

Article

An Energy-Saving Evaluation Method for Driving Behavior Based on the SHAP Scorecard Model

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Abstract: In order to fully examine how driving behavior affects vehicle energy consumption and further cut down on excessive energy use while driving, an energy-saving evaluation method for driving behavior based on the SHAP (Shapley Additive exPlanations) scorecard model is proposed. First, to categorize short trip segments, a LightGBM model is built, which performs better and has high interpretability. The SHAP method is then used to statistically assess the categorization findings in order to ascertain how various driving events and driving behavior characteristics affect energy consumption. After that, the data are converted into scores using a scorecard model, which is then used to examine the evaluation outcomes of each sample and individual driver. Lastly, by checking the distribution of scores and the pertinent factors for various scores, the scorecard model's correctness and reasonableness in evaluating energy-saving driving practices of short-trip segments are confirmed.

Keywords: scorecard model; energy saving; driving behavior evaluation; SHAP algorithm

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1. Introduction

With the rapid development of the new energy vehicle industry, new energy vehicles (NEVs) have become an essential component of daily life. However, the casual driving behavior of car users often leads to significant energy loss when using NEVs. Therefore, it is necessary to establish scientific and rational energy consumption scoring indexes and models to guide users in developing excellent driving habits and enhancing the energy utilization efficiency of NEVs.

Numerous scholars have conducted extensive research on the construction of scoring models associated with indicators. For instance, Saaty utilized the analytic hierarchy process (AHP) method to construct scoring models [1], while Wu combined AHP with functional models for the same purpose [2]. However, AHP is prone to subjectivity when determining index weights, resulting in a significant deviation in the accuracy of the constructed scoring model. To address this issue, Ni and others have combined AHP with the entropy weight method for evaluating land development capacity [3]. Similarly, Wang and colleagues have employed the entropy weight method in conjunction with AHP to study the scoring model for railroad selection [4]. Although this approach effectively resolves the problem of excessive subjectivity, it has been found to encounter challenges in dealing with nonlinear correlations.

In order to establish an effective correlation between indicators and scores, several scholars have utilized the scorecard model for further research. For instance, Casas and others developed a scorecard model to assess the competitiveness of enterprises and provide strategic planning [5]. Keivanpour and colleagues employed the scorecard model to evaluate the logistics industry [6]. Li and colleagues utilized a scorecard model to construct a driving behavior scoring model, analyzing driving habits, safety coefficients, and energy consumption of users [7]. Shi compared the AHP method with the scorecard model and found that the score distribution in the scorecard model was more uniform and continuous, indicating its superiority over AHP [8].

Currently, the scorecard model is used to study driving behavior by categorizing positive and negative samples based on energy consumption. However, energy consumption is influenced by factors beyond driving behavior, which limits the scorecard model's ability to effectively characterize the impact of driving behavior on energy consumption. To ensure a correlation between the scoring model and driving behavior, this paper innovatively incorporates the SHAP algorithm to analyze relevant characteristic parameters that represent driving behavior. The positive and negative samples are then divided based on the results of the SHAP algorithm, and a scorecard model is established.

2. Data Pre-Processing

2.1. Data Source

The data utilized in this research were sourced from the Jiangxi New Energy Vehicle Big Data Center. The data collection frequency was 1 Hz, and the format adhered to the national standard GB/T 32960 [9]. The data consist of operational data from 17 pure electric taxis operating within the geographical boundaries of Nanchang City in November 2023. The total volume of data amount to approximately 25,360,000 entries, covering a total operational duration of about 7044 h. The dataset encompasses 18 fields, including vehicle number, vehicle type, data collection time, and data collection duration. The specific data fields are shown in Table 1.

Table 1. Overview of data fields.

Data Type	Data Field	
Vehicle Information	Vehicle number	Vehicle type
Vehicle Operating Status Signals	Data collection time	Accumulated mileage
	Vehicle status	Accelerator pedal travel
	Speed	Brake pedal status
Body Condition Signals	Air conditioning status	Turn signal status
Battery Status Signals	Charging status	SOC (state of charge)
	Total voltage	Max battery cell temperature
	Total current	Lowest battery cell Temperature
GPS Status Signal	Latitude	Longitude

2.2. Data Cleaning

To enhance data quality and eliminate unnecessary data so as to improve calculation efficiency, further cleaning is necessary after data collection. The data cleaning process primarily involves handling duplicate data, vehicle status that is not in the “started” state, air conditioning status that is “on”, abnormal speed, and abnormal acceleration.

Among them, according to the time share of data in different speed ranges in Figure 1, speeds greater than 110 km/h are regarded as outliers to be excluded; according to Figure 2, speeds that continue for at least 10 s at a speed of about 1 km/h after completing acceleration and deceleration behaviors for a short period of time are excluded; according to Figure 3, it

can be seen that acceleration of more than 3 m/s^2 and less than 4 m/s^2 account for a very small proportion of the data, and thus, this part of the data is excluded.

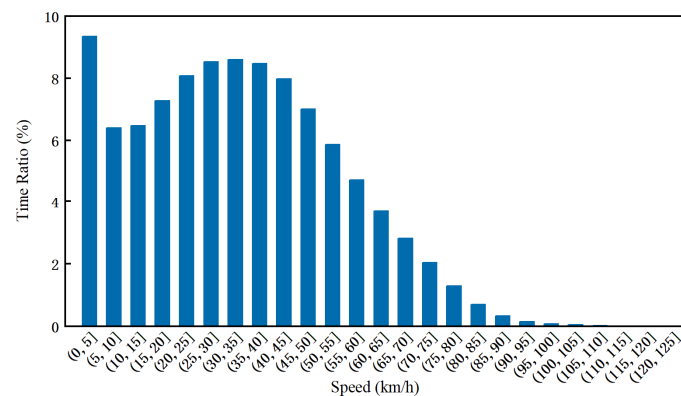


Figure 1. Time share for different speed ranges.

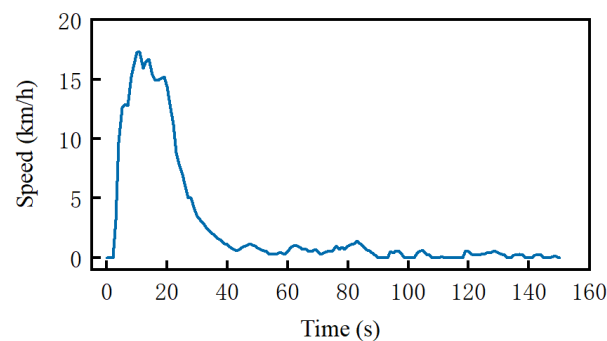


Figure 2. Velocity versus time relationship.

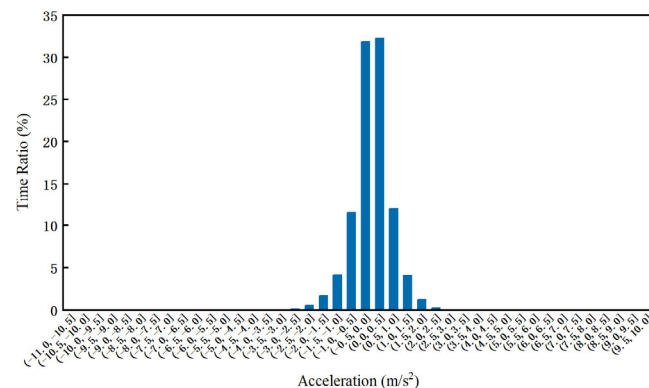


Figure 3. Time share for different acceleration ranges.

2.3. Division of Segments

2.3.1. Driving State Classification

A driving event consists of various states, such as idling, starting, running, and stopping. This study divides the different driving states by examining their characteristics in the raw data.

2.3.2. Short Trip Segmentation

The short trip segments are divided into segments that begin when the vehicle transitions from idle to start and end when the vehicle returns to idle from a stop. This includes complete start, run, and stop segments.

2.4. Driving Event Classification

Based on the analysis of the impact of driving behavior characteristic parameters on energy consumption under different driving states, this study establishes five types of driving events for investigation: rapid acceleration start, slow start, rapid acceleration, rapid deceleration, and bad parking. The judgement thresholds for different driving events are shown in Table 2.

Table 2. Driving event judgement threshold.

Driving Events	Rapid Acceleration Start	Slow Start	Rapid Acceleration	Rapid Deceleration	Bad Parking
Judgement threshold	95th percentile of average accelerator pedal travel	Average speed less than 10 km/h	95th percentile acceleration	Deceleration greater than -1.5 m/s^2	Average rate of change in speed less than -1.5 m/s^2 or greater than -0.5 m/s^2

2.5. Characteristic Parameter Establishment

To analyze the influence of driving behavior on energy consumption under different driving states, it is necessary to establish driving behavior feature parameters that characterize different driving behaviors [10]. This paper establishes a total of 22 driving behavior feature parameters, including those of speed, speed change, accelerator pedal and time-based, which can effectively characterize most driving behaviors during the driving process. The specific feature parameters are shown in Table 3.

Table 3. Characteristic parameters of driving behavior.

	Characteristic Parameters	Symbolic	Unit
Speed	Average speed	V_m	km/h
	Maximum speed	V_{max}	
	Standard deviation of speed	V_s	
Speed Change	Average speed change rate	dV_m	m/s ²
	Standard deviation of speed change rate	dV_s	
	Average acceleration	A_m	
	Maximum acceleration	A_{max}	
	Standard deviation of acceleration	A_s	
	Average deceleration	D_m	
	Maximum deceleration	D_{max}	
Accelerator Pedal	Standard deviation of deceleration	D_s	%
	Average accelerator pedal travel	P_m	
	Maximum accelerator pedal travel	P_{max}	
Time-based	Standard deviation of accelerator pedal travel	P_s	%
	Low-speed time ratio	Tp_l	
	Medium-speed time ratio	Tp_m	
	High-speed time ratio	Tp_h	
	Constant-speed time ratio	Tp_e	
	Acceleration time ratio	Tp_a	
Time	Deceleration time ratio	Tp_d	s
	Regenerative braking Time ratio	Tp_r	
Distance	Travel time	T	km
	Travel distance	S	

2.6. LightGBM Feature Importance Selection of Feature Parameters

The feature importance of the LightGBM model can be utilized to identify key variables and select driving behavior feature parameters that have a greater impact on energy consumption [11]. Therefore, the LightGBM model is employed to screen the driving

behavior feature parameters with a significant impact on energy consumption from the 22 feature parameters listed in Table 3. The screening results are as follows.

- (1) **Starting Clip:** average accelerator pedal travel and average speed.
- (2) **Low-speed Acceleration Clip:** average accelerator pedal travel and average speed.
- (3) **Medium Speed Acceleration clip:** average accelerator pedal travel, standard deviation of accelerator pedal travel and average speed.
- (4) **High Speed Acceleration Clip:** average accelerator pedal travel, average speed and average speed change rate.
- (5) **Uniform Speed Clip:** average accelerator pedal travel and average speed.
- (6) **Deceleration Clip:** average accelerator pedal travel and average speed.
- (7) **Regenerative Braking Segment:** average speed, maximum deceleration and average deceleration.
- (8) **Parking Clip:** average speed and average speed change rate.

3. SHAP Algorithm Analysis

3.1. Energy Consumption Prediction Model Establishment

The input variables of the model consist of driving behavior parameters that have a substantial impact on energy consumption under different driving states, as well as driving events that significantly affect energy consumption, as analyzed. Meanwhile, the output variable of the model is specific energy consumption.

Firstly, the sample data are divided into a training set, a validation set, and a test set in a ratio of 8:1:1. Subsequently, the LightGBM energy consumption prediction model is constructed and trained using Python software version 3.8.8. The evaluation indexes of the model on the test set, MAE and MSE, are 1.72 and 5.24, respectively. These values indicate that the model exhibits a small error in both categories and performs well in predicting energy consumption over a distance of 100 km.

3.2. Explanation of SHAP Algorithm on the Effect of Feature Parameters on Energy Consumption

The SHAP (Shapley Additive Explanations) algorithm, proposed by Lundberg and Lee, is a method used to explain the model by quantifying the contribution of features to the prediction results [12]. The Shapley value reflects the marginal contribution of each feature to the model and is calculated using Equation (1).

$$\phi_j(f, x) = \sum_{S \subseteq F \setminus \{x_j\}} \frac{|S|!(M - |S| - 1)!}{M!} [f(S \cup x_j) - f(S)] \quad (1)$$

where f is the model being interpreted, x is a sample of data, x_j is the j -th feature in the sample of data, ϕ_j is the Shapley value of the j -th feature in the sample of data, M is the number of features, F is the set of all features, $S \subseteq F \setminus \{x_j\}$ denotes the subset of all the sets F that do not contain the feature, $|S|$ is the number of all the S sets, $f(S)$ is the predicted value of the model when all features in the set are used as inputs, $f(S \cup x_j)$ is the predicted value of the model when all features in the set are used as inputs, $f(S \cup x_j) - f(S)$ denotes the contribution of the feature and $\frac{|S|!(M - |S| - 1)!}{M!}$ denotes the probability of the situation.

A positive Shapley value for a feature indicates that the feature has a positive effect on the predicted value, leading to an increase in the predicted result. Conversely, a negative Shapley value for a feature indicates that the feature has a negative effect on the predicted value, resulting in a decrease in the predicted result. The absolute value of the Shapley value indicates the importance of the feature. The predicted value of a sample is determined by the baseline value of the model, which is the average value of the target output variable

of all samples, and the sum of the Shapley values of all features of the sample, as shown in Equation (2).

$$y_i = y_{base} + \sum_{j=1}^M \phi_j \quad (2)$$

where y_i is the predicted value of the i -th sample, y_{base} is the model baseline value, ϕ_j is the Shapley value of the j -th feature of that sample and M is the number of features.

3.3. Full Explanation of SHAP Algorithm

The global interpretation of the SHAP algorithm is based on the entire sample set, providing an explanation of the importance and degree of influence of different features on the predicted values of the model output. The dependency plot of each driving behavior feature parameter is presented in Figure 4, where the vertical axis represents the Shapley value of the driving behavior feature parameter, indicating the degree of influence on the energy consumption of 100 km. The horizontal axis represents the magnitude of the driving behavior feature parameter.

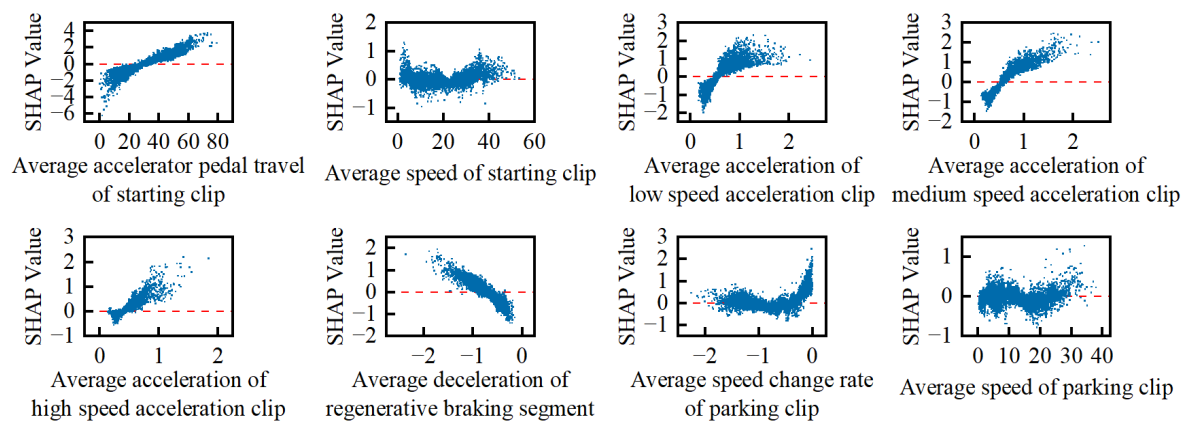


Figure 4. Dependency graphs of parameters characterizing driving behavior.

Figure 5 displays the dependency plot of each driving event. It can be observed that there is a clear linear relationship between the number of occurrences per kilometer of the driving events that have a negative effect on energy consumption and the Shapley value. The Shapley value increases with the number of occurrences per kilometer of the driving events, indicating that an increase in the number of occurrences per kilometer of the driving events will result in an increase in the predicted value of the energy consumption.

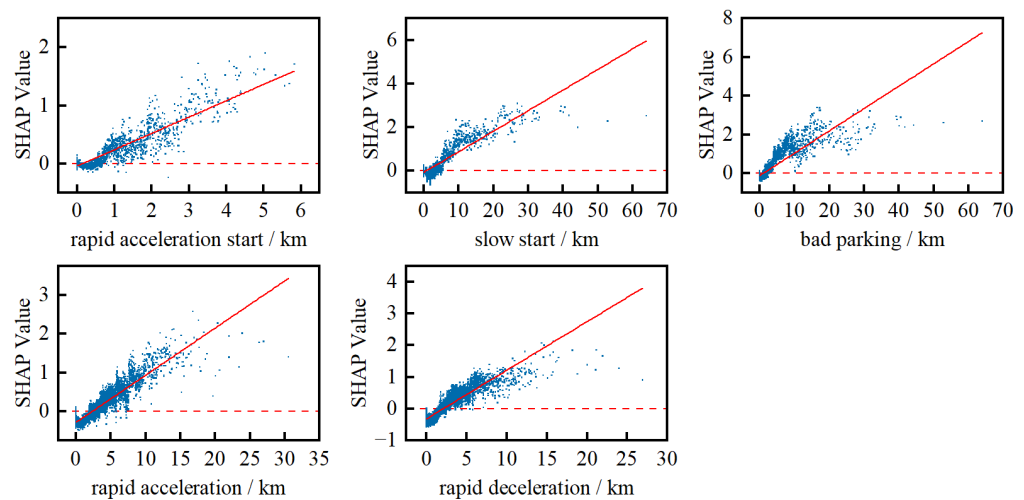


Figure 5. Dependency graphs of driving events.

4. Scorecard Modeling Based on the SHAP Algorithm

4.1. Construction of Positive and Negative Sample Sets

To eliminate the influence of other factors and solely focus on driving behavior, this chapter marks the positive and negative samples based on the results of the SHAP algorithm analysis in the previous section. The sample set consists of 8 driving behavior parameters and 5 driving events, totaling 13 feature variables. Based on the calculation results, when the SHAP value is less than 0, it signifies that the feature variable can reduce energy consumption and save energy. Therefore, the positive and negative samples can be classified by evaluating the number of SHAP values less than 0 in the feature variables of a single sample.

Firstly, the average number of feature variables with SHAP values less than 0 in all samples is calculated to be 8.77. Different conditions for dividing positive and negative samples are designed with this value as the center, and the positive and negative samples that meet these conditions are presented in Table 4 (number of feature variables with SHAP values less than 0 = n).

Table 4. Positive and negative samples when different conditions are met.

Positive and Negative Sample Division Conditions	Positive Sample Size	Negative Sample Size	Positive Sample Average of 100 km Energy Consumption (kw·h)	Negative Sample Average of 100 km Energy Consumption (kw·h)
$n \geq 10$ or $n \leq 7$	28,522	19,632	12.760	16.097
$n \geq 11$ or $n \leq 6$	15,950	10,775	12.234	16.594
$n \geq 12$ or $n \leq 5$	6645	5058	11.773	17.169
$n \geq 13$ or $n \leq 4$	1891	1556	11.279	17.669

According to Table 4, when the number of feature variables with a SHAP value less than 0 is greater than or equal to 11 or less than or equal to 6, 15,950 positive samples and 10,775 negative samples can be obtained. This accounts for close to 20% of all the samples. Therefore, based on this condition, the positive and negative samples are labeled and the positive and negative sample set is constructed.

4.2. Energy-Saving Classification Modeling and Performance Evaluation

Since the score conversion of the scorecard model is related to the probability of a sample being predicted as a positive or negative sample [13], an energy-saving classification model needs to be built. This model will output the probability that a particular sample conforms to energy-saving driving behaviors. The energy-saving classification model can be trained based on the WOE-coded (Weight of Evidence) training set [14], and the optimal model can be selected by evaluating the model on the WOE-coded testing set for the scorecard score conversion.

The performance of a classification model is often evaluated by means of a confusion matrix after it has been built [15]. The performance of the built energy-saving classification model is evaluated, and the best model is selected by calculating the model's *accuracy*, *precision*, *recall* and *F1 – score*.

The positive and negative sample set based on the analysis results of the SHAP algorithm is named as sample set 1, and the positive and negative sample set based on the energy consumption is named as sample set 2. The performance of the model trained based on sample set 2 is also evaluated and added for comparison. The energy-saving classification model's input and output variables are shown in Table 5, and the obtained classification model evaluation metrics are shown in Table 6. It can be seen that the LightGBM model works better and is more effective when trained with sample 1.

Table 5. Input and output variables for the energy-saving classification model.

Variable Type	Variable Name	
Input Variables	Average accelerator pedal travel WOE value of starting clip	Average speed change rate WOE value of parking clip
	Average speed WOE value of starting clip	WOE value of rapid acceleration start times per kilometer
	Average acceleration WOE value of low-speed Acceleration clip	WOE value of slow start times per kilometer
	Average acceleration WOE value of medium-speed Acceleration clip	WOE value of rapid acceleration start times per kilometer
	Average acceleration WOE value of high-speed acceleration clip	WOE value of rapid deceleration times per kilometer
	Average deceleration WOE value of regenerative braking clip	WOE value of poor parking times per kilometer
	Average speed WOE value of parking clip	
Output Variable	Positive and negative sample labels	

Table 6. Model evaluation indicators.

Assessment Metrics	Logistic		Random Forest Algorithm		XGBoost		LightGBM	
	Sample Set 1	Sample Set 2	Sample Set 1	Sample Set 2	Sample Set 1	Sample Set 2	Sample Set 1	Sample Set 2
Accuracy	98.09%	84.81%	99.29%	84.35%	99.38%	85.34%	99.40%	85.39%
Precision	98.13%	84.40%	99.40%	85.12%	99.41%	85.51%	99.47%	85.92%
Recall	98.68%	85.41%	99.40%	83.25%	99.56%	85.10%	99.53%	84.65%
F1-score	98.41%	84.90%	99.40%	84.17%	99.48%	85.30%	99.50%	85.28%

4.3. Score Conversion Based on Model Results

Firstly, based on the output of the classification prediction probabilities from the LightGBM model, the ratio odds of the probability p that the sample is an energy-saving driving behavior to the probability $1 - p$ that the sample is a non-energy-saving driving behavior can be calculated, as shown in Equation (3).

$$odds = \frac{p}{1 - p} \quad (3)$$

After calculating the relative probability $odds$, a linear expression for the scorecard score based on the logarithm of the relative probability can be established, as shown in Equation (4). As the probability p of the sample demonstrating energy-saving driving behavior increases, the $odds$ increase, resulting in a higher scorecard score.

$$score = offset + factor \times \ln(odds) \quad (4)$$

where $offset$ and $factor$ are constants, denoting the two hyperparameters to be solved, i.e., bias and factor coefficients, respectively.

The $offset$ and $factor$ can be calculated by setting the benchmark score P_0 and the relative incremental score PDO with the initial relative probability θ_0 . The baseline score P_0 is the scorecard score when the relative probability odds are θ_0 , and the relative incremental score PDO is the value by which the scorecard score increases compared to the baseline score when the relative probability is $2\theta_0$.

$$score = P_0 = offset + factor \times \ln(\theta_0) \quad (5)$$

$$score' = P_0 + PDO = offset + factor \times \ln(2\theta_0) \quad (6)$$

Based on the calculations, the expressions for offset and factor can be obtained as shown in Equations (7) and (8).

$$factor = \frac{PDO}{\ln 2} \quad (7)$$

$$offset = P_0 - factor \times \ln(\theta_0) \quad (8)$$

Next, by setting the baseline score P_0 , the relative incremental score PDO with the initial relative probability θ_0 , and substituting the computed *offset* and *factor* back into Equation (8), the conversion formula for the scorecard score can be obtained, and the sample score is output according to the classification prediction probability of the sample.

5. Analysis of Results

5.1. Analysis of Scoring Results

By setting the baseline score $P_0 = 80$, the relative incremental score $PDO = 1$, and the initial relative probability $\theta_0 = 0.5$, the scoring results are shown in Figure 6. It is evident that as the score decreases, the number of negative samples shows a growing trend, while the number of positive samples shows a growing trend as the score increases. Additionally, the distribution of positive and negative samples does not significantly intersect in the mid-value portion of the scoring results. This indicates that the current scorecard model is capable of effectively differentiating between positive and negative samples and conducting reasonable evaluations.

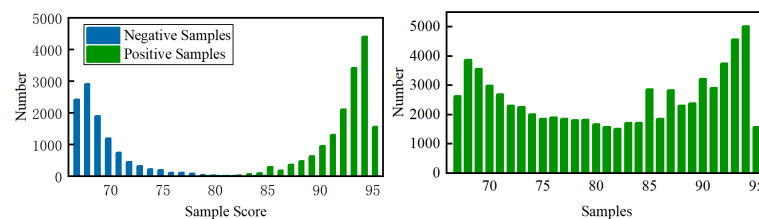


Figure 6. Positive and negative sample sets and all sample scoring results.

- (1) **Analysis of Sample Distribution:** As depicted in Figure 6, the distribution of scores for all the samples is relatively even overall. However, there appears to be a slightly larger distribution of lower and higher scores, suggesting that drivers are more inclined to either adopt energy-saving driving behaviors or not adopt them at all.
- (2) **Analysis of Characteristic Variable SHAP Values:** Figure 7 illustrates the average sum of the sample characteristic variable SHAP values at different scores. The SHAP value reflects whether a driving behavior is able to save energy or not, while the score represents the energy-saving evaluation of all the driving behaviors in a short trip segment. As the score increases, the sum of the SHAP values of the sample characteristic variables gradually decreases. This indicates that the scorecard model can more accurately capture the energy-saving enhancement of a driver's driving behaviors when they adopt more energy-saving driving behaviors, leading to more accurate evaluations.
- (3) **Analysis of Average Energy Consumption:** Figure 8 displays the average value of 100 km energy consumption for samples with different scores. It can be observed that the 100 km energy consumption decreases gradually as the scores increase. This suggests that the improvement of energy saving in driving behavior leads to improved energy consumption performance. Furthermore, the scores are able to correctly reflect the changes in driving behavior and energy consumption.
- (4) **Noise Analysis:** There is a small portion of the total number of short trip segments where the duration and distance travelled are too short to result in a difference from

the stable duration of the short trip segments, and therefore the values in this portion of the short trip segments are dispersed.

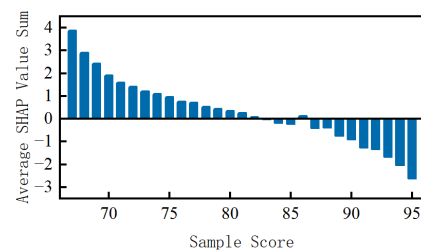


Figure 7. Mean of the sum of SHAP values of the sample characteristic variables at different scores.

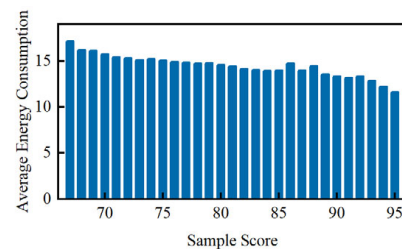


Figure 8. Mean value of 100 km energy consumption of the sample at different scores.

5.2. Driver Evaluation

Drivers may exhibit different driving behaviors in response to varying traffic conditions, resulting in changes in their energy-saving scores across multiple samples. To accurately evaluate energy-saving driving behaviors, this study divides the different samples belonging to 17 drivers from the entire sample set. Based on the trained scorecard model, the output of all samples from different drivers is scored, and the K-means clustering algorithm is employed to cluster the drivers. Using the elbow method, it was determined that the drivers can be divided into four classes. The characteristic parameters of these four clusters are presented in Table 7.

Table 7. Driver clustering results.

Category	Scoring Mean	Scoring Standard Deviation	Scoring 25th Percentile	Scoring Median	Scoring 75th Percentile
1	75.9932	8.3084	68.9860	72.6836	82.3992
2	79.4211	8.8714	71.0047	77.9284	87.7088
3	83.2113	8.8222	74.9560	84.8776	91.4712
4	85.5552	8.2321	78.9986	88.0395	92.7438

According to the clustering results in Table 7, the energy-saving nature of drivers' driving behaviors can be classified into four categories: poor energy saving, relatively poor energy saving, relatively good energy saving, and good energy saving. Analysis of the results indicates that drivers with poor energy-saving performance have generally low sample scores, suggesting that their driving habits are inadequate and need to be improved. Drivers with both relatively poor and relatively good energy-saving performance have more evenly distributed sample scores, with a slightly higher number of samples having low or high scores. This suggests that drivers may have some awareness of energy-saving driving but have not yet developed good energy-saving driving habits. On the other hand, drivers with good energy-saving performance have generally higher sample scores, indicating that they exhibit low energy consumption in their daily driving. Furthermore, these drivers also maintain good energy-saving driving behavior when facing different traffic conditions during daily driving.

5.3. Evaluation of Environmental Factors

Since the model input variables include the percentage of driving time reflecting traffic conditions, the interference of traffic conditions can be excluded when quantitatively analyzing the impact of driving behavior on energy consumption, and drivers can be provided with suggestions for energy-saving driving behavior based on the conclusions of the analysis.

6. Conclusions

- (1) The SHAP algorithm is utilized to interpret the results and quantitatively analyze the impact of different driving behavioral characteristic parameters and driving events on energy consumption. This enables the identification of driving behaviors that contribute to energy saving and the determination of the time of relevant driving events occurring during driving.
- (2) A driving behavior energy-saving evaluation method based on the SHAP scorecard model is proposed. This method accurately and reasonably scores energy-saving driving behaviors of short trip segments. It completes the research and evaluation of energy-saving driving behaviors by integrating the relevant eigenvalues of all sample scores from different drivers. Additionally, it classifies drivers using the K-means clustering method and analyzes the distributions of sample scores of typical drivers from different categories.
- (3) The evaluation of a driver's energy-saving driving behavior is conducted and the scores can be fed back to the driver after a single trip. This helps drivers improve their driving behavior and observe whether they can maintain energy-saving driving behavior in the long term and form energy-saving driving habits. Different categories of drivers can be adjusted through the scoring feedback frequency or form of targeted assistance to help improve or maintain energy-saving driving behavior. Ultimately, the goal is to decrease vehicle energy consumption through energy-saving driving behavior evaluation, thereby improving vehicle energy efficiency.

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Conflicts of Interest: Author Guowen Zheng is employed by Nanchang Intelligent New Energy Vehicle Research Institute, China. Author Zhanping Liu is employed by Jiangxi Jiangling Group New Energy Vehicle Co., Ltd., China. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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