Assessment of truck driver safety efficiency based on data envelopment analysis

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Abstract. This paper introduces a safety efficiency evaluation framework that integrates Data Envelopment Analysis (DEA) and Super-Efficiency Data Envelopment Analysis (SE-DEA) for quantitatively assessing the safety of truck drivers. The framework utilizes data from onboard equipment to capture drivers' dangerous behaviors and poor driving states. Subsequently, it evaluates safety efficiency using the DEA combination model, providing safety rankings. Improvement suggestions are offered to underperforming drivers based on slack variable values. The proposed method is compared with EWM-Topsis and Critic-Topsis models using fixed weights, demonstrating better stability. The study's outcomes enable freight companies to identify high-risk drivers and offer personalized, targeted safety training.

1.Introduction

According to a 2018 World Health Organization report, road traffic accidents cause 1.35 million deaths globally each year, making it the eighth leading cause of death worldwide [1]. Of these, the weight, size, and poor maneuverability of trucks make them more likely to cause serious collisions. U.S. government statistics show that trucks have a higher fatality rate per 100 million miles traveled than all other motor vehicles [2]. In a survey of truck-related crashes, 90% of the causes were found to be related to driver factors [3]. Therefore, safety and efficiency assessment and management of truck drivers is an effective means to reduce road traffic accidents and control driving risks.

In recent years, high-precision satellite positioning and in-vehicle driving monitoring systems have been widely used in the field of heavy vehicles [4]. The data is transmitted to the regulatory cloud platform through the vehicle networking technology, which provides the basis for comprehensive control of drivers and vehicles and scientific and reasonable driving safety performance evaluation. However, in practical application, most transportation enterprises pay insufficient attention to data, lack data mining capabilities, and only realize basic vehicle positioning supervision. Unable to fully utilize the Netlink data to evaluate driving performance, they still use subjective questionnaire evaluation. Therefore, how to make full use of heavy-duty vehicle netlink big data, deeply mining driving behavior characteristics, comprehensively measuring driver safety efficiency, accurately identifying high-risk drivers, and proposing improvement strategies is an urgent problem to be solved.

In this study, the DEA method is used to evaluate the safety efficiency of truck drivers. This method can effectively analyze multiple input-output decision-making units and solve the problem that the evaluation index scale is not uniform and the weights are fixed [5]. Although there have been studies applying DEA to the transportation field, such as evaluating public transportation performance [6], traffic safety efficiency [7], and driver cognitive efficiency [8], there are relatively few applications to natural driving data. In this paper, we constructed a safety scoring model by combining the CCR model with the SE-DEA model, quantitatively evaluated all drivers, and compared it with other fixed-weight evaluation methods to verify the excellent stability of the model. The method helps to identify high-risk drivers and provide quantitative improvement strategies, which provides an important reference for the safety management of truck drivers and assists freight forwarding companies in developing personalized safety training systems to improve traffic safety.

2.Methodology

2.1. DEA model

DEA is a non-parametric analytical method used to assess the performance of homogeneous units by considering multiple input and output indicators. The most basic CCR method, proposed by Charnes [9], has been widely used in various fields to assess the relative efficiency of decision-making units. Although the driver's context is different from that of a traditional industrial production unit, "efficiency" in terms of driving safety can be understood as minimizing the number of risky behaviors while driving longer distances.
The following is the basic mathematical formula of the CCR model: Suppose there are \( n \) DMUs in the sample, and each DMU has \( p \) inputs and \( s \) outputs. Where \( x_{ij} \) represents the \( i \)-th input of the \( j \)-th DMU, \( y_{rj} \) represents the \( r \)-th output of the \( j \)-th DMU, \( u_i \) represents the weight of the \( i \)-th input, and \( u_r \) represents the weight of the \( r \)-th output. So, the mathematical model of \( DMU_j \) is as follows:

\[
\max \left( \frac{u_r y_{rj}}{v_i x_{ij}} \right) \\
\text{s.t.} \begin{cases} 
\frac{u_r y_{rj}}{v_i x_{ij}} \leq 1, (j = 1, 2, \ldots, n) \\
u_i > 0, v_i > 0
\end{cases}
\]  

(1)

Using the DEA model, we obtain safety efficiency values for all drivers. In this thesis, we refer to drivers with safety efficiency values equal to 1 as DEA effective and drivers with safety efficiency values less than 1 as non-DEA effective.

2.2. SE-DEA model

To solve the problem that the traditional CCR model makes it difficult to compare drivers with all efficiency values of 1, we introduce the SE-DEA [10] model for secondary analysis to rank the DEA-effective drivers in terms of safety. The core idea of this model is to filter out DMUs with an efficiency value of 1 and recalculate the relative efficiency. By integrating the efficiency values of all drivers, we can perform a safety efficiency ranking. In the SE-DEA model, the mathematical expression for the decision unit \( j0 \) is as follows:

\[
\max \left( \frac{u_r y_{rj0}}{v_i x_{ij0}} \right) \\
\text{s.t.} \begin{cases} 
\frac{u_r y_{rj0}}{v_i x_{ij0}} \leq 1, (j = 1, 2, \ldots, n; j \neq j_0) \\
u_i > 0, v_i > 0
\end{cases}
\]  

(2)

We will use DEA to quantify drivers' driving safety efficiency. With the slack variables in the model, we can access the direction of behavioral improvement for drivers with lower efficiency values. Further, we will apply the super-efficiency DEA model to perform secondary analysis on drivers with high-efficiency values to finalize the safety ranking of all drivers.

3. Data acquisition

This study covers 56 trucks traveling from December 2022 to March 2023 using data provided by a freight management platform. All of these vans were equipped with GPS, ADAS, and DMS systems. The platform relies on these in-vehicle devices to receive satellite telemetry data in real-time to obtain critical information about driver status and driving behavior. Ultimately, we obtained the cumulative number of each type of risky event during the data collection period and the mileage driven by each driver, as detailed in Table 1.

Given the substantial total mileage of all drivers, it is reasonable to assume that differences in risky events among them are not influenced by external factors such as roads and weather but are primarily determined by individual driving styles. Consequently, we utilized risky driving behaviors (rapid acceleration, rapid braking, near collision, insufficient headway, lane departure) and driver risk states (fatigue driving, cell phone use, smoking, distracted driving) as model inputs for each driver. The mileage traveled was considered as the model output, forming a set of indices to evaluate the safety efficiency of a driver, as outlined in Table 1. The DEA model was employed to assess each driver's safety efficiency, with a higher efficiency value indicating a safer driver.

In summary, this study constructed the indicators for the assessment model based on three months of naturalistic driving data from 56 drivers. Statistical information is given in Table 1, in which all drivers drove more than 2,000 kilometers during the data collection period, and the descriptive statistical values of the indicators are in hundred-kilometer frequency.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Indicators</th>
<th>Indicator description</th>
<th>Mean</th>
<th>Std</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Driving behavior</td>
<td>X 1</td>
<td>Harsh acceleration</td>
<td>Harsh acceleration during driving</td>
<td>4.93</td>
<td>4.56</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>X 2</td>
<td>Harsh braking</td>
<td>Harsh braking during driving</td>
<td>6.26</td>
<td>3.90</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>X 3</td>
<td>Insufficient headway</td>
<td>The headway is less than 1s</td>
<td>25.23</td>
<td>21.06</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>X 4</td>
<td>Near crashes</td>
<td>Time to collision with front vehicle is less than 4s</td>
<td>8.38</td>
<td>10.60</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>X 5</td>
<td>Lane deviation</td>
<td>Drivers making a lane change or turn without turning signal on</td>
<td>30.13</td>
<td>26.91</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>X 6</td>
<td>Fatigue driving</td>
<td>Drivers yawning, dozing, and close eyes</td>
<td>3.46</td>
<td>5.82</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>X 7</td>
<td>Distracted driving</td>
<td>Drivers did not look ahead for a long time</td>
<td>6.97</td>
<td>11.09</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>X 8</td>
<td>Using mobile phone</td>
<td>Drivers check their cell phones while driving</td>
<td>0.10</td>
<td>0.34</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>X</td>
<td>Smoking</td>
<td>Drivers smoke while driving</td>
<td>0.02</td>
<td>0.06</td>
<td>0</td>
</tr>
</tbody>
</table>
4. Safety efficiency assessment results

We applied the CCR model to evaluate the safety efficiency of 56 freight drivers and calculated them. The final results show that 41 drivers are non-DEA effective, while 15 drivers have reached DEA effective with a safety efficiency value of one. These 15 drivers reached the efficient level in terms of inputs and outputs, defining the efficiency boundaries, and therefore can be used as "peers" for the other non-DEA efficient drivers. In other words, these DEA-effective drivers define the production frontier for this group of drivers and provide the direction and reference for other non-DEA-effective drivers to improve their safety efficiency values.

In the model, slack variables are used to measure the degree of input redundancy or output deficiency in the decision unit. When the value of the slack variable of the input indicator is greater than 0, it indicates that there are too many inputs without a corresponding increase in outputs, thus leading to a waste of resources. By analyzing the slack variables of the input metrics, the direction of improvement for each DMU can be determined. When the slack variable of an input indicator is greater than 0, it indicates that the corresponding risky behavior occurs in excessive numbers, leading to the inefficiency of non-DEA effective drivers. Therefore, based on the results, driver safety behaviors can be targeted for improvement. Table 2 shows several non-DEA effective drivers and their corresponding "peers", as well as the risky driving behaviors that need to be improved.

<table>
<thead>
<tr>
<th>Table 2. Relaxation variables and peers</th>
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<tr>
<td>DMU</td>
</tr>
<tr>
<td>------</td>
</tr>
<tr>
<td>D1</td>
</tr>
<tr>
<td>D9</td>
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<tr>
<td>D40</td>
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<td>D22</td>
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</tbody>
</table>

The safety efficiency values of the non-DEA effective drivers are between 0 and 1, which can be used to rank their safety levels, while the safety efficiency values of the DEA effective drivers are all 1. Therefore, to rank the safety efficiencies of all the drivers in a more detailed way, we used the SE-DEA model to perform a quadratic analysis of these 15 DEA-effective drivers. Eventually, we obtained the safety efficiency values of 56 all drivers and ranked them in descending order to form a safety ranking of all drivers, which is detailed in Fig. 1. Among them, the D2 driver had the highest safety efficiency value, while the D22 driver had the lowest value.

5. Stability verification experiment

Meanwhile, we adopted two evaluation methods, EWM-TOPSIS and Critic-TOPSIS, which use fixed weights to calculate and rank the safety efficiency of drivers. By comparing these three methods, we conclude that the DEA model is superior for driver safety evaluation. Since the DEA and Topsis models are not predictive models, they do not apply to traditional model validation techniques (e.g., cross-validation, etc.). To verify the stability of the model results, we conducted a stability analysis [11]. The purpose of this analysis is to test whether the model's ranking of driver safety fluctuates significantly due to changes in sample size. We referenced Tselentis' study [12] by randomly removing 20% of the drivers in the dataset and recalculating their efficiency scores and rankings. This process was repeated five times and the value of the difference in...
ranking was calculated for each change in ranking. By analyzing the mean and standard deviation of the ranking differences for all drivers, we can assess the stability of the three model effectiveness scores and ranking results. The experimental results are shown in Figures 2 and 3.

Fig. 2. Mean of driving safety ranking difference.

Fig. 3. Standard deviation of driving safety ranking difference

As seen in Figures 2 and 3, the mean difference values and standard deviations of driver safety rankings obtained using the DEA model were better than the other two models in all three models. The proportion of drivers with a mean value of ranking difference less than 5 was 84% in the DEA model, compared with 82% and 73% in the EWM-TOPSIS and Critic-TOPSIS models, respectively. In addition, all drivers in the DEA model had a ranking difference of less than 15; meanwhile, the percentage of drivers with a standard deviation of the ranking difference of less than 10 was 96% in the DEA model, compared to 89% and 87.5% in the other two models, respectively. The results show that the DEA model has better ranking stability compared with the other models, indicating that the DEA model has strong practicality in solving the problem of ranking drivers' safety efficiency.

6. Conclusion and discussion

This study proposes a driving safety assessment framework based on the DEA model and the SE-DEA model. Specifically, driving safety efficiency was calculated by considering the distance driven and the number of various types of risky behaviors of 56 truck drivers over 3 months, using a method that sets non-fixed weights for risky driving behaviors. After obtaining the results of the CCR model, a secondary analysis was performed using the SE-DEA model to achieve a ranking of the safety profiles of all drivers. The slack variables of the DEA model were used to provide reasons for poor driving performance for drivers with low safety efficiency. Finally, the stability of the methodology of this paper is validated by comparing it with EWM-TOPSIS and Critic-TOPSIS.

The findings have practical implications for individual drivers and freight transportation companies. For individual drivers, by comparing with other drivers with high safety, they can have a better understanding of their driving performance enhance safety control, and reduce risky driving behaviors in their daily driving. For freight companies, they can personalize driver training and targets to reduce the safety risk level of drivers, thus improving the overall driving safety level.

Future research directions include the following. Extend the research period to focus on driver safety efficiency over a longer period and introduce a time factor to provide a more comprehensive understanding of changes in driver safety. Analyze driving conditions at different periods and consider the effects of factors such as traffic volume and lighting on risky driving behavior to improve the accuracy of safety assessments.

Acknowledgments

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References


