou	1.000	1.000	Sanya	1.000	1.000
Hangzhou	0.945	0.953	Chongqing	1.000	1.000
Ningbo	0.789	0.887	Chengdu	0.836	1.000
Wenzhou	0.752	0.699	Guiyang	1.000	1.000
Hefei	0.663	0.661	Kunming	0.686	0.642
Huangshan	1.000	1.000	Lijiang	1.000	1.000
Fuzhou	0.737	0.712	Lasa	1.000	1.000
Xiamen	0.913	1.000	Xi’an	0.695	0.655
Quanzhou	0.884	0.897	Lanzhou	0.450	0.426
Nanchang	0.537	0.488	Xining	0.449	0.442
Jinan	0.580	0.539	Yinchuan	0.451	0.520
Qingdao	0.726	0.781	Urumqi	0.423	0.412

Table 4. Main effect, moderating effect and robustness checks.

efficiency	Model 1 PR	Model 2 RE	Model 3 RE	Model 4 RE	Model 5 FE	Model 6 RE	Model 7 RE	Model 8 RE
netatten	0.272***	0.202***	0.200***	0.130***	0.235***	0.250***	0.051***	0.214***
	(0.059)	(0.058)	(0.056)	(0.036)	(0.063)	(0.083)	(0.019)	(0.060)
dige	0.600**	0.420**	0.406**		0.534*	0.421*	0.115*	0.443**
	(0.237)	(0.192)	(0.189)		(0.287)	(0.224)	(0.064)	(0.200)
interaction			0.814***				0.284***	0.852***
			(0.287)				(0.096)	(0.304)
controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−2.970***	−2.150**	−1.857**	−0.100		−2.228**	0.342	−2.143**
	(0.897)	(0.971)	(0.934)	(0.529)		(1.191)	(0.314)	(0.996)
sigma_u		0.256***	0.234***	0.288***		0.247***	0.078***	0.252***
		(0.034)	(0.031)	(0.037)		(0.035)	(0.010)	(0.034)
sigma_e		0.094***	0.094***	0.105***		0.093***	0.032***	0.099***
		(0.008)	(0.008)	(0.005)		(0.012)	(0.003)	(0.009)
Chi-square	58.227	20.551	29.374	82.409	80.210	26.02	28.117	29.281
Prob > Chi2	0.000	0.024	0.002	0.000	0.000	0.004	0.003	0.002
Log likelihood	−45.814	14.130	18.197	108.792		52.7	129.453	12.166
Observations	150	150	150	450	150	100	150	150

Notes: Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; PR, RE, and FE denote pooled regression, random effect, and fixed effect, respectively.

5.3 Main effect and moderating effects

Table 4 shows the main effect and moderating effect determined by the regression analysis. Model 1 and model 2 are measured by the pooled Tobit regression and panel Tobit regression with random effects, respectively. In this paper, we used the standard Tobit regression model, namely panel Tobit regression with random effects, to test the main effect. According to model 2, both online attention ($\beta_1 = 0.202$, $p < 0.01$) and digital economy ($\beta_2 = 0.420$, $p < 0.05$) have a significant positive effect on destination performance. Furthermore, the estimation of the partial effects shows that the average marginal effects of online attention and digital economy on destination performance are 0.201*0.01 and 0.419*0.01, respectively. This main conclusion is also consistent with the estimated result of model 1. Thus, **H1a** and **H1b** are supported.

With the development of Internet technology, tourists can readily obtain a wide range of information on tourism destinations (Zhang & Huang, 2021). Search behaviour is therefore likely to reflect their travel intentions and so be a precursor of actual tourism demand (Xiang & Pan, 2011). Therefore, tourists' online attention is expected to positively influence the economic dimension of sustainability, and thus improve destination performance. At present, the digital economy is playing an increasingly strong role in promoting the transformation and upgrading of urban economies and innovative industrial development (Zhao et al., 2020) and hence destination performance. Moreover, China's Digital Economy Index covers a wide range of digital applications, and so is a very useful indicator for the urban digital economy.

Regarding the moderating effect, the Hausman test shows that the panel Tobit regression with random effects should be adopted for the regression analysis. The regression result of model 3 in Table 4 shows that the level of the digital economy ($\beta_2 = 0.406$, $p < 0.05$) enhances the positive impact ($\xi = 0.814$, $p < 0.01$) of online attention ($\beta_1 = 0.200$, $p < 0.01$) on destination performance. Thus, **H2** is supported. Generally, it indicates that a 1% increase of online attention (digital economy) results in a 0.200*0.01 (0.406*0.01) unit increase of destination performance, respectively. As an important part of the digital economy, the urban information base includes digital infrastructure of urban services, urban governance and industrial integration. A good digital infrastructure can provide tourists with more convenient information seeking, that is, Internet search (Pan & Fesenmaier, 2006). Digital marketing promotes the formation of online attention and potential demand (Almeida-Santana & Moreno-Gil, 2017). Therefore, the digital economy can improve the tourism economy of smart destinations, and strengthen the positive impact of online attention on destination performance.

Among the control variables, the estimated coefficient of urbanization level ($\delta_1 = -0.133$, $p < 0.05$) is significantly negative, indicating that greater city size is not conducive to better destination performance. In addition, the estimated coefficient of economic development level ($\delta_2 = -0.290$, $p < 0.05$) is significantly negative, which is consistent with the prediction of long-term convergence of regional economic growth by the neoclassical economic growth model. In the sample of 50 smart destinations, smaller cities and those with a lower level of economic development have a richer tourism resource endowment, which is likely to be one of the reasons why they attract more attention than larger cities (e.g. the provincial capitals). That is, smaller cities with lower levels of economic development benefit more from their rich tourism resources in terms of a higher growth rate of their tourism economy. Other control variables have no significant impact on destination performance.

5.4 Robustness checks

We carried out several robustness checks to validate the results as shown in Table 4. We estimate the result in different time periods. To verify the impact of online attention on destination performance, after removing the variable related to the digital economy from the model, we present the result of the regression analysis with more samples in different time periods. Model 4 verifies the significant positive impact of online attention ($\beta_1 = 0.130$, $p < 0.01$) on destination performance with 450 city-year observations from 2011 to 2019. Furthermore, we test the results using panel Tobit regression with fixed effects with 150 city-year observations from 2017 to 2019 as shown in model 5. It also verifies the significantly positive impact of online attention ($\beta_1 =$ 0.235, $p < 0.01$) on destination performance.

Next, the dependent variable is treated with a lag of one year to alleviate concerns about endogeneity with 100 city-year observations from 2018 to 2019. The estimation of model 6 shows that it is not likely that destination performance contributes to the online attention. Finally, we change the measurement model of the dependent variable. In order to ensure the robustness of the main effect and the moderating effect, the estimated results of RAM (see model 7) and BAM (see model 8) are used as the dependent variables for the regression analysis. Regression analysis based on a panel Tobit model with random effects verifies the robustness of the main findings.

6. Conclusion and implications

6.1 Main findings

This paper proposed a two-stage analysis framework using a DEA-Tobit model to investigate the measurement and determinants of smart tourism destinations. The main findings are as follows. Firstly, after calculating the adjusted SBM-DDF model, we find that the average value of destination performance for the sample of smart destinations is 0.74. It indicates that destination performance still has a lot of room for improvement. Secondly, considering the impact of ICT on smart destinations, we verify the positive effect of online attention and digital economy on destination performance. Additionally, we find that the development of the local digital economy can enhance the positive effect of online attention on destination performance. Thirdly, the inclusion of tourist satisfaction produces some interesting changes in the rankings of the smart destinations.

6.2 Theoretical implications

This paper contributes to the advanced modelling of DEA in measuring sustainability or performance. Focusing on resource-based view and competitive advantage theory, the resource inputs (such as employed labour, energy consumption, capital stock and tourism resource) can be linked with the economic (such as tourist numbers and tourism revenue), environmental (such as AQI), and social (such as TSI) dimensions of sustainability. This paper enriches the literature on performance-based research methods in the field of tourism destination sustainability and competitiveness (Cronjé & du Plessis, 2020).

This paper contributes to the identification of ICT factors influencing destination performance. Based on attention theory and planned behaviour theory, we analyzed the impact of online attention on destination performance. Based on transaction cost theory and dynamic capabilities theory, we explored the influence of the local digital economy on destination performance. This paper enriches the literature on intangible factors brought by the development of ICT on destination performance (Yuan et al., 2019).

This paper contributes to the literature investigating how online attention influences destination performance. Based on the dual system theory and the two-process theory of human information processing, we extracted the moderating effect of the digital economy on the relationship between online attention and destination performance. This paper adds empirical evidence to help understand the role the digital economy plays in smart tourism destinations from a cognitive perspective.

6.3 Practical implications

This paper provides some practical implications for tourism policy makers, tourism destination managers and tourists or consumers. Firstly, there is a need to recognize the impact of the development of ICTs on the industrial transformation of the tourism industry. For tourism destinations with weak ICT infrastructure or particular development constraints, it is necessary to seek appropriate policy support to enable them to use the digital economy to promote the tourism industry.

Secondly, attention should be paid to the impact of intangible assets such as online attention, electronic word of mouth and destination branding on performance. Tourism destination managers should have a clear understanding of their own development status and characteristics, and highlight the special characteristics of smart destinations. For example, digital marketing can be developed to promote the integration of culture and tourism, and to building a reputation as a smart destination.

Thirdly, digital technology can be actively adopted to obtain tourism-related information or services, so as to obtain a fantastic travel experience. At the same time, tourists or consumers should also pay attention to the potential negative forms of online attention, such as tourist complaints and other satisfaction-related attributes. Furthermore, additional attention should be paid to avoiding the possible digital marketing pitfalls of smart destinations when making travel plans.

6.4 Limitations and future research

This paper has the following limitations. Firstly, due to the availability of tourist satisfaction data, the DEA modeling results derived using the TSI could not be used for regression analysis. Secondly, due to the availability of the Digital Economy Index, that regression analysis may have had an inadequate sample size (year-level observations). Thirdly, although we have tried our best to control for factors influencing regression analysis, due to data availability, there may be still some confounding factors with endogeneity issues.

The following directions are suggested for future research. Firstly, this paper focuses on a specific form of tourist behaviour, namely the online search attention given to a smart destination, and future research can be extended to examine the impact of news media coverage (online or otherwise), for example. Secondly, online attention paid to their destinations, as well as various online measures of tourist satisfaction, are increasingly being used by destination managers and researchers. The traditional techniques of data-gathering, such as questionnaire surveys seems more limited and cumbersome in the era of big data. Keywords text mining to evaluate satisfaction is also an important indicator of tourism destination image building, and this is an interesting aspect of ICTs' influence on smart destinations. Thirdly, exploring how the spatial heterogeneity of ICTs may affect smart destinations is also an important research direction because the spillover and diffusion of ICTs have a significant impact on economic development.

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ORCID

Dongdong Wu http://orcid.org/0000-0002-9784-401X
Hui Li http://orcid.org/0000-0002-5822-2795
Qing Huang http://orcid.org/0000-0001-9632-5907
Chunlin Li http://orcid.org/0000-0003-3045-3679
Sai Liang http://orcid.org/0000-0001-5776-2768

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Appendix

RAM and BAM model

Considering weak disposability and variable return to scale, the range-adjusted measure (RAM) proposed by Cooper et al. (1999) can be modeled as $\alpha = \min 1 - \frac{1}{m+q_1+q_2}\left(\sum_{i=1}^{m}\frac{s_i^{x-}}{R_i^{x-}} + \sum_{r=1}^{q_1}\frac{s_r^{y+}}{R_r^{y+}} + \sum_{t=1}^{q_2}\frac{s_t^{b-}}{R_t^{b-}}\right)$ with the same constraints as model (2) in the main text. R_r^{y+}, R_t^{b-}, and R_i^{x-} denote the range of possible improvements for desirable, undesirable outputs, and inputs. Accordingly, the ranges for RAM are defined in Equation (A1).

$$\begin{cases} R_i^{x-} = \max\{x_{ij}\} - \min\{x_{ij}\}, i = 1, 2, \ldots, m \\ R_r^{y+} = \max\{y_{rj}\} - \min\{y_{rj}\}, r = 1, 2, \ldots, q_1 \\ R_t^{b-} = \max\{b_{tj}\} - \min\{b_{tj}\}, t = 1, 2, \ldots, q_2 \end{cases} \tag{A1}$$

Further, the bounded adjusted measure (BAM) proposed by Cooper et al. (2011) can be modeled as $\beta = \min 1 - \frac{1}{m+q_1+q_2}\left(\sum_{i=1}^{m}\frac{s_i^{x-}}{B_i^{x-}} + \sum_{r=1}^{q_1}\frac{s_r^{y+}}{B_r^{y+}} + \sum_{t=1}^{q_2}\frac{s_t^{b-}}{B_t^{b-}}\right)$ with the same constraints as model (2) in the main text. B_r^{y+}, B_t^{b-}, and B_i^{x-} denote the range of possible improvement for desirable, undesirable outputs, and inputs. Accordingly, the ranges for BAM are defined in Equation (A2).

$$\begin{cases} B_i^{x-} = x_{ik} - \min\{x_{ij}\}, i = 1, 2, \ldots, m \\ B_r^{y+} = \max\{y_{rj}\} - y_{rk}, r = 1, 2, \ldots, q_1 \\ B_t^{b-} = b_{tk} - \min\{b_{tj}\}, t = 1, 2, \ldots, q_2 \end{cases} \tag{A2}$$

If we set $g_i^x = \frac{(m+q_1+q_2)}{2m}R_i^{x-}$, $g_r^y = \frac{(m+q_1+q_2)}{2(q_1+q_2)}R_r^{y+}$ and $g_t^b = \frac{(m+q_1+q_2)}{2(q_1+q_2)}R_t^{b-}$, then the objective function of RAM with an inefficiency value of $1-\alpha$ can be transformed into $\min \sum_{i=1}^{m}\frac{s_i^{x-}}{2m}\frac{2m}{(m+q_1+q_2)R_i^{x-}} + \sum_{r=1}^{q_1}\frac{s_r^{y+}}{2(q_1+q_2)}\frac{2(q_1+q_2)}{(m+q_1+q_2)R_r^{y+}} + \sum_{t=1}^{q_2}\frac{s_t^{b-}}{2(q_1+q_2)}\frac{2(q_1+q_2)}{(m+q_1+q_2)R_t^{b-}}$, which has a similar form to model (2) in the main text. Similarly, the objective function of BAM with an inefficiency value of $1-\beta$ can also be transformed. As a result, the adjusted SBM-DDF model, RAM and BAM are all weighted additive models, but with different weights and efficiency or inefficiency measures.

The assumption of variable return to scale and the setting of ranges enable the efficiency value of RAM and BAM to be bounded in the interval [0, 1]. Comparing the ranges of possible improvement for desirable, undesirable outputs, and inputs in Equation (A1) and (A2), it is obvious that $B_r^{y+} \le R_r^{y+}$, $B_t^{b-} \le R_t^{b-}$, and $B_i^{x-} \le R_i^{x-}$. As a result, the inefficiency value of RAM $1-\alpha$ is less than or equal to BAM $1-\beta$, while the efficiency value of RAM is equal to or greater than BAM, that is, $\alpha \ge \beta$.