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Data-Driven Evaluation and Optimisation of Livelihood Improvement Efficiency

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Abstract: In this study, we developed a data-driven approach for the evaluation and optimisation of livelihood improvement efficiency (LIE) to address slowing global economic growth and the decline in well-being in the broader population, enhance the quality of people's livelihoods, and promote sustainable social development. We designed a questionnaire survey and constructed an evaluation index system based on a comprehensive consideration of economic resources, social security and employment, education, and health. Using principal component analysis, entropy weighting, and data envelopment analysis, we optimised the evaluation indicators and quantitatively assessed LIE. We used a Tobit regression model to analyse the factors influencing LIE and provide decision-making support for proposing countermeasures to optimise LIE. Based on the research data, we administered the questionnaire survey to 3125 residents in 16 cities in China's Anhui Province and demonstrated the applicability of the aforementioned method. The results indicate that there is room for optimising LIE in cities in Anhui Province, which needs to be achieved through the following steps: controlling costs and avoiding waste, encouraging entrepreneurship, increasing income, guiding the direction of industrial growth, optimising regional population structure, and promoting public participation to enhance people's livelihoods.

Keywords: data-driven; livelihood improvement efficiency; PCA–DEA; Tobit regression; optimisation measures

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1. Introduction

The efficiency of governance is a focal point of concern for politicians and academics [1]; it ensures sustainable regional development [2], and robust measures of efficiency and the implementation of effective incentive policies are essential for its improvement [3]. Consequently, in recent years, the assessment of government efficiency and the factors influencing it have been at the centre of political and academic debates [4].

Livelihood improvement is an important element of social governance. Livelihoods encompass a wide range of issues, including social security and employment, education, and health, that are closely related to people's lives. Increasing the efficiency of livelihood improvement means achieving the same, or even better, governance outcomes with fewer resources. Moreover, studying livelihood improvement efficiency (LIE) is of great significance to the improvement of people's quality of life [5] and their happiness [6]. For example, in terms of health, research shows that, in the absence of economic resource inputs and guarantees, population health can also be improved by implementing appropriate efficiency improvement strategies, such as optimising resource allocation and implementing accurate policy guarantees [7,8]. Meanwhile, some scholars have pointed out that LIE critically impacts the efficiency of government governance [9,10].

However, owing to the novel coronavirus disease (COVID-19), livelihood security has been severely threatened in some countries [11–14]. For example, some people in Europe are losing access to their rightful education [13,15]; the pandemic has slowed economic development in many countries [16], incomes are declining, and employment has become precarious, with unemployment rates increasing in many countries and regions, including the EU28 and the US [17–20]. This may further create or exacerbate the problems of employment equity and employment discrimination [21]. Owing to the severe global shortage of health resources, it is difficult to secure people's health, and this is especially evident in developing countries [22–25]. These factors also contribute to greater anxiety, which has led to mental health issues in residents of countries such as Israel and China [26,27] and has resulted in the intensification of social conflicts in some European countries [25,28]. Policy analysts at the Organisation for Economic Co-operation and Development (OECD) have pointed out that the challenges of social crises can be addressed by improving the efficiency of public sector governance [29]. In the current social and economic context, optimising the efficiency of livelihood improvements is urgent and critical. Meanwhile, people's subjective perceptions regarding how well their livelihoods are being improved and protected cannot be ignored, as when these perceptions are positive, people can better cope with anxiety.

Based on the importance of LIE for social governance and the real-life challenges faced in this regard, this study aimed to construct a method for evaluating and optimising LIE that considers residents' subjective feelings. Based on the existing research and aiming to address its shortcomings, this study features the following salient aspects: designing a livelihood improvement questionnaire and constructing a set of input–output evaluation indicators based on the questionnaire indicators to cover residents' subjective evaluations; using the PCA–DEA model and entropy method to measure and compare the efficiency of livelihood improvement in various regions of Anhui Province, China; and applying the Tobit econometric model to test the effects of several factors on the efficiency of livelihood improvement in Anhui Province.

2. Literature Review

Most current scholars discuss education, health, and employment when exploring the efficiency of livelihood improvement [30–33] but vary in how they further refine the indicators. For example, various indicators have been constructed for educational improvement efficiency: Andonova et al. constructed public expenditure as an input indicator and set output indicators involving secondary education graduates, secondary education completion rate, and total net enrolment rate, among others [3]; Tulio et al. constructed evaluation indicators of the number of teachers and students, and the achievements of the students [34]; Cossani et al. used the area of teaching facilities, academic staff, and operating costs, among others, as input indicators and the number and quality of publications as output indicators to measure the efficiency of the inputs and outputs of higher education [35]; Azar et al. used public expenditure on education per capita as an input indicator and 'average years of schooling' and 'population with secondary education as the highest educational level attained' as output indicators [36]; and Afonso et al. adopted school buildings per capita and primary school enrolment as output indicators [37]. Regarding social security and employment, Giovannae et al. used childbearing services, kindergartens, services for minors, leisure facilities, and care facilities for older and migrant population groups as indicators [4], whereas the evaluation indicators designed by Yangming Hu et al. include coverage of endowment insurance and minimum living allowance, employment rate, and the gap between urban and rural areas [38]. Regarding sanitation, Afonso et al. used water supply per inhabitant and municipal waste collection per inhabitant as indicators [37], and Vivian et al. employed evaluation indicators including diagnostic and primary health services [39]. Hu et al. used hospital beds per 1000 people to represent the health level [38].

Thus, scholars have devised rich and detailed systems of indicators, and their study findings have laid an important theoretical foundation for the study of livelihood improvement. However, few studies have dealt with residents' subjective evaluation of livelihood improvement, leaving a gap in the current literature. The education services, social security and employment, and health services involved in livelihood improvement are closely related to residents' lives, and residents' subjective evaluation of livelihood improvement can more accurately reflect the real effect of livelihood improvement.

Data envelopment analysis (DEA) does not require pre-estimated parameters and allows the data to be calculated directly. Thus, it is widely used, as it is advantageous for conducting more complex multi-input, multi-output efficiency assessments. DEA as an efficiency evaluation method was first proposed by Charnes, a famous American logistics scientist, in 1978 [40]. In previous studies, some scholars emphasised that the combination of principal component analysis (PCA) and that DEA can achieve better index dimension reduction and efficiency evaluation effects [41,42]. Poldaru et al. used PCA–DEA to evaluate the quality of life of residents of Estonian counties [43], whereas Sarra et al. applied this method to evaluate the well-being of residents of Italian cities [44]. In addition, the combination of the two methods has been widely used in efficiency evaluation in other fields, such as the operational efficiency of transportation companies [45], the management efficiency of banks [46], and the work performance of governments [47]. When the dependent variable has data truncation characteristics, ordinary least-squares calculations can result in biased parameter estimates; thus, Tobin proposed a restricted dependent variable model in 1958 [48]. To explore the possible factors influencing efficiency, scholars have attempted to combine DEA and Tobit regression. For example, Azar et al. used the DEA–Tobit analysis method to explore the efficiency of public education expenditure in Latin America and its influencing factors [36]; Samut et al. analysed health system efficiency and its influencing factors in OECD countries [49]; Hsu et al. conducted two studies to measure the performance of public expenditure in OECD countries [50] and the efficiency of health expenditure in Europe and Central Asia [51], respectively; Shin et al. evaluated the efficiency and influencing factors of health and social welfare [52].

In general, the PCA–DEA and DEA–Tobit evaluation methods have been studied in the literature; however, while the PCA–DEA method can achieve the efficiency evaluation of complex index system, it cannot accurately determine the possible influencing factors; the DEA–Tobit method can evaluate the influencing factors of efficiency but is not applicable in the case of facing a complex index system. When facing the complex system of LIE, there is no literature on how to apply PCA–DEA–Tobit to accurately evaluate LIE and analyse the influencing factors.

Many possible factors affect the efficiency of improving people's livelihood, and no unanimous conclusion exists regarding some aspects. For example, regarding the financial burden of the government, Liu et al. believe that a large financial burden will lead to efficiency in public service supply, including health security [38,53,54]. However, Fishback et al. revealed that, when the government's financial burden is high, it forces local governments to introduce special policies to improve the efficiency of public services [7,8]. Many researchers agree that the population of a region impacts the provision of livelihood-related services in that region. For example, Lin et al. emphasise that population size and population structure can be important influencing factors but do not provide further evidence on their specific impact [55]. Cao et al. found empirically that the total population of a region was negatively associated with the efficiency of health services [56]. Khan et al. argue that this negative correlation is mainly because, as the population size of a region increases, it negatively affects the equity and fairness of public services, and, by extension, service efficiency [57]. Mainardi et al. further refined their analysis of the impact of total population size by arguing that increasing the population size of a region in education services will promote the efficiency of those services but will reduce the efficiency of healthcare services [58]. Further, Liu et al. found that an increase in population density effectively promotes efficiency in the allocation of public services [59], whereas Song et al. found contrasting results [60]. The demographic quality of regional populations has also been the focus of scholarly discussion, and it is common for scholars to use educational level as a proxy for demographic quality. For example, Song et al. found that people with higher levels of education tend to have higher levels of satisfaction with livelihood services [60]; Afonso et al. argue that higher levels of education of the population are an important condition for more efficient health services [61], and Cruz et al. reported that local governments tend to be more efficient and perform better in governance in countries or regions where the population has more years of education [1,51]. The level of urbanisation (usually expressed as urban population/total population of the region) is a regional development indicator that has been of great interest in China. No research has yet examined the impact of urbanisation level on the efficiency of livelihood improvement; further, only studies related to livelihood improvement have addressed this indicator, and the results of these studies have been inconclusive [38,60]. Regional economic development is also an influential factor considered by scholars in their studies of social governance, and scholars often use gross regional product (GDP) as a measure of regional economic development. Cen et al. and Cao et al. suggest that regional economic development can effectively contribute to the efficiency of health services [7,56]. Moreover, in their study on the efficiency of government social security spending, Hu et al. concluded that higher GDP contributes to more efficient government work [38].

Although scholars have paid attention to the analysis of the possible influencing factors, there are still some research gaps: first, some researchers judge the influencing factors based on quantitative analysis and empirical judgments, and the results of such judgments tend to provide insufficient support for scientific arguments; second, when most researchers discuss the influencing factors, they either only analyse the impact of the factor on a particular aspect of the efficiency of livelihood improvement or examine the impact of the factor on overall social governance. Thus, few scholars focus specifically on the factors influencing the efficiency of livelihood improvement. Moreover, a review of the existing literature to speculate on the impact of factors such as fiscal burden and population situation on the efficiency of livelihood improvement does not lead to a consistent conclusion, the lack of which interferes with the government's efforts to introduce appropriate policies to optimise the efficiency of livelihood improvement. Therefore, what are the factors that influence the efficiency of livelihood improvement? How do these factors affect efficiency? These questions still need to be answered and clarified urgently.

To address the challenges raised above, bridge the existing knowledge gaps, better optimise the efficiency of livelihood improvement, improve livelihood governance, and promote sustainable development, this study proposes a data-driven approach to evaluating and optimising the efficiency of livelihood improvement. This study makes theoretical and practical contributions. The theoretical contributions are as follows: first, the study clarifies that, in the current economic and social context, an evaluation index of LIE should fully consider the subjective feelings of residents. Thus, a questionnaire on the improvement of people's livelihood was designed and conducted for the purposes of this study. The questionnaire was comprehensive, including social security and employment indicators, education indicators, and health indicators. The DEA evaluation index system was constructed using residents' subjective evaluation scores for livelihood improvement as output indicators and the amount and proportion of government financial expenditure as input indicators. This bridges the gap in output evaluation indicators, that is, they ignore residents' subjective feelings. The reflected results are more accurate and realistic, laying the foundation for the accurate evaluation of LIE. Second, PCA, DEA, and Tobit analysis methods are integrated to study LIE, which extends the theory in this field. Third, we construct a data-driven evaluation and optimisation process for LIE, analyse the possible influencing factors of LIE using scientific mathematical methods, and empirically demonstrate the influencing mechanisms of the factors to provide a scientific basis for the proposed optimisation strategy. The practical contributions of this study are as follows. First, it constructs an efficiency evaluation method for complex systems, which can help the government and researchers evaluate the efficiency of livelihood improvement more objectively than before and solve other similar problems. Second, based on the key factors influencing LIE, an action strategy for optimising LIE is proposed, which will improve people's quality of life and promote sustainable social development.

3. Data and Methodology

This section presents the data and methods used, including the index system and data sources, methodology, and empirical model. Section 4 shows the analytical and empirical process of applying these methods in Anhui, China. In Section 5, we discuss LIE in 16 cities in Anhui region using existing literature, consider the influencing factors and analyse their causes, and present the main contributions of this study. In Section 6, we conclude the article, propose an optimal response to LIE, and explain the study limitations and future outlook.

3.1. Data Collection

To better understand residents' subjective feelings about the improvement of people's livelihood, we designed a questionnaire for scoring and evaluating individuals according to their access to livelihood improvement. The design of the questionnaire was mainly based on the 'Decision on Several Major Issues on Modernizing the National Governance System and Governance Capacity' [62] promulgated by the Chinese government on 31 October 2019, with reference to the previous research base [30–33,63]. To more comprehensively reflect the improvement of people's livelihood, we designed the questionnaire indicator system to cover three broad areas: social security and employment, education, and health care; each area was then further refined. Each option is set at a score of 1–10. Residents will be required to evaluate their regions. The evaluation will be based on whether the changes that occurred in 2020 compared to 2019 are consistent with the situation described in the questionnaire. 10 means exactly consistent; 1 means absolutely not consistent. Obviously, a higher score indicates more acceptance of the situation described in the question, reflecting residents' higher recognition of this aspect of livelihood improvement work. The questionnaire contains 21 indicators (Table 1).

Table 1. Index system of the respondents' LIE questionnaire.

Category		Indicator Description	Serial Number
Social security and employment	Employment	providing wider range of employment opportunities	x_1
		Providing higher labor income	x_2
		Providing better employment public services	x_3
		Providing more robust employability skills training	x_4
		Reduced discrimination in employment	x_5
		Providing better management of the labor environment	x_6
	Social security	Better safeguards and services for children, women, and the older adults	x_7
		More robust support for people with disabilities	x_8
		Better protections and services for the poor	x_9
		Better social welfare and social assistance	x_{10}
		More rational development and planning of rural areas	x_{11}
Education		Better guidance services for home education	x_{12}
		Better online educational resources	x_{13}
		Providing more innovative and diverse popular science education	x_{14}
		Providing educational resources or learning materials that are better tailored to individual needs	x_{15}
		Providing more equitable educational opportunities	x_{16}
Health		Providing better supply of medicines	x_{17}
		Providing better public health services	x_{18}
		Providing better medical care	x_{19}
		Providing better accident and health insurance services for the older adults	x_{20}
		Providing better risk management of infectious disease outbreaks and public health emergencies	x_{21}

In order to further evaluate LIE scientifically and to make the evaluation results fully consider the subjective feelings of residents, we established DEA econometric model evaluation indicators based on the questionnaire indicators. Meanwhile, in order to more comprehensively evaluate the complex system of ILE, the evaluation indicators are refined into three aspects and the evaluation results of each aspect are obtained:

(1) Social security and employment: The input indicators include regional social security and employment fiscal expenditures, and social security and employment fiscal expenditures as a percentage of total regional fiscal expenditures. However, owing to the large number of indicators covered by social security and employment, it is not possible to directly apply the DEA method for calculation. Therefore, the output indicators (x_1–x_{11}) of the system need to be reduced by the PCA method; after this treatment, the output indicators are optimised, and most of the information of the original variables is retained. The final output variables in this study are calculated by PCA, with the simplified result $f_{output1} \ldots f_{outputi}$. The method and process of PCA calculation are shown in Section 3.2.2. The social security and employment input–output indicator system is shown in Table 2.

(2) Education: The input indicators include regional financial expenditures on education services and financial expenditures on education services as a percentage of total regional financial expenditures. The output indicator is the mean value of the results of residents' evaluation scores on employment services in the livelihood improvement questionnaire survey, with specific indicators x_{12}–x_{16}. The input–output indicator system is shown in Table 3.

(3) Health: Input indicators include regional financial expenditures on health services and the percentage of financial expenditures on health services to total regional financial expenditures. The output indicator is the mean value of the results of residents' evaluation scores on health services in the livelihood improvement questionnaire survey, with specific indicators x_{17}–x_{21}. The input–output indicator system is shown in Table 4.

The evaluation data for the questionnaire were obtained from a social survey, conducted in 16 cities in Anhui Province, China, from February–April, 2021. We surveyed a total of 3125 samples, of which 2265 were valid; the fiscal expenditure data were obtained from the Statistical Yearbook of Anhui Province and the statistical yearbooks of each region.

Table 2. Social security and employment input–output indicators.

Indicator Type	Index	Variable	Unit
Input index	Regional social security and employment fiscal expenditures	y_1	10,000 RMB
	Regional social security and employment fiscal expenditures/total regional fiscal expenditures	y_2	%
Output index	New variables obtained after processing the evaluation results of social security and employment(x_1–>x_{11}) in the questionnaire using the PCA method	$f_{output1}$ $f_{output2}$ $\vdots$ $f_{outputi}$	-

Table 3. Education input–output indicators.

Indicator Type	Index	Variable	Unit
Input index	Regional financial expenditures on education services	y_3	10,000 RMB
	Regional financial expenditures on education services/total regional financial expenditures	y_4	%
Output index	Mean value of the results of the sample's evaluation of x_{12}–>x_{16} in the questionnaire	$\overline{x_{12}}$	—
		$\overline{x_{13}}$	
		$\overline{x_{14}}$	
		$\overline{x_{15}}$	
		$\overline{x_{16}}$	

Table 4. Health input–output indicator.

Indicator Type	Index	Variable	Unit
Input index	Regional financial expenditures on health services	y_5	10,000 RMB
	Regional financial expenditures on health services/total regional financial expenditures	y_6	%
Output index	Mean value of the results of the sample's evaluation of x_{17}–>x_{21} in the questionnaire	$\overline{x_{17}}$	—
		$\overline{x_{18}}$	
		$\overline{x_{19}}$	
		$\overline{x_{20}}$	
		$\overline{x_{21}}$	

3.2. Methodology or Empirical Model

3.2.1. Method Flow

This study established a data-driven approach to measuring, evaluating, and optimising LIE. For data collection, we used questionnaire survey data on social security and employment, education, and health as output indicators and employed corresponding government finance data as the input indicator to construct a DEA model for the evaluation index system. During data processing, we reduced and simplified the output indicators of the social security and employment system by combining PCA and the modified extreme difference method. We built the DEA model to quantitatively analyse the regional social security and employment system, education system, and health system and applied the entropy weighting method to compute the overall LIE. Based on these calculations, we applied the Tobit regression model to examine the main influencing factors of LIE and proposed an optimisation method for efficiency in a targeted manner.

3.2.2. Data Processing

Principal Component Analysis (PCA)

The DEA model requires two basic conditions to be met: (1) the input and output indicators cannot be negative, and (2) the sum of the input and output indicators cannot be more than one half of the number of decision-making units (DMUs). The total number of variables in the social security and employment system exceeded the requirements of the operation and could not be calculated directly using the DEA model. The common methods of dimensionality reduction were entropy weighting, PCA, and hierarchical analysis. Given the strong correlation between indicators, PCA is usually chosen to reduce the overlap of information expressed by these indicators. This method can transform multiple indicators into a few composite ones that can retain as much information about the original variables as possible and that are not correlated with each other. We proposed using objectively assigned PCA to simplify the indicators.

Assume that there are n samples, each with m variables. The m indicator variables first need to be standardised by the Z-score, which in turn, constructs the $n \times m$ standardised raw variable matrix of the order set as

$$Z = \begin{bmatrix} z_{11}\ z_{12}\ \ldots\ z_{1m} \\ z_{21}\ z_{22}\ \ldots\ z_{2m} \\ \vdots\vdots\vdots \\ z_{n1}\ z_{n2}\ \ldots\ z_{nm} \end{bmatrix}.$$

Assuming $f_1, f_2, \ldots, f_t\ (t < m)$ denotes the principal component, the relationship between the principal component and the standardised original variable can be expressed through Equation (1):

$$\begin{cases} f_1 = \alpha_{11}z_1 + \alpha_{12}z_2 + \ldots \alpha_{1m}z_m \\ f_2 = \alpha_{21}z_1 + \alpha_{22}z_2 + \ldots \alpha_{2m}z_m \\ \vdots\vdots\vdots\vdots \\ f_t = \alpha_{t1}z_1 + \alpha_{t2}z_2 + \ldots \alpha_{tm}z_m \end{cases} \tag{1}$$

Equation (1) can be matrix transformed and expressed as: $F = AX$, where

$$\mathrm{F} = \begin{bmatrix} \mathrm{f_1} \\ \mathrm{f_2} \\ \vdots \\ \mathrm{f_t} \end{bmatrix}, A = \begin{bmatrix} \alpha_{11}\ \alpha_{12}\ \ldots\ \alpha_{1m} \\ \alpha_{21}\ \alpha_{22}\ \ldots\ \alpha_{2m} \\ \vdots\vdots\vdots \\ \alpha_{t1}\ \alpha_{t2}\ \ldots\ \alpha_{tm} \end{bmatrix},\ \mathrm{X} = \begin{bmatrix} \mathrm{z_1} \\ \mathrm{z_2} \\ \vdots \\ \mathrm{z_m} \end{bmatrix}$$

Equation (1) satisfies the following conditions: (1) the coefficient matrix A is an orthogonal matrix, each row is a unit vector, with $\alpha_{i1}^2 + \alpha_{i2}^2 + \ldots \alpha_{im}^2 = 1, (i = 1, 2, 3 \ldots t)$; (2) $\mathrm{Var}(\mathrm{f_1}), \mathrm{Var}(\mathrm{f_2}), \ldots \mathrm{Var}(\mathrm{f_t})$ the value of which is gradually decreasing; (3) $\mathrm{f_i}$ with $\mathrm{f_j}$ $(\mathrm{i} \neq \mathrm{j}, \mathrm{I}, \mathrm{j} = 1, 2, \ldots, \mathrm{t})$ are not correlated with each other, that is, $\mathrm{Cov}(\mathrm{f_i}, \mathrm{f_j}) = 0$.

This method allows for the conversion of the standardised original variables into new composite variables, also known as principal components.

Data Standardisation

Assuming that p effective principal components are obtained, the effective principal component score of each sample obtained is denoted as $f_{si},\ s = 1, 2, 3 \ldots n, i = 1, 2, 3 \ldots, p$. The individual principal component scores are further averaged regarding the corresponding survey sample for each city and denoted as $\overline{f_{ri}},\ r = 1, 2, 3 \ldots 16, i = 1, 2, 3 \ldots p$. In the obtained $\overline{f_{ri}}$, there may be negative values, and considering the operational requirements of the DEA model, it is necessary to convert $\overline{f_{ri}}$. The new variables obtained are converted to positive values and $f_{outputi}$. The new variables obtained are substituted for the original variables in the DEA model for calculation, and the transformation method is as follows:

$$f_{outputri} = 0.1 + \frac{\overline{f_{ri}} - min\left\{\overline{f_{ri}}\right\}}{max\left\{\overline{f_{ri}}\right\} - min\left\{\overline{f_{ri}}\right\}} \times 0.9 \tag{2}$$

This method of calculation effectively prevents the appearance of '0' and 'negative' values, effectively reduces and simplifies the indicators, and makes the DEA model outcomes more scientifically accurate.

3.2.3. Evaluation Model

Data Envelopment Analysis Model

It is assumed that the evaluation process has n decision-making units, DMU$_i$ ($\boldsymbol{i = 1, 2, \ldots, n}$), where n decision units satisfy the assumption of homogeneity and all are comparable. Each DMU has t input elements and yields s outputs. Next, there are input and output vectors, respectively:

$$\boldsymbol{X_i = (x_{1i}, x_{2i}, \ldots x_{ti})^T > 0, i = 1, 2, \ldots n}$$

$$\boldsymbol{Y_i = (y_{1i}, y_{2i}, \ldots y_{si})^T > 0, i = 1, 2, \ldots n}$$

$\boldsymbol{x_{ji}}$ denotes the input of the jth input of the ith DMU, where $\boldsymbol{x_{ji} > 0}$, and $\boldsymbol{y_{ji}}$ refers to the output quantity of the jth output of the ith *DMU*, where $\boldsymbol{y_{ji} > 0}$.

To integrate all DMUs uniformly, each input and output need to be assigned a value such that the weight vectors of the inputs and outputs are, respectively

$$\boldsymbol{v = (v_1, v_2, \ldots v_t)^T}$$

$$\boldsymbol{u = (u_1, u_2, \ldots u_s)^T}$$

where $\boldsymbol{v_j}$ denotes the weight of the jth input and $\boldsymbol{u_r}$ signals the weight of the rth output. Define each $\boldsymbol{DMU_i}$ of the efficiency evaluation index as $\boldsymbol{k_i = \frac{\sum_{r=1}^{s} u_r y_{ri}}{\sum_{j=1}^{t} v_j x_{ji}}}$.

Based on the analysis given above, the CCR model (this method was proposed by Charnes, Cooper, and Rhodes; hence, it is commonly known as the CCR model [40]). The mathematical expression of the CCR model is shown below (note $\boldsymbol{X_0 = X_{i_0},\ Y_0 = Y_{i_0}}$):

$$\boldsymbol{MAXk_{i_0} = \frac{\sum_{r=1}^{s} u_r y_{ri_0}}{\sum_{j=1}^{t} v_j x_{ji_0}}}$$

$$s.t.\begin{cases} \boldsymbol{\frac{\sum_{r=1}^{s} u_r y_{ri}}{\sum_{j=1}^{t} v_j x_{ji}} \leq 1, i = 1, 2, \ldots n} \\ \boldsymbol{v = (v_1, v_2, \ldots v_t)^T \geq 0} \\ \boldsymbol{u = (u_1, u_2, \ldots u_s)^T \geq 0} \end{cases}.$$

Using the Charnes–Cooper transformation, it can be transformed into an equivalent linear model:

$$\begin{cases} \boldsymbol{max\mu^T Y_0} \\ \boldsymbol{s.t\ \omega^T X_i - \mu^T Y_i \geq 0, i = 1, 2, \ldots, n} \\ \boldsymbol{\omega^T X_0 = 1} \\ \boldsymbol{\omega \geq 0, \mu \geq 0} \end{cases} \quad (3)$$

According to linear pairwise theory, the pairwise programming model of Model (3) is obtained as:

$$\begin{cases} \boldsymbol{min\theta} \\ \boldsymbol{\sum_{i=1}^{n} X_i \lambda_i \leq \theta X_0} \\ \boldsymbol{\sum_{i=1}^{n} Y_i \lambda_i \geq Y_0} \\ \boldsymbol{\lambda_i \geq 0, i = 1, 2, \ldots, n} \end{cases} \quad (4)$$

where θ is the parameter to be estimated and the optimal solution is $\boldsymbol{\theta^*}$, which is the efficiency value of the DMU, $\boldsymbol{0} \leq \theta^* \leq \boldsymbol{1}$. When $\theta^* = \boldsymbol{1}$, the DMU is on the efficiency frontier, and there is no possibility of the equal reduction of each input, and, thus, it is DEA-effective. When $\theta^* < \boldsymbol{1}$, the DEA is ineffective, and the inputs and outputs can be further optimised to improve efficiency. Clearly, when θ^* is higher, the greater is the efficiency value represented, which indicates the highest overall level of sustainability in this study.

The CCR model includes the premise that returns to scale (RTS) are constant. The model can only measure 'technical efficiency', and when the CCR model DEA is valid, the DMU is both purely technically efficient and scale-efficient. However, to further explore 'pure technical efficiency' and 'scale efficiency' (SE), the BCC model (this method was proposed by Banker, Charnes, and Cooper; hence, it is commonly known as the BCC model [64]) should be introduced. When variable RTS are assumed, it is known as the BBC model. The linearity of the BCC model is obtained by introducing the constraint in Model (4), $\sum_{i=1}^{n} \boldsymbol{\lambda} = \mathbf{1}$. The linear expression for the BCC model is obtained as:

$$\begin{cases} \boldsymbol{min\theta} \\ \sum_{i=1}^{n} \boldsymbol{X_i \lambda_i} \leq \boldsymbol{\theta X_0} \\ \sum_{i=1}^{n} \boldsymbol{Y_i \lambda_i} \geq \boldsymbol{Y_0} \\ \sum_{i=1}^{n} \boldsymbol{\lambda} = \mathbf{1} \\ \boldsymbol{\lambda_i} \geq \mathbf{0}, \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{n} \end{cases} \quad (5)$$

The optimal solution of Model (5) is $\boldsymbol{\theta}^*$, and $\mathbf{0} \leq \boldsymbol{\theta}^* \leq \mathbf{1}$.

In comparing the CCR model and the BCC model, the effective values obtained from the two models have different meanings in economics; the CCR model leads to technical efficiency (TE), whereas the BCC model results in pure technical efficiency (PTE). Both models satisfy the relationship TE = PTE × SE, solving both Models (4) and (5), which yields TE, PTE, SE, and RTS.

TE is the ratio of the minimum potential input to the actual input. The higher the TE, the more efficient the government's resource allocation, resource usage capacity, and technical means of management in improving people's livelihoods. PTE is influenced by the ability to employ resources and the technology, means, and methods of management. SE is influenced by the appropriateness of the scale of resource input for livelihood improvement. The closer the value is to 1, the closer the existing scale is to the optimal scale. RTS refer to a state in which the input–output system of livelihood governance of a DMU is in, and the extent to which the corresponding output is expanded when the input is expanded by a factor of N. The optimal solution $\boldsymbol{\lambda}^*$ can be found using the CCR model (Model 4). If SE = 1, this means that, at this time, when the livelihood governance inputs are expanded by a factor of N, the output indicators are also expanded by a factor of N. It is called constant RTS. If SE $< \mathbf{1}$, and, in any optimal solution $\sum \boldsymbol{\lambda}^* < \mathbf{1}$, this means that, when the inputs are expanded by a factor of N, the expansion of the output indicators should be greater than a factor of N. This is called increasing RTS, and increasing the input scale of the input indicators needs to be considered at this point. If the efficiency of scale $< \mathbf{1}$, and in any optimal solution $\sum \boldsymbol{\lambda}^* > \mathbf{1}$, it means that when the input is expanded by a factor of N, the expansion of the output indicator has to be less than a factor of N. This is called diminishing RTS, and reducing the size of the input needs to be considered at this point.

Entropy Weight Method

Simultaneously solving Models (4) and (5) leads to TE, PTE, SE, and RTS. Based on the input–output index system (see Tables 2–4) for the three aspects of livelihood improvement (social security and employment, education, and health), the corresponding efficiency values were measured using the DEA model to evaluate the efficiency of the three aspects. To further acquire the LIE, the efficiency values obtained from the three aspects need to be assigned and combined, and the study used the entropy-weighting method to integrate the three efficiency values.

The entropy method is a calculation technique that objectively assigns weights to indicators based on the amount of information they contain, and it is widely employed in statistical analysis. The entropy weighting method can reflect the utility value of the indicator information entropy value, and the indicator weighting value has high credibility, which is suitable for use in combination with DEA [65]. Specific calculations are issued as follows.

With n samples and m indicators, the information entropy value of each indicator is h_j, then $h_j = -K\sum_{i=1}^{n}(P_{ij}lnP_{ij})$, where $P_{ij} = x_{ij}/\sum_{i=1}^{n}x_{ij}$, and $K = 1/ln(n)$. If $P_{ij} = 0$, then $P_{ij}lnP_{ij} = 0$ is defined. Let the weight value of each indicator be w_j, then $w_j = e_j/\sum_{j=1}^{m}e_j$, where $e_j = 1 - h_j$, and it is obvious that $\sum_{j=1}^{m}w_j = 1$, and $0 \leq w_j \leq 1$.

3.2.4. Regression and Analysis

Relying on the above data processing and the DEA model can achieve an accurate evaluation of regional LIE; however, it is not possible to evaluate the influencing factors of efficiency. The optimisation of LIE needs to be supported by scientific analysis, which requires appropriate regression models to accurately determine the influencing factors and provide a scientific basis for the improvement of efficiency. Since the efficiency value measured by the DEA model is $(0,1]$, the LIE, integrated by the entropy weighting method, is also in the range of $(0,1]$. In reference to Azar et al. [36,48–52], we used a Tobit model based on great likelihood estimation to analyse the factors influencing LIE. The model equation is as follows.

$$\mathbf{Y_i} = \alpha_0 + \sum_{i=1}^{n}\alpha_i\mathbf{X_i} + \varepsilon_i \ \mathbf{i} = 1, 2, 3 \ldots \mathbf{n} \tag{6}$$

where $\mathbf{Y_i}$ is the dependent variable for the regression analysis, which, in this study, refers to LIE. $\mathbf{X_i}$ denotes the independent variable, that is, the influencing factor. α_i represents the parameter to be estimated. ε_i signals the random disturbance term, and n represents the number of independent variables.

Because we intended to verify the possible influences of LIE, LIE was chosen as the dependent variable. Six possible influencing factors were hypothesised for this study, as follows:

(1) Financial burden (FB): Based on previous studies [7,8,53,54], we hypothesise that the financial burden of the region would be an influential factor in the efficiency of livelihood improvement. This is because the government will adopt different action strategies depending on the fiscal expenditure and revenue; for example, the government will prioritise limited funds to other key areas and reduce attention to livelihood improvement areas, or it will introduce some special efficiency optimisation strategies to improve the efficiency of funds. The study expresses the financial burden in terms of total annual fiscal expenditure/total annual fiscal revenue.

(2) Population size (PS): An increase in population size may lead to the inequitable distribution of public service resources but may also increase the efficiency of government service delivery owing to the agglomeration effect of population. Based on previous research findings [55–58], it is speculated that the total population is a possible influence; however, based on the existing research literature, inconsistent conclusions have been reached, and further validation is needed to determine how this affects LIE. This study uses the total population of the region to represent the population size.

(3) Population density (PD): Because population density and population size may have similar mechanisms of influence on LIE based on our analysis of the literature [59,60], we speculate that population density is also a factor influencing LIE. However, whether the effect of population density on LIE is a facilitator or a hindrance has not been consistently concluded by previous studies and requires further validation. In this study, population density was expressed as total regional population/regional land area.

(4) Population quality (PQ): Based on the analysis of existing literature [1,51,60,61], the regional population's quality affects their evaluation of regional livelihood improvement and influences their participation behavior in government governance, so we estimate that regional population quality will be an influencing factor in the efficiency

of livelihood improvement. In this study, the regional population quality is expressed in terms of the number of college degrees per 100,000 people in the region.

(5) Urbanisation Level (UL): As the level of regional urbanisation changes, the aggregation of industries and means of production will change, along with the quality of social security and public services, as verified in the previous research literature [38,60]. Therefore, the study hypothesises that the level of regional urbanisation impact LIE. The urbanisation level is represented by urban population/total population of the region.

(6) Economic Development Level (EDL): The regional level of economic development will affect the overall social governance efficiency of the region [7,38,56], and, as the income level of the residents changes, people will have higher demands on the level of social governance, resulting in changes in their evaluation. Thus, we assume that the regional level of economic development will impact LIE. In this study, GDP is used to express the level of economic development.

The units and descriptions of the influencing factors for the above hypotheses are summarised in Table 5:

Table 5. Regression model index system of LIE influence factors.

Independent Variable	Unit	Calculation
Financial burden (FB)	(%)	total annual fiscal expenditure/total annual fiscal revenue
Population size (PS)	persons	Total population of the region
Population density (PD)	persons/km^2	total regional population/regional land area
Population quality (PQ)	persons	the number of college degrees per 100,000 people in the region.
Urbanisation Level (UL)	%	urban population/total population of the region
Economic Development Level (EDL)	100 billion RMB	GDP

4. Case Study

4.1. Data Collection

Anhui Province is located in central–eastern China and is part of the dynamic Yangtze River Delta. Anhui Province is approximately 570 km long from north to south and 450 km wide from east to west, with a total area of 140,100 square kilometres, accounting for approximately 1.45% of China's territory. By the end of 2021, Anhui Province had a population of 61.13 million residents. There are 16 cities in Anhui: Hefei, Huabei, Bozhou, Suizhou, Bengbu, Fuyang, Huainan, Chuzhou, Liuan, Maonshan, Wuhu, Xuancheng, Tongling, Chizhou, Anqing, and Huangshan (see Figure 1). Studying LIE in each city in Anhui and summarising its influencing factors is crucial for effectively allocating social resources and improving the quality of livelihoods. It is essential to distribute social resources effectively, boost the quality of livelihood governance, and promote sustainable social development.

Based on the questionnaire shown in Table 1, this study conducted an extensive social survey in 16 cities in Anhui Province, China, from February to April 2021. A total of 3125 samples were collected, among which, 2265 were valid samples. The descriptive statistics are shown in Table 6.

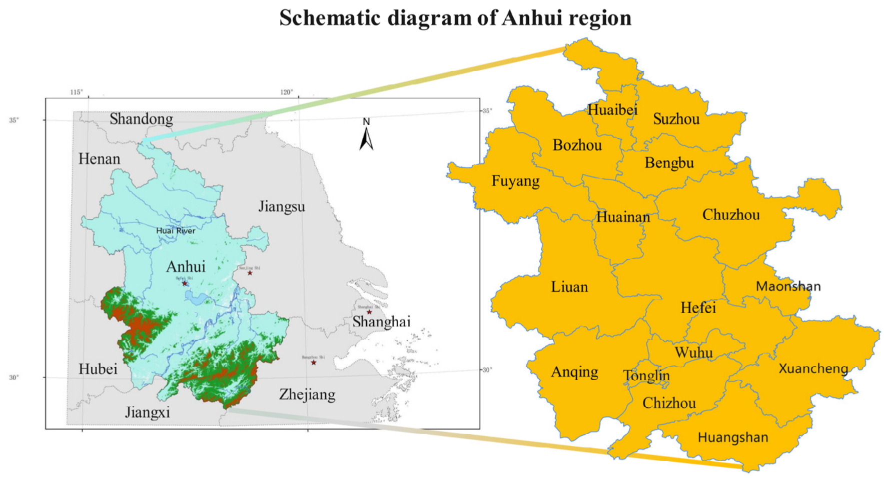

Figure 1. Schematic diagram of the administrative divisions of Anhui Province.

Table 6. Descriptive statistics of the questionnaire results.

Variables	Sample Size	Minimum	Maximum	Mean	Standard Deviation
x_1	2265	1	10	6.030	2.272
x_2	2265	1	10	6.190	2.190
x_3	2265	1	10	6.180	2.217
x_4	2265	1	10	5.800	2.304
x_5	2265	1	10	6.080	2.270
x_6	2265	1	10	6.490	2.127
x_7	2265	1	10	6.440	2.175
x_8	2265	1	10	6.470	2.182
x_9	2265	1	10	6.570	2.187
x_{10}	2265	1	10	6.510	2.175
x_{11}	2265	1	10	5.950	2.229
x_{12}	2265	1	10	6.160	2.192
x_{13}	2265	1	10	6.660	2.190
x_{14}	2265	1	10	6.220	2.186
x_{15}	2265	1	10	6.650	2.200
x_{16}	2265	1	10	5.890	2.221
x_{17}	2265	1	10	6.600	2.141
x_{18}	2265	1	10	6.720	2.091
x_{19}	2265	1	10	6.730	2.117
x_{20}	2265	1	10	6.620	2.138
x_{21}	2265	1	10	6.890	2.116

The data of input indicators were obtained by consulting the statistical yearbook of Anhui Province and the statistical yearbook of each city; the corresponding descriptive statistics are shown in Table 7.

Table 7. Descriptive statistics of input indicators.

Variables	Sample Size	Minimum	Maximum	Mean	Standard Deviation
y_1	16	186,538.000	1,107,714.000	541,093.000	274,903.467
y_2	16	0.092	0.167	0.134	0.020
y_3	16	225,563.000	1,975,427.000	703,203.063	449,379.511
y_4	16	0.109	0.205	0.165	0.025
y_5	16	192,826.000	914,630.000	456,196.125	225,891.215
y_6	16	0.074	0.146	0.114	0.018

4.2. Application of the Method and Model

4.2.1. Data Processing Results

Based on the processing method outlined in Section 3.2.2, we used SPSS 23.0 from IBM, USA to separately analyse the employment indicators ($\mathbf{x_1}, \ \mathbf{x_2} \ldots \mathbf{x_6}$), the social security indicators ($\mathbf{x_7}, \ \mathbf{x_8} \ldots \mathbf{x_{11}}$), and the composite variable values, that is, the principal component scores, which we obtained for each sample. The data source comprised 2265 valid questionnaires obtained from the 16 abovementioned cities in Anhui Province. After the data analysis, the KMO sample suitability test results for the employment and social security indicators were 0.926 and 0.914, respectively, both higher than 0.5. The outcome of Bartlett's sphericity test was 0.000, which is less than the general significance level, suggesting that the corresponding indicators were well suited for PCA, and the analysis was effective. Through the calculation, we extracted one principal component for each of the employment and social security indicators, recorded as f_1 and f_2. The results of the calculation are shown in Tables 8 and 9.

Table 8. Eigenvalues and variance contributions of the principal components.

Principal Component	Eigenvalue	Variance Contribution Rate
f_1	4.775	79.581
f_2	4.237	84.732

Table 9. Initial variable loading matrix for the principal components.

Variable	Principal Component f_1	Variable	Principal Component f_2
x_1	0.934	x_7	0.953
x_2	0.800	x_8	0.950
x_3	0.929	x_9	0.956
x_4	0.926	x_{10}	0.945
x_5	0.913	x_{11}	0.801
x_6	0.842		

The calculation results showed that the variance contribution rate of both principal components reached above 75%, and the loading coefficients of the initial variables all reached above 0.8, thereby indicating that the extracted principal components could explain the information of the initial variables better. The linear expressions of the initial variables and each principal component can be calculated according to the coefficients of the loading matrix, which are calculated as

$$a_{ij} = \frac{x_{ij}}{\sqrt{\lambda_i}} \tag{7}$$

where a_{ij} denotes the coefficient of the jth indicator in the linear combination of the i-th principal component, x_{ij} refers to the loading coefficient of the jth indicator on the i-th principal component, and λ_i is the characteristic root of the i-th principal component.

The linear expression of the two principal components can be obtained from Equation (7):

$$\begin{cases} \mathbf{f_1 = 0.427 * z_1 + 0.366 * z_2 + 0.425 * z_3 + 0.424 * z_4 + 0.418 * z_5 + 0.385 * z_6} \\ \mathbf{f_2 = 0.462 * z_7 + 0.460 * z_8 + 0.425 * z_9 + 0.424 * z_{10} + 0.418 * z_{11}} \end{cases} \quad (8)$$

Based on Equation (8), the principal component scores of each research sample can be calculated. Subsequently, based on the computed mean principal component scores for each urban survey sample, we performed further normalisation using Equation (2). The results of the calculations are shown in Table 10.

Table 10. Calculation of principal components and normalisation for employment and social security indicators.

Region	$\overline{f_1}$	$\overline{f_2}$	$f_{output1}$	$f_{output2}$
Anqing	0.0287337	−0.0143122	0.531938941	0.444850064
Bengbu	−0.2150978	−0.2604501	0.1	0.141746056
Bozhou	0.0326928	0.1442181	0.538952348	0.640070586
Chizhou	−0.2007589	−0.1691086	0.125400858	0.254227615
Chuzhou	0.1252315	0.1903883	0.702881406	0.696926408
Fuyang	−0.1472267	−0.1899701	0.220231271	0.228537933
Hefei	0.0841773	0.0093293	0.630155332	0.473963148
Huaibei	−0.117267	−0.2557187	0.273303827	0.14757249
Huainan	−0.048999	−0.143835	0.394238192	0.285350532
Huangshan	−0.1771068	−0.2943503	0.167299723	0.1
Luan	−0.112277	−0.0876711	0.282143437	0.354512994
Maonshan	0.0024162	0.1145062	0.485318414	0.60348217
Suzhou	0.0602352	0.1196129	0.587742742	0.609770763
Tongling	0.011817	0.0407191	0.501971601	0.512617797
Wuhu	−0.0537476	−0.1192959	0.385826214	0.315568957
Xuancheng	0.2929563	0.4365015	1	1

After PCA, using two composite indicators ($f_{output1}$ and $f_{output2}$), the information was expressed via the original 11 indicators ($x_1, x_2, \ldots x_{11}$). It simplified the original index system by solving the problem of overlapping information of indicators in the original index system, reducing the indicators, and optimising the index system. As the total number of input–output indicators in the education and health systems was less than one-half of the DMU, the original indicator data were used for direct calculations.

4.2.2. Model Evaluation Results

The input–output variables in Tables 2–4 were imported into MaxDEA 8 software, and the CCR model and BBC model were applied to derive the TE, PTE, SE, and RTS values for social security and employment, education, and health in Anhui Province in 2020. The calculation results are presented in Table 11.

Table 11. Results of the DEA evaluation in Anhui Province in 2020.

DMU	Social Security and Employment				Education				Health			
	TE	PTE	SE	RTS	TE	PTE	SE	RTS	TE	PTE	SE	RTS
Anqing	0.478	0.778	0.614	IRS	0.683	0.698	0.978	DRS	0.796	0.844	0.943	DRS
Bengbu	0.124	0.732	0.169	IRS	0.675	0.690	0.979	DRS	0.878	0.883	0.994	IRS
Bozhou	0.487	0.689	0.707	IRS	0.590	0.602	0.981	DRS	0.672	0.725	0.927	DRS
Chizhou	0.543	1.000	0.543	IRS	0.996	1.000	0.996	DRS	0.857	0.905	0.946	IRS
Chuzhou	0.656	0.844	0.777	IRS	0.754	0.775	0.973	DRS	0.865	0.996	0.868	DRS
Fuyang	0.170	0.594	0.286	IRS	0.635	0.642	0.988	DRS	0.639	0.642	0.995	DRS
Hefei	0.839	1.000	0.839	IRS	0.738	0.756	0.975	DRS	1.000	1.000	1.000	-
Huaibei	0.484	0.940	0.515	IRS	0.697	0.698	0.999	IRS	0.874	0.937	0.933	IRS
Huainan	0.326	0.648	0.503	IRS	0.721	0.734	0.981	DRS	0.707	0.718	0.985	IRS
Huangshan	0.242	0.787	0.308	IRS	1.000	1.000	1.000	-	1.000	1.000	1.000	-
Luan	0.316	0.733	0.432	IRS	0.655	0.665	0.985	DRS	0.730	0.731	0.999	DRS
Maonshan	0.719	0.893	0.805	IRS	0.870	0.985	0.883	DRS	0.987	0.989	0.998	IRS
Suzhou	0.536	0.774	0.692	IRS	0.686	0.704	0.975	DRS	0.792	0.901	0.880	DRS
Tongling	0.832	1.000	0.832	IRS	1.000	1.000	1.000	-	1.000	1.000	1.000	-
Wuhu	0.382	0.828	0.461	IRS	0.726	0.741	0.980	DRS	1.000	1.000	1.000	-
Xuancheng	1.000	1.000	1.000	-	0.972	1.000	0.972	DRS	0.849	1.000	0.849	DRS
Average	0.508	0.828	0.593		0.775	0.793	0.978		0.853	0.892	0.957	

Note: DRS in the table indicates decreasing RTS;—refers to constant RTS, and IRS denotes increasing RTS.

To compare the results of the governance evaluation in each area in more detail, we converted the data in Table 11 into a 3D scatter plot, as displayed in Figure 2.

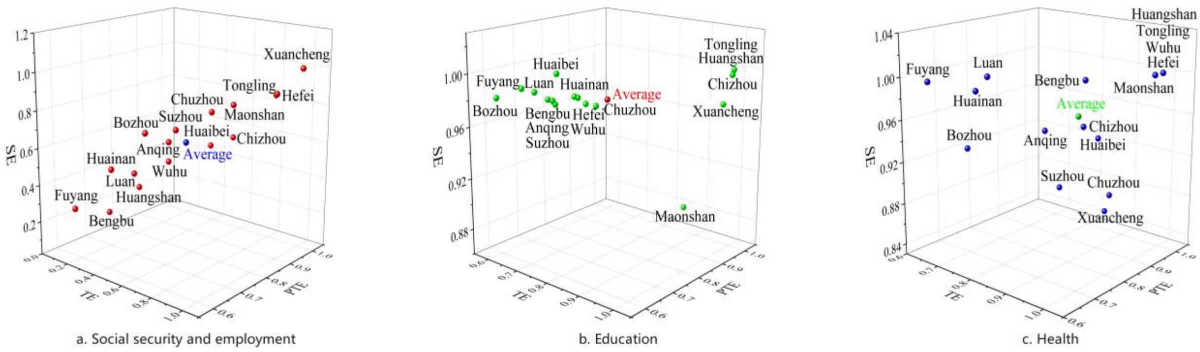

Figure 2. 2020 DEA evaluation results of Anhui Province.

Only when TE = 1 are the PTE and SE of the region effective, that is, the resource allocation and governance capacity are in the best condition. As shown in Table 11 and Figure 2, most technical efficiencies for improving people's livelihoods in terms of social security and employment, education, and health in Anhui Province have not reached 1, implying that there is room for optimising the efficiency of resource utilisation, management techniques, and resource allocation.

Based on the evaluation outcomes reported in Table 11, we processed the results of the DEA evaluation of the improvement efficiency of social security and employment, education, and health in Anhui Province in 2020 using the entropy-weight method via EXCEL software and combined them into LIE. The integration results are shown in Table 12.

Table 12. Evaluation results of LIE in Anhui Province in 2020.

DMU	TE	PTE	SE
Anqing	0.645802455	0.757443219	0.803398158
Bengbu	0.54949543	0.750292732	0.627187549
Bozhou	0.578245574	0.657733757	0.838458743
Chizhou	0.805474925	0.976555123	0.771853279
Chuzhou	0.751357139	0.850002954	0.844639768
Fuyang	0.48306782	0.628320886	0.680199606
Hefei	0.841031805	0.88784337	0.923452426
Huaibei	0.672172731	0.827863661	0.755705454
Huainan	0.586874699	0.704915436	0.770477614
Huangshan	0.749980567	0.937974081	0.691333406
Luan	0.563745943	0.701121297	0.745638442
MaOnShan	0.851253825	0.959028768	0.891601021
Suzhou	0.665273795	0.77318612	0.81216636
Tongling	0.942944288	1	0.9233847
Wuhu	0.68764476	0.830742396	0.758335426
Xuancheng	0.947180501	1	0.935996326

To visually represent and compare the evaluation outcomes of LIE in each city and region, based on the calculation results reported in Table 12, we plotted a radar chart, shown in Figure 3.

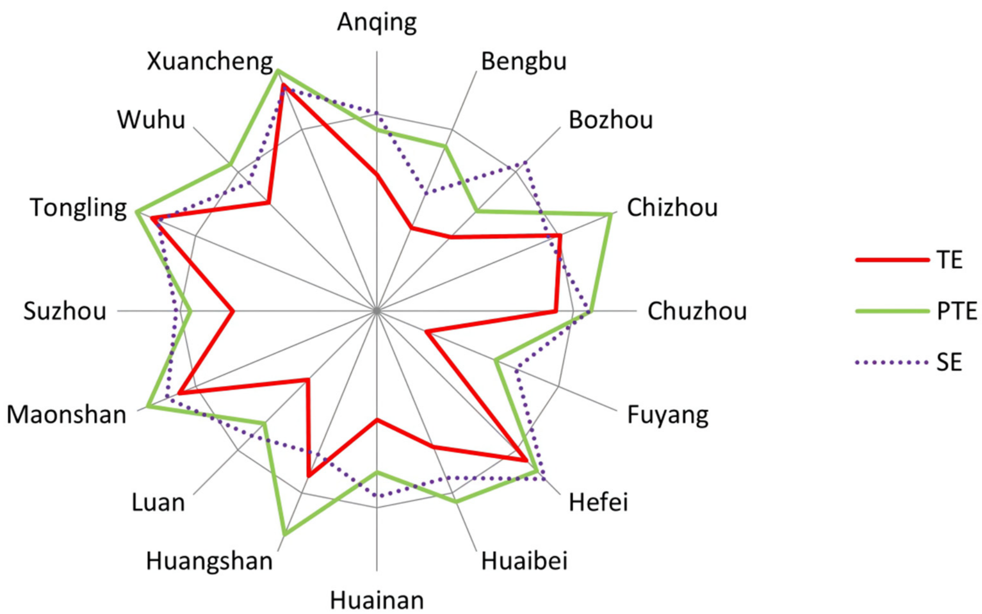

Figure 3. Radar chart of LIE evaluation results in Anhui Province in 2020.

As shown in Table 12 and Figure 3, the trend of TE in improving people's livelihoods in each region of Anhui Province was found to be similar to that of PTE, implying that the TE of Anhui regions is mainly influenced by PTE. Regarding TE, Huangshan, Chuzhou, Chizhou, Hefei, Maonshan, Tongling, and Xuancheng performed better and exceeded the average TE level of Anhui Province. As for PTE, Wuhu, Chuzhou, Hefei, Huangshan, Maonshan, Chizhou, Tongling, and Xuancheng performed better, thus reflecting the higher efficiency of these regions in enhancing people's livelihoods.

4.2.3. Regression Analysis Results

The TE of livelihoods is a composite indicator obtained by multiplying the PTE and SE of livelihoods. PTE reflects the ability to manage and utilise the resources employed for livelihood improvements and demonstrates the government's management tools and efficiency. SE underscores the reasonableness of the scale and the quantity of resource allocation. Therefore, we used PTE as the dependent variable, mainly because this value eliminates the influence of SE and can most accurately reflect the efficiency of local governments in enhancing people's livelihoods. To further investigate the influencing factors of LIE, we performed more calculations according to the regression method in Section 3.2.4. As shown in Table 5, PTE was used as the dependent variable, and FB (%), PZ (people), PD (people/km_2), PQ (people), UL (%), and EDL (100 billion RMB) were used as the independent variables (the statistical description of the independent variables is shown in Table 13). We imported the corresponding data for each region of Anhui Province into Stata 16.0 and conducted the Tobit regression analysis using Model (6). The regression model fitted well, and the chi-square test was significant. The results of the calculation are presented in Table 14.

Table 13. Statistical description of influencing factors.

Variables	Sample Size	Minimum	Maximum	Mean	Standard Deviation
FB	16	1.466	3.803	2.521	0.766
PS	16	1,311,700.000	9,369,900.000	3,814,206.250	2,332,106.051
PD	16	135.679	818.689	470.768	219.756
PQ	16	6710.000	26,390.000	12,852.563	4608.884
UL	16	0.420	0.823	0.591	0.113
EDL	16	850.400	10,045.720	2417.534	2192.462

Table 14. Regression results of the Tobit model of LIE in Anhui Province in 2020.

Independent Variable	Coefficient	Standard Error	T-Value	*p*-Value
FB	−0.1490831 **	0.0535295	−2.79	0.019
PS	8.20×10^{-8}	4.70×10^{-8}	1.74	0.112
PD	−0.0003293**	0.0001131	−2.91	0.015
PQ	0.0000572 **	0.000022	2.59	0.027
UL	−0.5303047	0.6431146	−0.82	0.429
EDL	−0.0001462 **	0.0000651	−2.24	0.049

Note: ** indicate significance at the 95% confidence levels.

According to Table 14, in 2020, the LIE in each region of Anhui Province experienced a significant negative correlation with government FB, PD, and EDL and a significant positive correlation with regional PQ. There was no significant correlation with PS or UL.

5. Discussion

5.1. Discussion of Model Evaluation Results

Based on Table 11 and Figure 2, we obtained the following results: (1) In terms of social security and employment, the TE of people's livelihoods in Suzhou, Chizhou, Chuzhou, Maonshan, Tongling, Hefei, and Xuancheng is relatively good and exceeds the average TE level of Anhui Province, with Xuancheng performing the best with a TE of 1. This result indicates that the region has a strong ability to utilise resources for social security and employment, has a mature and reasonable management approach, and can allocate resources appropriately without wastage. The PTE of Hefei, Tongling, and Chizhou is effective, implying that these two cities can use their financial resources well; however, the scale of their resource inputs is not reasonable, and thus, TE is not optimal. Both Hefei and Tongling have IRS, which suggests that the TE of social security and employment can be increased by further expanding the financial resources invested. The other regions have not reached PTE, but the RTS in each region is rising in scale, indicating the potential for the development of social security and employment in each region of Anhui Province. Furthermore, efficiency can be enhanced by increasing the financial resources invested. (2) As for education, Maonshan, Huangshan, Tongling, Xuancheng, and Chizhou perform relatively well, with their TE being higher than the average TE of Anhui Province. Xuancheng and Chizhou perform well in terms of resource utilisation, but there is still room for the greater optimisation of financial investments. As Xuancheng and Chizhou have diminishing RTS, the total amount of investment in education should be appropriately reduced or its proportion lowered in order to achieve greater efficiency. (3) Concerning health, there are differences in the efficiency-related performance of each region. Wuhu, Hefei, Huangshan, and Tongling are in a relatively good position. The other regions have shortcomings with regard to the scale of resource input or efficiency of resource use and management levels. In 2020, Fuyang's efficiency in improving social security and employment, education, and health was poor, which indicates that objective factors limit the improvement and quality of livelihood in the region. Based on the Tobit regression results, we can further discuss the factors influencing the efficiency of livelihood improvements and provide support for optimisation methods in each region.

In contrast to the existing literature [3,4,34–39], this study did not rely exclusively on publicly available government data, but rather conducted a social survey and had a sizeable sample. As explained earlier, in the current economic and social context, people's subjective perceptions of government performance should not be ignored. Therefore, an advantage of this study is that, compared with previous studies [22–28], our evaluation index system can better reflect people's actual feelings towards the government's work on improving people's livelihood, and the subsequent evaluation results can also lay the foundation for the improvement of people's sense of well-being and stable social development. In terms of evaluation methods, this study adopted a PCA–DEA–Tobit method. Compared with the existing literature [36,49–52], this study can reduce the dimensionality of the complex evaluation index system while retaining the information of the original variables, overcome the limitation of the number of indicators in the DEA evaluation method, and improve the accuracy of the evaluation results. Moreover, in contrast to the existing literature [41–47], this study used the Tobit method to analyse the influencing factors of LIE. This contributes to the completeness of research on LIE evaluation and optimisation, improves the scientificity of the judgment of the influencing factors, and lays the foundation for policy recommendations.

5.2. Discussion of Regression Results

The study constructed a data-driven LIE optimisation process and used scientific quantitative analysis to empirically demonstrate the LIE influencing factors, laying the foundation for scientifically accurate policy proposals. Combined with the empirical results presented in Table 14, the present study discusses the following: (1) LIE in Anhui Province regions shows a significant negative correlation with the government's fiscal burden, an evaluation that supports the view of Liu et al. [38,53,54] but differs from the findings of Fishback et al. [7,8]. This may be because a larger fiscal burden brings difficulties to the government's financial expenditure on livelihood improvement. Owing to the lack of government financial resources, in addition to livelihood improvement work, various supporting projects related to livelihood improvement are also negatively affected, causing a reduction in the efficiency of livelihood improvement. (2) LIE shows a significant negative correlation with population density, which is consistent with the findings of Song et al. [60]. Therefore, social conflicts are concentrated in more populated areas, and the government will face further challenges and difficulties in providing various livelihood services. (3) Regional GDP is a proxy for the level of economic development of a region, and the regression finds that the level of economic development in each region has a certain hindering effect on the efficiency of livelihood improvement, which is inconsistent with the findings of most studies [7,38,56]. On the one hand, this is because higher levels of economic development weaken the government's efforts in cost control, resulting in lower efficiency. On the other hand, the higher the level of economic development of a region, the higher the income level of the population, which inevitably leads to a higher demand for the provision of public services. This leads to a more demanding rating of livelihood services by the residents of the region in the actual research process. (4) The study found that the quality of the district's population plays a positive role in promoting the efficiency of livelihood improvement, which is congruent with the findings of previous studies [1,51,60,61]. This is mainly because an increase in the educational level of residents in the district will improve their awareness of participation in the process of social and livelihood protection, as well as their ability to act politically, thus reducing blind spots in government's governance and improving its monitoring ability. These efforts will eventually lead the local government to increase its efforts in public service work and improve the efficiency of livelihood improvement. (5) In addition, we found no significant correlation between regional population size and LIE, a result that differs from the findings of some previous studies [55–58]. However, we can draw an important conclusion. The real influencing factor for the efficiency of regional livelihood improvement is not the region's population size, but rather its population density, that is, the level of population concentration [6]. According to our research hypothesis and the findings of previous research, regional urbanisation would influence the efficiency of livelihood improvement; however, the empirical results of the present study are contrary to previous findings. This may be owing to the following two reasons: first, this study is based on residents' subjective evaluation of livelihood improvement; although a higher level of urbanisation increases the quality of government public services, livelihood services and provision will be severely affected during specific time periods, such as during the COVID-19 pandemic, and there may even be a decline in the level of livelihood services during this particular period. Second, regions undergoing urbanisation will lead to a concentration of industries and means of production in cities, which will inevitably lead to greater differences in livelihood services between cities and villages, thus causing the evaluation results for villages to be much lower than those for cities. This may also reveal that urbanisation has no significant impact on the efficiency of livelihood improvement.

5.3. Summary and Contribution

Sustainable development necessitates continuous improvement in the quality of people's livelihoods, which requires ongoing optimisation of LIE. Compared with the existing literature, this study has the following advantages. First, the evaluation indicators cover social security, employment, education, health, and wellness, and consider people's subjective feelings, thus rendering the index system more scientific and comprehensive. The data were obtained from the questionnaire survey, which provided a basis for objective, accurate judgments of LIE. Second, we built an evaluation model to perform a quantitative evaluation of LIE in each city and an inter-city comparison. Finally, by constructing a regression model, the factors influencing efficiency were accurately determined, which can offer decision-making support for the government and researchers to better respond to social challenges and enhance LIE.

We obtained the following management insights from the findings: (1) the improvement in people's livelihoods covers a wide range of areas. Additionally, with the ongoing changes in economic and social factors, continuously optimising the evaluation index system is crucial to better reflect the quality of public service provision and governance efficiency. Furthermore, to cope with the global economic slowdown and people's reduced sense of well-being, it is important to focus on the efficiency of the government's use of economic resources and people's feelings towards the government's work. (2) As a comprehensive and complex system, LIE cannot be accurately evaluated by simple qualitative methods; thus, the use of mathematical models to determine the efficiency of livelihood governance is inevitable. (3) LIE is an important indicator of a region's level of sustainable growth. By making full use of the data-driven approach, the shortcomings of LIE and the influencing factors can be identified more objectively and quickly, providing a scientific basis for the proposal of optimal countermeasures.

6. Conclusions and Implications

Currently, livelihood security is under multiple pressures globally, which seriously affects people's quality of life and hinders sustainable social development. Thus, to better address the challenges and fill in the research gaps, we proposed a data-driven approach to evaluate and optimise LIE. The main findings are as follows: (1) we built an 'input–output' LIE index system that is comprehensive in scope, representative in its selection, and fully reflects people's feelings. (2) We built an evaluation model of LIE. (3) We constructed a data-driven process to determine the influencing factors and propose countermeasures for optimising LIE.

6.1. Policy Recommendations

Based on the findings of the evaluation and discussion, we propose the following suggestions for optimising LIE in Anhui Province. (1) In Anhui Province. each region's steps to boost LIE should differ depending on their local conditions. In particular, a reasonable scale of investment is necessary to optimise LIE in Anhui Province and in regions with IRS to expand investment. Regions with decreasing RTS should reduce their RTS accordingly to enhance overall LIE. Furthermore, each region should improve its institutional mechanisms for strengthening people's livelihoods, focus on the optimisation of management techniques and the improvement of staff management levels, and reinforce the effectiveness of the use of funds. It is also important to pay attention to the standard management of financial funds, strictly control costs, and avoid resource wastage. (2) Entrepreneurship should be encouraged among all people, the direction of industrial growth should be actively guided, and companies should be urged to engage in industrial projects related to people's livelihoods. This will not only enable governments to increase revenue and reduce their financial burden but will also allow enterprises to provide support to enhance the quality of people's livelihoods and compensate for the blind spots in governance, thereby forming a positive interaction between economic development and the improvement of people's livelihoods. (3) The regional population structure should be optimised; balanced development should be promoted among various regions, and the burden of governance caused by the over-concentration of the population should be avoided in some regions. The system and mechanism for public participation should be enhanced in livelihood governance so that the public can jointly participate in the provision of public services through proper procedures and reasonable channels of expression, and realise the monitoring of the process and outcomes of provision.

6.2. Research Limitations

This study has three limitations. First, due to the limited available time of this study, there are relatively few sample areas, which may limit the external validity of our research results; second, when measuring LIE, the calculation results may differ due to the different input–output indicator systems, which may lead to less accurate calculation results; third, many other factors may affect LIE, and, although this study has verified the different influencing factors from social and economic perspectives, other perspectives could be further considered.

6.3. Future Outlook

Follow-up studies could conduct more extensive social surveys to evaluate LIE in a wider range of regions. In addition, they could improve the selection of evaluation indicators for livelihood improvement efficiency to be more scientific, comprehensive, and diverse in order to achieve a more accurate evaluation of LIE. Finally, they could combine the development characteristics of regions or countries and verify more diverse influencing factors to lay a more scientific theoretical foundation for the optimisation of regional LIE and the proposal of sustainable development policies.

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