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Research on the Efficiency of Human-Machine Collaborative Delivery Management for Takeout Riders Under Algorithmic Control

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Abstract

In the current digital economy era, the takeout industry is expanding, which makes human-machine collaborative delivery management between takeout riders and intelligent algorithms increasingly important. Based on this, this paper takes takeout riders as Decision Making Units to study the management efficiency of the delivery algorithm from the perspective of input and output. Firstly, a comprehensive evaluation index system for input and output is constructed. Secondly, the entropy method is used to obtain the weights of the delivery input indicators at all levels and the comprehensive input index. Then, the output-oriented DEA-BCC model is established by combining the comprehensive input index and several delivery output indicators. Finally, the efficiency of the delivery algorithm in managing takeout riders is evaluated using the results calculated from the DEA-BCC model. Additionally, this paper also proposes suggestions for personalized human-machine collaborative delivery management in terms of quantity, quality and safety based on the slack variables of the output indicators.

Keywords: takeout delivery, algorithm management efficiency, DEA-BCC model, human-machine collaboration

1. Introduction

Currently, the fast-developing digital economy is contributing to the continuous growth of the takeout industry scale, and this has given rise to an increasingly large occupational group "takeout riders". According to the data released by Meituan (2024), 7.45 million takeout riders earned income on the platform in 2023. For rider scheduling during takeout delivery, platforms often rely on algorithmic control to realize automated management. However, the algorithm as a rational control machine method, may not be able to make timely adjustments and responses in the face of complex and changing scheduling needs. At this point, the algorithm is prone to imbalance and incoherence with the actual work of the riders.

In 2020, an article titled "Takeout riders, stuck in the system" revealed the situation of riders working under algorithmic control, which attracted widespread attention in China at the time (Lai, 2020). In takeout delivery, the essence of the rider's pursuit of delivery speed and the number of orders is to meet the requirements set by the algorithm, so as to get more compensation. And the purpose of algorithmic control is to make full use of the delivery capacity of the riders in order to maximize the profit. Therefore, how to realize human-machine collaborative management between the algorithm and riders is the core problem of this paper.

Human-machine collaboration refers to the complementary advantages of human cognitive abilities and machine computing abilities based on the interaction between human and machine, in order to achieve higher performance (Geng & Varshney, 2022). This means that not only can machine act on human, but human can also have a reciprocal effect on machine. In the process of following machine instructions, human often generates behaviors based on actual situation, and these behaviors can improve efficiency by feedback to the machine.

Based on this, many previous studies have focused on algorithm design for optimizing delivery routes (Fan et al., 2023; Xia & Jiang, 2023; Zhang et al., 2022; Zhou et al., 2022), with few studies addressing the efficiency issues between human-machine interaction. This research aims to fill this critical gap. Therefore, this paper focuses on the efficiency of the delivery algorithm in rider management from an input-output perspective. Firstly, this paper constructs a comprehensive evaluation index system for the input-output of the delivery algorithm. Secondly, the entropy method is used to calculate the comprehensive input index. Combined with multiple output indicators, the DEA-BCC model is used to measure the management efficiency of the delivery algorithm. Finally, based on the measurement results, specific suggestions are proposed for human-machine collaborative delivery management.

2. Literature Review

2.1 Takeout Delivery Management

In takeout delivery, the platform is unified online through algorithms, and the riders are controlled by algorithms as offline performers. Regarding the delivery process. Chen (2020) studied it from the perspectives of organizational technology and scientific technology, and proposes that "digital control" makes the management of riders more invisible, and more process control is transformed into result control. In the relationship between adaptation and collaboration during takeout delivery, Fu (2021) analyzed the autonomy of workers under the algorithm control, which not only makes them more flexible, but also helps the algorithmic technology to better match the actual situation. Regarding the work of riders. Huang (2023) found that task allocation can reduce the probability of generating stress based on labor process theory, but behavioral norms and customer evaluations can conversely increase. Li et al. (2024) analyzed the factors affecting takeout riders' job satisfaction and work willingness by constructing an algorithm awareness model. Regarding the emotional labor. Xiang and Wu (2021) discussed the management and optimization of takeout delivery from the levels of organizational and employee. Through the field survey, Shen (2022) found that takeout riders have formed the "the pattern of difference sequence" strategy map with interest-based connections as the core, to cope with different subjects and overcome the dual uncertainties in the labor process, which compensate for the shortcomings of the algorithm through the role of human.

2.2 Human-Machine Collaboration

In previous research on human-machine collaboration, most of it was achieved by combining human knowledge and behavior with machine algorithms and strategies to improve the performance of the methods. Regarding human-machine collaborative manufacturing. Wang et al. (2024) proposed a swarm intelligence optimization algorithm, which led to algorithmic performance improvements in shop scheduling and production. In the research on reducing the cost of developing semiconductor manufacturing processes, Kanarik et al. (2023) found that by combining human expertise with algorithms through a "human first-computer last" strategy, the cost could be halved compared to relying on human alone. Regarding human-machine collaborative control. Feng et al. (2024) proposed a human-machine cooperative control framework for intelligent vehicles, which not only enhances the handling performance of vehicles but also mitigates human-machine conflict arising from interaction uncertainty. Shein et al. (2023) explore human-machine collaboration from the perspectives of the surgeon and the machine and show that balancing machine autonomy and surgeon expertise is crucial for the development of AI-assisted surgery. Regarding human-machine collaborative decision-making. Liu and You (2024) proposed a human-machine collaborative decision-making method based on the deficit function, thus helping to solve the transportation scheduling problems with flexible constraints. Wang et al. (2022) proposed a confidence-based human-machine collaborative decision-making method (HMCDM/C), which coordinates the interactions between machines and workers with different levels of experience in order to achieve a better dynamic scheduling of the smart workshop.

2.3 DEA Model Measures Efficiency

Data Envelopment Analysis (DEA) is a linear programming method for evaluating the relative efficiency among Decision Making Units (DMUs) proposed by Charnes et al. (1978). And with the increase of related theories, a series of DEA models have been derived, and the practical application scenarios have become richer. For the technical innovation efficiencies of CNC machine tools listed enterprises, Zhang et al. (2024) used the three-stage DEA model and Malmquist productivity index to evaluate them dynamically and statically. In order to comprehensively measure the allocation efficiency of healthcare resource, Hu and Chen (2023) used the DEA-Malmquist index model and thus analyzed its spatio-temporal evolution. Based on the perspective of the level of farmland suitability, Zhang et al. (2024) used the DEA-SBM model to calculate the technological efficiency of agricultural diesel. Li et al. (2024) applied the DEA-BCC model and the DEA-Malmquist index model in order to measure the efficiency of technological innovation in local universities. When oriented to electromechanical system, Wang (2024) combined the methods of fuzzy DEA and TOPSIS to scientifically measure and evaluate the efficiency of the power consumption. Abdul Rashid et al. (2024) designed a two-stage dynamic network DEA framework with innovation capital taken into account, which enabled the measurement of airline efficiency.

3. Method

3.1 Comprehensive Input-Output Evaluation Indicator System

For the delivery algorithm, it is a method of accomplishing delivery tasks by controlling takeout riders. Therefore, the algorithm can be regarded as an input-output medium, which takes rider delivery capability as delivery input and tasks completion performance as delivery output. Based on this, this paper chooses to construct a comprehensive evaluation index system from the perspective of input and output.

Table 1. Comprehensive evaluation index system of delivery algorithm

Delivery perspective	Primary indicator	Secondary indicator	Tertiary indicator	Dummy variable	Symbol	Type
Input	Comprehensive input	Personal features	Gender	Male	x_1	*
				Female	x_2	*
			Age	18-25	x_3	*
				26-35	x_4	*
				36-45	x_5	*
				46 and above	x_6	*
			Education	Junior high school and below	x_7	*
				Senior high school	x_8	*
				Junior college	x_9	*
				Undergraduate college and above	x_{10}	*
		Job features	Rider category	Full-time	x_{11}	*
				Part-time	x_{12}	*
			Rider grade	/	x_{13}	+
			Riding tool	Battery powered vehicle	x_{14}	*
				Motorcycle	x_{15}	*
			Length of employment	/	x_{16}	+
Output	Daily delivery order quantity	/	/	/	y_1	+
	Simultaneous delivery order quantity	/	/	/	y_2	+
	Positive evaluation rate	/	/	/	y_3	+
	Timeout frequency	/	/	/	y_4	-
	Monthly number of bad evaluations or complaints	/	/	/	y_5	-
	Traffic accident experience	/	/	/	y_6	-

Note. The type is +, which represents a positive variable. The type is -, which represents a negative variable. The type is *, which represents a dummy variable. The symbol "/" in the table represents none.

For delivery inputs, this paper considers both personal features and job features. That is, personal features include gender, age and education. Job features include rider category, rider grade, riding tool and length of employment, the specific content is shown in Table 1. Moreover, since some of the indicators belonging to nominal variables in the inputs are not suitable to be included in the evaluation system directly, this paper subsequently transforms them into several dummy variables and then calculates them.

For delivery outputs, in addition to the number of delivery orders, positive evaluation rate, timeout and complaint, this paper also takes the traffic accident experience as one of the indicators to be measured. That is, the delivery task under algorithmic control should not only consider the delivery completion, but also the riding safety performance, which is shown in Table 1.

3.2 DEA-BCC Model

In real life, returns to scale are usually variable, which means that inputs and outputs often change disproportionately (Zhang et al., 2023). Therefore, in order to analyze the output maximization with given inputs, this paper chooses the output-oriented DEA-BCC model with variable returns to scale as the evaluation model. And, the DEA-BCC model is proposed by Banker et al. (1984). It differs from the DEA-CCR model with constant returns to scale by adding a constraint. That is, the specific formula of the output-oriented DEA-CCR model is shown in eq (1).

$$\max\ \theta-\varepsilon\left(\sum_{j=1}^{J}s_j^-+\sum_{k=1}^{K}s_k^+\right)$$
$$s.t.\begin{cases}\sum_{i=1}^{n}\lambda_i X_i+s^-=X_0,\\ \sum_{i=1}^{n}\lambda_i Y_i-s^+=\theta Y_0,\\ \theta\ge 0,\lambda_i\ge 0,\\ s^-\ge 0,s^+\ge 0.\end{cases} \tag{1}$$

Where, $X_i=\left(x_{i1},x_{i2},\dots x_{iJ}\right)^T$ is the input vector of the DMU_i, $Y_i=\left(y_{i1},y_{i2},\dots y_{iK}\right)^T$ is the output vector of the DMU_i, s^- is the residual variable of inputs, s^+ is the slack variable of outputs, ε is the non-Archimedean infinitesimal, θ is the comprehensive efficiency of DMU, and λ is the weight coefficient. Then, the results based on θ, s^- and s^+ can be used to judge the DEA efficiency of DMUs, and its specific judgment rules are shown in Table 2.

Table 2. DEA Efficiency Judgment Rules

θ	s^-	s^+	Judgment result
= 1	= 0	= 0	Strong Efficiency
= 1	≠ 0	= 0	Weak Efficiency
= 1	= 0	≠ 0	Weak Efficiency
<1	/	/	Inefficiency

Accordingly, based on eq (1), the DEA-BCC model is formed after adding $\sum_{i=1}^{n}\lambda_i=1$ constraint (Guo & Zhang, 2018). And the pure technical efficiency (*PTE*) and scale efficiency (*SE*) can be decomposed by the comprehensive technical efficiency (*TE*), i.e.

$$TE=PTE\times SE. \tag{2}$$

4. Empirical Analysis

To evaluate the management efficiency of delivery algorithm, this paper uses statistical data provided by Life Plus for empirical analysis. After filtering and processing for outliers and other issues in the data, the data of 154 takeout riders are ultimately retained. And, combined with the data, some nominal variable indicators are transformed into dummy variables (see Table 1), and the values and meanings of other indicator variables are explained (see Table 3).

Life Plus is a digital platform whose main business is takeout delivery and its main operation is located in Guizhou Province, China. To date, the platform has been in continuous operation for six years, serving more than 25 million orders (Sunshine HaiNa, 2025).

Table 3. Explanation of Indicator Variables

Indicator variable	Corresponding value and meaning
x_{13}	1, 2, 3, 4, 5.
x_{16}	1: $(0,1]$ months, 2: $(1,3]$ months, 3: $(3,6]$ months, 4: $(6,12]$ months, 5: $(12,+\infty)$ months.
y_1	1: $(0,20]$, 2: $(20,30]$, 3: $(30,50]$, 4: $(50,70]$, 5: $(70,+\infty)$.
y_2	1: $(0,3)$, 2: $[3,5]$, 3: $(5,+\infty)$.
y_3	$[0,100]$%.
y_4	1: Never, 2: Occasionally, 3: Often, 4: Always.
y_5	1: $[0,3]$, 2: $(3,6]$, 3: $(6,10]$, 4: $(10,+\infty)$.
y_6	1：Have been involved in a traffic accident while delivering. 0：Have not been involved in a traffic accident while delivering.

4.1 Calculating the Comprehensive Input Index Based on Entropy Method

In this paper, takeout riders are considered as Decision Making Units (DMUs). And for delivery inputs, it is not suitable to directly include them in the evaluation model calculation after transforming some nominal variables into dummy variables. Therefore, this paper uses the entropy method to calculate the weights of input indicators at all levels, in order to obtain the comprehensive input index, which can be applied to subsequent management efficiency calculations.

The entropy method calculates objective weights for variables by measuring their information content, which helps eliminate subjective biases. The specific calculation steps are as follows (Zhang et al., 2023).

Step 1: Data standardization. Combining Table 1, it can be seen that the types of indicator variables include positive variable (+), negative variable (-) and dummy variable (*). Therefore, the standardization methods for various types of indicator variables are different, and the specific calculation formula is

$$\tilde{x}_{ij}=\begin{cases}\dfrac{x_{ij}-\min\left(x_{ij}\right)}{\max\left(x_{ij}\right)-\min\left(x_{ij}\right)}, & x_{ij} \text{ is } +;\\ \dfrac{\max\left(x_{ij}\right)-x_{ij}}{\max\left(x_{ij}\right)-\min\left(x_{ij}\right)}, & x_{ij} \text{ is } -;\\ x_{ij}, & x_{ij} \text{ is } *.\end{cases} \tag{3}$$

Where, if x_{ij} is a dummy variable (*), then x_{ij} is also a 0-1 variable and its original value is retained. Considering the need to avoid the impact of zero values on subsequent calculations, all $\tilde{x}_{ij}=0$ are replaced with $\tilde{x}_{ij}=0.0001$. In addition, for the indicator variable $\tilde{y}_{ik}$ of delivery output, the standardized variable $\tilde{y}_{ik}$ is obtained using the same method, and $\tilde{y}_{ik}$ will be applied to subsequent efficiency calculations.

Step 2: Normalize processing. The contribution degree is calculated through normalization, and the calculation formula is

$$P_{ij} = \frac{\tilde{x}_{ij}}{\sum_{i=1}^{n} \tilde{x}_{ij}}. \tag{4}$$

Step 3: Calculate the entropy value of the indicator. The specific formula for calculating entropy value e_j is

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} P_{ij} \ln\left(P_{ij}\right). \tag{5}$$

Where, $0 \le e_j \le 1$, and thus the coefficient of variation $d_j = 1 - e_j$ can be obtained.

Step 4: Calculate the weight of the indicator. According to d_j, the weight w_j of the indicator can be obtained, and its calculation formula is

$$w_j = d_j \Big/ \sum_{i=1}^{n} d_j . \tag{6}$$

Step 5: Calculate the comprehensive score. The final comprehensive input index $Score_i$ can be obtained by combining w_j and $\tilde{x}_{ij}$, and its calculation formula is

$$Score_i = \sum_{j=1}^{J} w_j \tilde{x}_{ij} . \tag{7}$$

Thus, the weights of various indicators in the delivery input are calculated using the entropy method, as shown in Table 4, and the comprehensive input index *Score* for each DMU is obtained from this.

Table 4. The Weights of Indicators for Delivery Input at Different Levels

Weight	Secondary indicator	Weight	Tertiary indicator
0.7926	Personal features	0.1149	Gender
		0.3530	Age
		0.3247	Education
0.2074	Job features	0.1265	Rider category
		0.0052	Rider grade
		0.0669	Riding tool
		0.0088	Length of employment

4.2 Measuring Management Efficiency

Based on the comprehensive input index $Score_i$ in the previous section (as input X_i in eq (1) is included in the calculation) and the standardized delivery outputs $\tilde{Y}_i = \left(\tilde{y}_{i1}, \tilde{y}_{i2}, \ldots, \tilde{y}_{i6}\right)^T$, this paper takes takeout riders as Decision Making Units (DMUs) , so as to establish the output-oriented and single input multiple output DEA-BCC model.

$$\max\ \theta - \varepsilon\left(s_{Score}^{-} + \sum_{k=1}^{6} s_k^{+}\right)$$
$$s.t.\begin{cases} \sum_{i=1}^{154} \lambda_i Score_i + s_{Score}^{-} = Score_0, \\ \sum_{i=1}^{154} \lambda_i \tilde{Y}_i - s^{+} = \theta \tilde{Y}_0, \\ \sum_{i=1}^{154} \lambda_i = 1, \\ \theta \geq 0, \lambda_i \geq 0, s^{-} \geq 0, s^{+} \geq 0. \end{cases} \tag{8}$$

Then, in order to eliminate the error generated by ε, a two-stage approach (Ali & Seiford, 1993) is used in this paper to solve the linear programming problem of eq (8). That is, in the first stage, the optimal solution θ^* of θ is obtained by solving eq (9).

$$\max\ \theta$$
$$s.t.\begin{cases} \sum_{i=1}^{154} \lambda_i Score_i \leq Score_0, \\ \sum_{i=1}^{154} \lambda_i \tilde{Y}_i \geq \theta \tilde{Y}_0, \\ \sum_{i=1}^{154} \lambda_i = 1, \\ \theta \geq 0, \lambda_i \geq 0. \end{cases} \tag{9}$$

In the second stage, eq (10) is solved in conjunction with θ^* so as to compute the slack variables.

$$\max\ s_{Score}^{-} + \sum_{k=1}^{6} s_k^{+}$$
$$s.t.\begin{cases} \sum_{i=1}^{154} \lambda_i Score_i + s_{Score}^{-} = Score_0, \\ \sum_{i=1}^{154} \lambda_i \tilde{Y}_i - s^{+} = \theta^* \tilde{Y}_0, \\ \sum_{i=1}^{154} \lambda_i = 1, \\ \lambda_i \geq 0, s^{-} \geq 0, s^{+} \geq 0. \end{cases} \tag{10}$$

Accordingly, this paper utilizes DEAP2.1 software to implement the calculation and in this way measures the management efficiency of the delivery algorithm, and the results are specifically shown in Table 5.

Table 5. Evaluation Results of Management Efficiency

DEA Efficiency	Percentage of DMUs	Corresponding to practical significance
Strong Efficiency	5.84%	The management of DMUs by delivery algorithm has reached the level of optimal delivery output.
Weak Efficiency	0.65%	The management of DMUs by delivery algorithm has not yet reached the level of optimal delivery output, and there is still space for optimization.
Inefficiency	93.51%	The delivery algorithm leads to resource waste in the management of DMUs, and the algorithm configuration needs to be adjusted.

As shown in Table 5, for most DMUs, there is still much room for improvement in the management efficiency of the delivery algorithm. At the same time, this also highlights the need for personalized management. In addition, this paper plots the outputs $\tilde{y}_1, \tilde{y}_2, \ldots, \tilde{y}_6$ produced by each DMU with unit input *Score* (i.e., $\tilde{y}_1/Score, \tilde{y}_2/Score, \ldots, \tilde{y}_6/Score$), which is shown in Figure 1. Among them, considering that there are 6 dimensions in outputs, Figure 1 shows them separately, i.e., presented using two three-dimensional scatter plots.

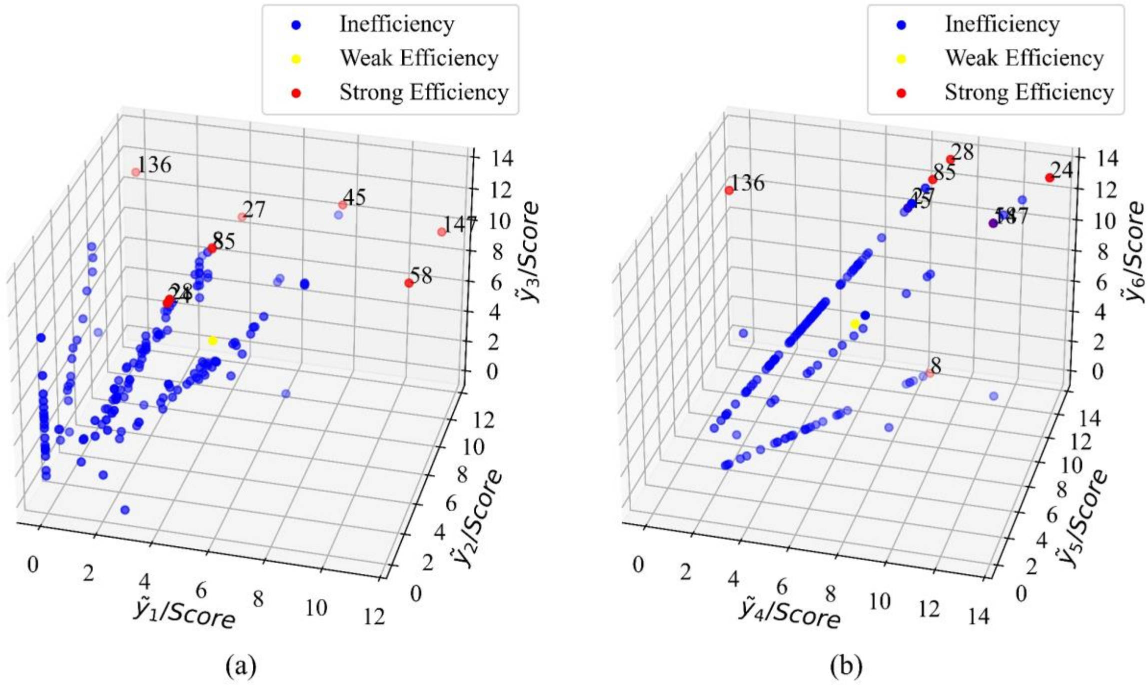

Figure 1. Efficiency frontier

In Figure 1, $\mathrm{DMU}_8, \mathrm{DMU}_{24}, \mathrm{DMU}_{27}, \mathrm{DMU}_{28}, \mathrm{DMU}_{45}, \mathrm{DMU}_{58}, \mathrm{DMU}_{85}, \mathrm{DMU}_{136}, \mathrm{DMU}_{147}$ with Strong Efficiency belongs to the efficiency frontier, and their positions in (a) and (b) can be combined to form the frontier surface in six dimensions. When the other DMUs are projected onto the frontier surface, their distance from the efficiency frontier is then the slack case that exists.

Finally, the calculation results of the comprehensive technical efficiency (*TE*) are then statistically analyzed by interval, as shown in Figure 2. The percentage of DMUs with $TE > 0.5$ is about 66.23%. That is, the delivery algorithm has a management efficiency of more than 50% for most takeout riders. Additionally, in order to comprehensively evaluate the management efficiency of delivery algorithm, this paper divides the comprehensive technical efficiency (*TE*) into pure technical efficiency (*PTE*) and scale efficiency (*SE*) for further analysis.

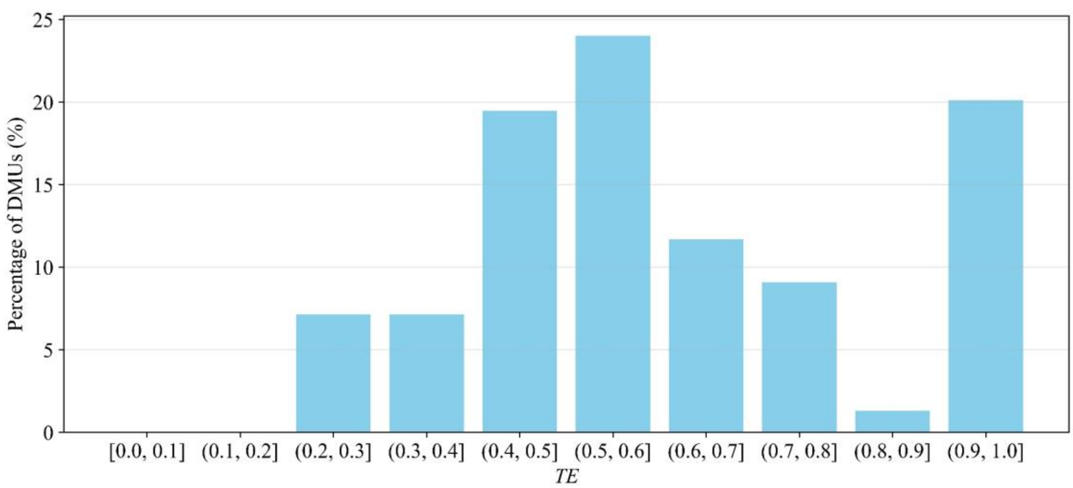

Figure 2. *TE* distribution

According to the calculation results, the *PTE* of all DMUs is equal to 1, indicating that DMUs have utilized their best delivery technology at the current delivery input level. Combined with the weight of personal features in Table 4, which is as high as 0.7926, it can be analyzed that it is crucial for riders to fully exert their autonomy in the delivery process to complete the delivery task. In addition, at this time *TE*=*SE*, so the comprehensive technical efficiency and scale efficiency of the delivery algorithm are closely related. And it is statistically found that the return to scale of DMUs with Strong Efficiency and Weak Efficiency are constant, but the return to scale of DMUs with Inefficiency are decreasing. The delivery capacity of most takeout riders will experience a decrease in efficiency after reaching a certain scale of work, so it is necessary to adjust the management configuration of the algorithm in a timely manner to balance the input and output of delivery.

4.3 Suggestions for Algorithm Management Combined with Slack Variables

Due to the output-oriented of the DEA-BCC model constructed in this paper, which analyzes delivery outputs given delivery input. When there are slack variables greater than 0 in the delivery outputs, it indicates that there is still space for the DMUs to improve delivery outputs, and the size of the slack variables is the size of the improvement space. Therefore, statistics are conducted on DMUs with slack variables greater than 0, as shown in Table 6, in order to further analyze and propose corresponding suggestions.

Table 6. Slack Variable Statistical Results

Slack variable	$s_1^+ > 0$	$s_2^+ > 0$	$s_3^+ > 0$	$s_4^+ > 0$	$s_5^+ > 0$	$s_6^+ > 0$
Percentage of DMUs	91.56%	81.82%	48.70%	81.82%	1.30%	21.43%

Based on this, when the slack variable of daily delivery order quantity $s_1^+ > 0$ is greater than 0, it indicates that the daily delivery order quantity of the rider can continue to improve. The delivery algorithm can improve the level of quantity output by increasing the allocation of its orders. When the slack variable of simultaneous delivery order quantity $s_2^+ > 0$ is greater than 0, it indicates that the rider's simultaneous delivery capability has not been fully utilized. The delivery algorithm can appropriately relax its simultaneous delivery restrictions to improve the level of quantity output.

When the slack variable of positive evaluation rate $s_3^+ > 0$, the slack variable of timeout frequency $s_4^+ > 0$ or the slack variable of monthly number of bad evaluations or complaints $s_5^+ > 0$ are greater than 0, it indicates that the delivery service quality of the rider is poor, and the algorithm should be monitored and adjusted to improve the level of quality output.

When the slack variable of traffic accident experience $s_6^+ > 0$ is greater than 0, it indicates that the rider's riding safety performance during delivery needs to be improved, and the algorithm should pay attention to and remind it in a timely manner to improve the level of safety output.

Therefore, personalized algorithm management can be implemented for different takeout riders based on the slack variables of each output indicator, thereby achieving human-machine collaboration in delivery management. And, in summary, focusing on managing and adjusting the current delivery algorithm in terms of daily delivery order quantity, simultaneous delivery order quantity, and positive evaluation rate can improve the overall delivery output.

5. Conclusion

In takeout delivery, the algorithm as a crucial automated control method, is usually independently designed by the takeout platform. The job of takeout riders is often to exert a certain degree of autonomy under algorithmic control to complete delivery tasks. Therefore, this paper chooses to study the management efficiency of delivery algorithm, and the analysis results can be applied in reverse to adjust and improve the algorithm, which can contribute to the implementation of human-machine collaborative delivery management.

Based on this, this paper constructs a comprehensive evaluation index system from the perspective of input-output by takeout riders as Decision Making Units. Then, after calculating the comprehensive input index using the entropy method, an output-oriented DEA-BCC model is established by combining multiple delivery output indicators. Finally, based on the efficiency measurement results of the model, the evaluations of the algorithm management efficiency are obtained. Furthermore, personalized human-machine collaborative delivery management suggestions are proposed from three aspects: quantity, quality, and safety of output, combined with slack variables.

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