Research Article

Exploring the Energy Efficiency of Electric Vehicles with Driving Behavioral Data from a Field Test and Questionnaire

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With increasing concerns about urban air quality and carbon emissions, electric vehicles (EVs) have gained popularity in megacities, especially in Europe and Asia. The energy consumption of EVs has subsequently caught researchers’ attention. However, the exploration of energy consumption of EVs has largely focused on people’s revealed driving behavior and rarely touched on their self-perception of driving styles. In this paper, we developed a more human-centric approach, aiming to investigate how the energy efficiency of EVs is shaped by the driving behavior and driving style in the urban scenario from field test data and driving style questionnaires (DSQs). Field tests were carried out on a designated route for a total of 13 drivers in the city of Beijing, where vehicle operation parameters were recorded under both congested and smooth traffic conditions. DSQs were collected from a larger pool of drivers including the field test drivers to be applied to driving style factor analysis. The results of a correlation analysis demonstrate the dynamic interaction between drivers’ revealed behavior and stated driving style under different traffic conditions. We also proposed an energy consumption prediction model with the fusion of collected driving parameters and DSQ data and the result is promising. We hope that this study would draw inspiration for future research on people's transitioning driving behavior in an electric-mobility era.

1. Introduction

To cope with the challenges of reducing greenhouse gas emissions and curbing urban pollution, electrification of the urban vehicle fleet has been a trend, particularly in densely populated urban areas, such as Paris in Europe and Beijing in Asia [1–3]. EVs have the advantages of zero tailpipe emissions, low noise, and higher propulsion efficiency. By the end of 2016, a fast-growing market has been fostered with an accumulated EV stock reaching two million globally with the support from central and municipal governments [4].

However, potential EV buyers are still concerned about limited range, which is referred to as “range anxiety.” It is defined as anxiety or fear that one may not reach a destination before the battery is empty, which can occur while driving or prior to driving as the user worries about a later planned trip [5]. Even though EV motor efficiency is less sensitive to speed than are internal combustion engines, bidirectional energy flow resulting from regenerative braking and the dynamics of electric propulsion has caused substantial heterogeneity among drivers due to different driving behaviors, and this deserves further study [6].

On-road fuel consumption of vehicles can be influenced by drivers through three levels of decisions, including strategic decisions (vehicle selection and maintenance), tactical decisions (route selection and vehicle load), and operational decisions (driving behavior) [7]. Driving behaviors have been shown to result in fluctuations of vehicle energy efficiency with regard to conventional vehicles, where aggressive driving behavior can consume 30% more fuel [8]. In some EV pilot countries, researchers have pointed out the change of driving behaviors in the transition from conventional vehicles to EVs, which could be susceptible to the contexts and require further research [9, 10]. Hence, for progress to be made in the case of EVs, a comprehensive understanding of the interaction between people’s driving style, driving behavior, and energy efficiency is needed.
Since terminologies such as “driving behavior” and “driving style” are used in this study and can sometimes be confounding, we would like to give a concise description beforehand. As understood by the authors, driving behaviors emerge out of the interplay of contextual conditions (traffic, road, weather, vehicle, et cetera) and person-specific driving styles [11, 12]. In the real-world tests, contextual conditions are more of a dynamic nature. Driving styles, dispositions to drive in particular ways that have been acquired over time, are more or less stable in the short term and can be measured by questionnaires. The relationships between these terms are illustrated in Figure 1.

Primarily, since aftermarket devices which can record multiple vehicle operation data sources on EVs (including speed, energy consumption) through onboard diagnostics (OBD) are widely available, the tech-centric approach has been adopted to evaluate driving behaviors from the abundant data collected in field tests [13]. Some research on the energy consumption of EVs and driving behaviors was based on experiments on test tracks without actual traffic flow, and the results elucidated the potential of good driving behavior on the improvement of energy efficiency [14–16]. Other authors conducted real-world tests to cluster drivers according to their speed and energy consumption profiles or calculate the average energy consumption for different road types [17–20]. Besides, there has been another series of studies, namely, more human-centric approaches, focusing on the use of interviews, questionnaires, and travel diaries to understand driving behavior or attitudes towards EVs [21]. Psychological methods were adopted to evaluate people’s perception of EV display systems, portable driving feedback device, and their acceptance of EV itself [13, 22, 23]. Recently, Helman and Reed conducted an exploratory study on the correlation between driver behavior questionnaire (DBQ) scores and observed driving speed data [24], which inspired us to extend this comparative idea to the domain of EV energy consumption. These two strands of studies (field experiments and questionnaires) have remained parallel for most of the time, excluding the chance to understand driving behavior from people’s underlying dispositions.

In summary, none of the existing work analyzed the impact of driving behaviors on EVs’ energy consumption in the open driving environment from both Controller Area Network- (CAN-) based data and questionnaires. The overall EV energy consumption performance will depend on not only how well the vehicle works by itself but rather its interaction with the human driver. Analyzing behavior-related variables with multiple data sources allows for a comprehensive data triangulation [25], which could potentially yield a more accurate analysis result. In this study, compared with previous study that only featured measured field test data or questionnaire data separately [14, 22], a more “human-centric” experiment is proposed to explore how drivers’ stated driving styles are reflected and correlated with their actual way of driving and to understand how they together contribute to the energy consumption.

The remainder of the paper is organized as follows: after the introduction of the EV field test in Section 2.1; Section 2.2 describes the driving style questionnaires (DSQs) in detail; then, an analysis of the results follows in Section 3; and finally, conclusions of the investigation are given in Section 4.

2. Experiment and Methodology

The goal of this research is to improve the understanding of the driving behavior of EV drivers through the integration of experiments and questionnaires and its impact on the energy efficiency created by EV users. It is noteworthy that there are a number of factors that can affect the energy efficiency of a vehicle in the real world [11, 13], including external factors like infrastructure design, vehicle design, road grade, weather conditions, congestion level, and internal factors of the driver such as driving behavior and driving style. Since this paper concentrates on studying driving behavior and driving style under different traffic conditions, other external factors remain as controlled variables. To this end, we recruited 13 EV drivers to collect their real-world field test data on the same route, and we also built a pool of driving style questionnaires (DSQs) with these drivers included. The DSQ data (more than 300 samples) was used to conduct a valid factor analysis so we could further score each of
the 13 drivers in terms of different dimensions of driving style. Observations on driving behaviors were conducted on a designated route in a “semicontrolled” condition to increase the comparability of the results across drivers. With this research we seek to (a) identify the relationship between self-stated driving style and observed driving behavior under different traffic conditions and (b) advance understanding of the energy efficiency created by EV users in a real-world driving scenario from the perspectives of driving behavior and driving style.

2.1. Field Test Data Used in This Study. Detail of the experimental design in which energy consumption and other driving behavior data were collected as described in our previous work [11]. In short, the data was collected from 13 participants who drove on a selected typical commuting route in Beijing in the same time of day, starting from the residential area of Haidian District (near the 5th ring road) and ending in Sanlitun CBD (between the 2nd and 3rd ring road) in Chaoyang District (shown in Figure 2). The drivers were selected based on a snowball sampling method to be representative of the current EV drivers in Beijing as shown in a survey, which indicated that 63.4% of EV drivers in Beijing were male, 79% of the drivers fell into the age group of 20-39, and the majority were well educated [26]. The majority of drivers in the experiment were well-educated young male adults who had driven an EV before. The drivers were instructed to drive as they normally would (without violating the speed limit) at the same time of the day (including both congested and smooth traffic conditions) to normalize the data against traffic conditions.

The vehicle used for the study was a battery electric vehicle Nissan LEAF model with an OBD data logger connected to the Electronic Control Unit (ECU) along the driving tests. A number of variables including vehicle speed, motor torque, motor speed, battery pack current, and voltage were recorded. The acceleration and energy consumption data could be calculated as derived values accordingly. All tests were carried out within two months after commencement in October 2015, excluding days of extreme weather (rainy, windy), and special events.

To ensure consistency, the vehicle started with the same state of charge (SOC) of battery for different participants during all the tests (80% for the congested trip and roughly 65% for the smooth trip), and no additional ‘comfortable loads’ (i.e., air-conditioning and heating or radio) were used. Other controlled variables included the identical test route and same departure time. Note that unlike the ideal conditions in a simulation platform or chassis test, the operation conditions could not be maintained in an identical fashion in our tests. We recognize the existence of uncertainty (traffic conditions were similar but not the same) in our tests but believe it is inevitable when the aim is to obtain real-world data for analysis.

Since the drivers were instructed to drive “naturally” as they normally would, we assume the field test data reflects participants’ usual driving behavior under everyday traffic conditions. Each driver in the study also completed the DSQ, leaving us with the opportunity to examine how and to what extent their self-stated responses correspond to their driving behavior in the field test dataset.

2.2. Questionnaire Data Used in This Study. The Driving Style Questionnaire (DSQ) examines driving behaviors that are related to accidents and risks, including speed, headway (distance to the car in front), lane-changing behavior, violations of traffic signals, and human cognition and attitudes that are somehow associated with decision-making, for example, feelings of confidence, route planning, and en-route risk taking [27].

We designed a driving style questionnaire in Chinese according to previous research [28] and took into account the unique context in China to extract the driving characteristics. A total of 55 questions were included in the original version, and 40 questions were finally selected after eliminating unimportant questions. The questionnaire was mainly structured with each answer consisting of four ordinal measurements. For example, for question No. 30, “I can drive safely under complicated traffic conditions,” there were four degrees of agreement: (A) No, (B) Seldom, (C) Sometimes, and (D) Always. Full details of the questionnaire are given in the Appendix.

In order to perform a valid DSQ analysis, there should be a minimum sample size of 5 times the number of questions in the questionnaire (to avoid the “curse of dimensionality”), which equals 200. Hence it is necessary to extend the questionnaire dataset to include a wider group of drivers. While all the 13 drivers were requested to complete the questionnaire, DSQs were also disseminated online and offline among valid driving license holders in the City of Beijing. Finally, more than 400 questionnaires were completed including the 13 drivers in the driving experiment. After excluding invalid samples with extreme values, discrepancies, or missing values (in terms of age, responding time, cross-validation questions, et cetera), the remaining 331 (80%) questionnaires were taken for further analysis. The demographic information is listed in Figure 3. The respondents are across all age groups (mean=38.09, Std Dev=9.075), with a balanced gender mixture and an average driving experience of 5 years.

Statistical Product and Service Solutions (SPSS) was used to carry out the calculation and analysis process. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy>0.85 and the Bartlett test of the sphericity (sig=0.000) of the
questionnaires both indicate the suitability of a factor analysis (also called principal component analysis, PCA) [29]. Therefore, the factor analysis was applied to the DSQs and extracted eight components with eigenvalues greater than one (other factors with lower eigenvalues were ignored for interpretability purpose). Table 1 shows the contribution of the extracted factors to explain the variance after a varimax rotation. Together the eight factors accounted for 51.2% of the variance. The detailed interpretation of the extracted factors is given in Table 2.

### Table 1: Variance explained by each factor.

| Factor   | Total     | % of Variance | Cumulative % |
|----------|-----------|---------------|--------------|
| Factor 1 | 5.216     | 13.040        | 13.040       |
| Factor 2 | 3.631     | 9.077         | 22.116       |
| Factor 3 | 2.297     | 5.743         | 27.859       |
| Factor 4 | 2.094     | 5.236         | 33.095       |
| Factor 5 | 1.945     | 4.862         | 37.958       |
| Factor 6 | 1.882     | 4.704         | 42.662       |
| Factor 7 | 1.739     | 4.347         | 47.009       |
| Factor 8 | 1.664     | 4.159         | 51.169       |

3. Results

This section briefly summarizes the results from our experiments and continues with the analysis of the DSQs. It then explores the relationships between measured driving behavior and DSQ scores for the 13 recruited drivers under different traffic conditions. Finally, it proposes a concise multiple regression model to formulate the EV energy consumption using DSQ scores and the driving behavior data collected from the field tests.

### 3.1. Preliminary Results of the Field Tests and DSQ Scores.

The results (shown in Figure 4) illustrated that the average energy consumption during congested traffic conditions is 15.6% higher than during smooth conditions (151.7 Wh/km and 131.3 Wh/km, respectively), which is statistically significant at the 95% confidence level in the Mann-Whitney test. The energy consumption variation among drivers is slightly larger during congested traffic condition than during smooth condition. The worst-performing versus the best-performing driver is 32.4% during congested condition and 30.0% during smooth condition.

Previous research has suggested that fuel consumption and driving behavior variables such as speed and acceleration were correlated [30]. Corresponding to energy consumption, several driving behavior variables were recorded and calculated for each driver, respectively, including average speed, average acceleration, average deceleration, journey energy regeneration, and driving status distribution. Driving status distribution consists of acceleration, deceleration, constant speed, and idling. The idling mode means that the battery power is turned on to supply to the motor although the actual vehicle speed is 0; the acceleration mode is defined by the acceleration speed $a > 0.2m/s^2$ in the constant driving
| Factor                      | Loadings | Questions                                                                 |
|-----------------------------|----------|---------------------------------------------------------------------------|
| Factor 1: Self-confidence in driving |          | 0.79 I can drive safely under complicated traffic conditions.             |
|                             |          | 0.74 I can respond reasonably to unexpected events.                       |
|                             |          | 0.72 I can maneuver the vehicle properly as I wish.                      |
|                             |          | 0.71 I have confidence in teaching newcomers to drive.                    |
| Factor 2: Distraction in driving |          | 0.68 I am skillful in backing and parking.                               |
|                             |          | 0.54 I can drive normally in harsh weather (windy, foggy, rainy, snowy).  |
|                             |          | 0.42 I enjoy driving.                                                    |
|                             | -0.57    | I feel nervous when driving.                                             |
|                             | -0.43    | I am worried about a traffic accident when driving.                      |
| Factor 3: Impatience in driving |          | 0.78 I answer the phone when driving.                                    |
|                             |          | 0.69 I talk to my passengers when driving.                               |
|                             |          | 0.62 I check my phone/iPad during the red traffic signal period.          |
|                             |          | 0.47 I pay attention to the street scenery when driving.                 |
|                             | -0.56    | I concentrate during driving and always ignore what others say.          |
| Factor 4: Attachment to vehicles |          | 0.52 I feel upset during congestion.                                     |
|                             |          | 0.50 I maintain a close distance to the vehicle in front.                |
|                             |          | 0.45 I always drive fast.                                                |
|                             | -0.39    | I give way to other vehicles if they merge into my lane.                 |
|                             | 0.44     | I obey and have faith in traffic rules.                                  |
| Factor 5: Intersection acceleration behavior | 0.80 | I accelerate when approaching and crossing a yellow light when there is only one vehicle in front and it is accelerating. |
|                             | 0.79     | I accelerate when approaching and crossing a yellow light when there is no vehicle in front. |
| Factor 6: Proactive driving behavior |       | 0.57 I change to the expected lane early in preparation for the next intersection. |
|                             | 0.52     | I observe the traffic light patterns from a distance.                    |
|                             | 0.46     | I adjust my vehicle in advance when entering into a queue.              |
| Factor 7: Rude driving      |          | 0.52 I always honk the horn to the vehicle in front in congestion.       |
|                             | 0.44     | I brake hard when I decelerate.                                         |
|                             | -0.47    | I find it is easy to remain a proper distance from the front vehicle.    |
| Factor 8: Rigidity in driving |          | 0.74 I stick to my accustomed route even when the road is congested.     |
|                             | -0.50    | I feel annoyed when following heavy-duty vehicles like buses and vans.  |
|                             | 0.44     | I enjoy driving.                                                         |
process; deceleration mode happens when acceleration goes below \(a < -0.2 \text{m/s}^2\) in the constant driving process; and the constant speed mode is defined as instantaneous acceleration \(|a| < 0.2 \text{m/s}^2\) while speed is above 0. Series of continuous moments of each status have been aggregated across individual trips as episodes. The share of these four types of driving status is calculated as the percentage of the total number of episodes. The idling share is significantly different for the two traffic conditions, that is, 3.8% for the departure trip in congested conditions versus 1.8% for the return trip in smooth conditions. This discrepancy is not yet significant for other statuses, which is normal since whether to maintain a constant speed or to accelerate/decelerate is the joint result of the traffic conditions and drivers’ personal driving style. Full details of the field test results and spatial domain analysis can be found in our previous study [11].

As for the DSQs, the aforementioned extracted factors were further interpreted by examining the contents of the variable loadings accordingly. Loadings are the correlation coefficients between the variables and factor. A criterion of 0.4 was used as the minimum loading for a question item to be incorporated. Seven of the 40 question items were excluded, and the remaining 33 were used for further analysis. The loadings of the questions for each interpreted factor are shown in Table 2. According to the content of relevant question items, Factor 1 can be interpreted as the driver’s self-assessment of confidence in driving. The positive loading (0.79) of the question “I can drive safely under complicated traffic conditions” indicates its positive correlation with Factor 1, while the negative loading (-0.53) “I feel nervous when driving” denotes the negative correlation (this result is intuitive since when you feel nervous during driving you are always less confident in driving). Eight factors regarding driving styles are characterized as self-confidence in driving, distraction in driving, impatience in driving, attachment to vehicles, intersection acceleration behavior, proactive driving behavior, rude driving, and rigidity in driving.

With the loadings for each factor, the factor score for each driver can be calculated as follows:

\[
\text{Score}_{Ek} = \frac{\sum D_{ij} L_{jk}}{\sqrt{E_k}} \tag{1}
\]

where \(D_{ij}\) is the standardized value for driver \(i\) on question \(j\) and \(L_{jk}\) is the loading of variable \(j\) on factor \(k\). \(E_k\) is the Eigenvalue of factor \(k\). The positive and negative factor score means the associated driver is above or below average among the sample group, respectively.

We first check the results of the whole pool of samples rather than the recruited drivers only. The relationship between driving style factor, age, and gender were tested using Pearson’s correlation to explore changes in factor scores with age and the Mann-Whitney test for gender difference. The results are shown in Table 3. Males had higher scores on six out of eight factors; among them, self-confidence in driving, distraction in driving, attachment to vehicles, and proactive driving behavior were significant.

We categorized the population by age into four groups and plotted the average score for the eight factors accordingly (shown in Figure 5). Self-confidence and proactive behavior in driving increased with age (\(R=0.118\), significant at 0.05 level, and \(R=0.188\), significant at 0.01 level, respectively), while distraction in driving decreased with age (\(R=-0.219\), significant at 0.01 level). Impatience in driving was higher for people below 40 than people above 40, while attachment to vehicles was the opposite. Rude driving alleviated with age, though not significantly. As for rigidity in driving, people between 40 and 50 outperformed other groups. Other factors like impatience in driving, attachment to vehicles, intersection acceleration behavior, proactive driving behavior, and rigidity in driving did not show a prominent correlation with age.

### 3.2. Relationships between DSQ, Field Test Data and Energy Consumption

After extracting the factors and corresponding question loadings of the DSQ, factor scores for the 13 recruited drivers were calculated accordingly. Relationships between the DSQ factor scores and characteristics of the measured driving behaviors in both congested and smooth traffic conditions were investigated using Pearson’s correlations as shown in Table 4. Factor 1 (self-confidence in driving) is correlated significantly (negatively) with the idling share for congested and smooth conditions, which indicates more confident drivers are less likely to stand still; confidence level is also positively correlated with average speed, showing the

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**Table 3: Relationship of driving style factors with age and gender.**

| Factor | Correlation with Age | Male Mean | Female Mean | Mann-Whitney test p-value (2-tailed) |
|--------|----------------------|-----------|-------------|-------------------------------------|
| Factor 1 | 0.118*               | 0.337     | -0.448      | 0.000*                              |
| Factor 2 | -0.219**             | 0.098     | -0.131      | 0.030*                              |
| Factor 3 | -0.100               | 0.080     | -0.106      | 0.078                               |
| Factor 4 | 0.082                | 0.254     | -0.337      | 0.000 * *                          |
| Factor 5 | -0.032               | 0.025     | -0.033      | 0.704                               |
| Factor 6 | 0.188*               | 0.103     | -0.136      | 0.023*                              |
| Factor 7 | -0.086               | -0.129    | 0.171       | 0.016*                              |
| Factor 8 | 0.035                | -0.064    | 0.086       | 0.161                               |

N=331

* * Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).
Table 4: Correlations between DSQ and measured driving behaviors.

| Smooth Traffic | Average Speed | Acc Share | Dec Share | Constant Share | Idling Share | Average Acc | Average Dec | Energy Regeneration | Variation of Steering Wheel Angle |
|----------------|---------------|-----------|-----------|----------------|--------------|-------------|-------------|---------------------|-----------------------------------|
| Factor 1       | 0.50          | 0.15      | -0.11     | 0.26           | -0.76**      | 0.19        | -0.15       | 0.16                | -0.15                             |
| Factor 2       | -0.37         | -0.27     | 0.47      | -0.37          | 0.53         | -0.03       | 0.18        | -0.09               | 0.13                              |
| Factor 3       | -0.27         | 0.16      | 0.48      | -0.58*         | 0.08         | 0.28        | 0.18        | 0.30                | 0.59*                             |
| Factor 4       | 0.66*         | -0.35     | -0.27     | 0.63*          | -0.23        | -0.44       | -0.33       | -0.34               | -0.46                             |
| Factor 5       | 0.07          | 0.26      | 0.47      | -0.57*         | -0.15        | 0.48        | 0.35        | 0.60*               | 0.40                              |
| Factor 6       | 0.14          | 0.04      | 0.14      | -0.40          | -0.07        | -0.07       | 0.22        | 0.06                | 0.22                              |
| Factor 7       | -0.17         | -0.05     | 0.50      | -0.40          | 0.03         | 0.15        | 0.30        | 0.25                | 0.51                              |
| Factor 8       | 0.19          | -0.27     | -0.30     | 0.46           | 0.09         | -0.48       | -0.29       | -0.32               | 0.17                              |

| Congested Traffic | Average Speed | Acc Share | Dec Share | Constant Share | Idling Share | Average Acc | Average Dec | Energy Regeneration | Variation of Steering Wheel Angle |
|-------------------|---------------|-----------|-----------|----------------|--------------|-------------|-------------|---------------------|-----------------------------------|
| Factor 1          | 0.51          | 0.02      | -0.03     | 0.26           | -0.58*       | 0.17        | 0.15        | 0.18                | -0.23                             |
| Factor 2          | 0.05          | -0.05     | 0.50      | -0.33          | 0.21         | 0.03        | 0.22        | 0.02                | 0.16                              |
| Factor 3          | 0.10          | 0.29      | 0.48      | -0.38          | -0.08        | 0.30        | 0.30        | 0.30                | 0.48                              |
| Factor 4          | 0.31          | -0.36     | -0.21     | 0.47           | -0.36        | -0.20       | -0.19       | -0.15               | -0.55                             |
| Factor 5          | 0.12          | 0.60*     | 0.50      | -0.60*         | 0.01         | 0.62*       | 0.30        | 0.57*               | 0.62*                             |
| Factor 6          | 0.61*         | 0.07      | 0.42      | 0.00           | -0.58*       | -0.01       | 0.23        | 0.24                | -0.17                             |
| Factor 7          | -0.01         | 0.39      | 0.43      | -0.46          | 0.04         | 0.29        | 0.47        | 0.42                | 0.62*                             |
| Factor 8          | -0.39         | 0.14      | -0.37     | 0.01           | 0.25         | 0.02        | 0.02        | -0.04               | 0.06                              |

N=13

* = Correlation is significant at the 0.01 level (2-tailed).
** = Correlation is significant at the 0.05 level (2-tailed).

Speeding tendency among confident drivers. The constant speed share decreases with Factor 3 (impatience in driving) score, while the variation of steering wheel angle increases in smooth conditions, showing impatience potentially contributes to more speed variation and overtaking behavior. The pattern is similar in congested conditions, though less prominent due to the external constraint of traffic. Factor 4 (attachment to vehicles) is positively correlated with average speed and constant share in smooth conditions, showing people who are attached to vehicles tend to drive faster and also more stable. Factor 5 (intersection acceleration behavior) correlates negatively with constant speed share and positively with energy regeneration for both traffic conditions, and during congestion it shows positive correlations (0.60) with the average value and share of acceleration, as well as the variation of steering wheel angle, verifying the consistency and complementarity of these two data sources.

Further, we continued assessing the extent to which energy consumption is associated with DSQ factor scores and measured driving behavior. Pearson’s correlations were calculated and the results are demonstrated accordingly in Figure 6. It can be concluded that generally the measured driving behaviors are correlated with energy consumption in the same direction regardless of the driving conditions, except idling share. This implies that this indicator (idling share) poses a bidirectional impact on energy consumption depending on external traffic conditions. During congestion, energy consumption is strongly correlated (>0.60, significant at the 5% level) with the average value and share of acceleration, and with variation of steering wheel angle (correlated with overtaking behavior). During smooth traffic conditions, energy consumption is only strongly correlated (>0.60, significant at the 5% level) with energy regeneration and variation of steering wheel angle. As for DSQ scores, Factor 3 (impatience in driving), Factor 5 (intersection acceleration behavior), and Factor 7 (rude driving) are strongly correlated (all significant at the 5% level) with energy consumption, but the pattern becomes less prominent in congested conditions. As a matter of fact, the correlations between energy consumption and all DSQ factor scores become weaker in congested conditions. It seems that the revealed driving
parameters serve as better indicators of energy consumption during congested traffic conditions, while on the contrary DSQ scores perform better during smooth traffic conditions.

3.3. Multiple Regression Analysis. Using the correlation analysis conducted in Section 3.2, we adopted a concise regression formula to predict each driver’s journey energy consumption for the urban driving condition based on field test data and DSQ scores. Compared with microscopic models for energy consumption developed by other researchers [31, 32], our macro model serves to predict the journey energy consumption from highly generalized input data, which also help to advance the understanding of the contribution of these two data sources. At the current stage we only consider linear relationship between the variables while further study might be able to elaborate a more complex model.

In order to ensure that all possible predictor variables were included and to prevent multicollinearity of the input variables, a stepwise multiple regression analysis was carried out in which all those variables that had shown significant bivariate correlations with energy consumption were entered as possible predictors. Each input variable needs to contribute significantly to the regression results according to F test otherwise it will be rejected, and multicollinearity is avoided in this process. Collinearity diagnostics are also used in later stage to double-check that there are no significant signs of multicollinearity of the final constructed models.

We have proposed three scenarios in terms of input variable combinations: (a) Scenario 1: measured driving behavior data only; (b) Scenario 2: DSQ factor scores only; and (c) Scenario 3: measured driving behavior combined with DSQ factor scores. The selected criteria for input variables are based on Adjusted $R^2$ in the stepwise regression process since it penalizes the statistic as extra variables enter into the model to prevent overfitting, while $R^2$ increases automatically when more variables are included. The best-performance regression models with the best Adjusted $R^2$ are listed as follows (see Table 5). In order to show the predictive ability of the regression model, Mean Absolute Percentage Error (MAPE) statistics are calculated from the leave-one-out cross-validation procedure (LOOCV). In LOOCV, the regression model is trained on all the data except for one point and a prediction is made for that point. MAPE is used to measure the deviation between the predicted and actual value.

If the driving behavior data was taken as input variables alone (Scenario 1), the model in smooth conditions outperforms that in congested conditions (MAPE 3.52% < MAPE 7.24%). When there is less traffic, a driver will display a more naturalistic and consistent driving style. Energy regeneration
(more acceleration and deceleration behavior) and variation of steering wheel (more overtaking behavior) both increase energy consumption per kilometer. The situation is a bit more complicated in congested traffic, while average acceleration and deceleration (amplitude), constant speed share (frequency), energy regeneration, and variation of steering wheel jointly determine energy consumption per kilometer. Clearly, with only energy regeneration and variation of steering wheel data it is not enough to predict energy consumption in congested conditions.

The DSQ data alone (Scenario 2) also yields a better result in smooth conditions (MAPE 2.93% < MAPE 4.06%). Factor 3 (impatience), Factor 5 (intersection acceleration), Factor 6 (proactive driving), and Factor 7 (rude driving) appear in the final regression model in both traffic conditions with the same sign (only Factor 6, proactive driving, contributes negatively to energy consumption). Distraction appears in the smooth conditions as a negative input, which probably associates with familiarity with the road environment. And in the congested conditions, confidence and rigidity level serve as complements to the indicators mentioned above. More confident and rigid driving behavior seem to contribute negatively to energy efficiency in less smooth conditions. The MAPE and Adjusted R² denote that the driver’s energy consumption is more predictable in Scenario 2 when the traffic is less congested.

The fusion of observed driving behavior data from the field test with the data from the DSQ scores (Scenario 3) yields the best result for the energy consumption prediction model in both traffic conditions (MAPE 2.57% vs MAPE 3.17%). In smooth conditions, variation of steering wheel together with Factor 2 (distraction in driving), Factor 5 (intersection acceleration), Factor 6 (proactive driving), and Factor 7 (rude driving) is able to build a quite accurate regression model. Energy regeneration and Factor 3 (impatience) which appear in Scenarios 1 and 2 are no longer necessary in the Scenario 3 model, indicating their information is somehow included in the final remaining indicators. This pattern is also seen in the model constructed in congested conditions, where average deceleration, energy regeneration, Factor 3 (impatience), and Factor 7 (rude driving) are excluded in the Scenario 3 final model. The remaining indicators of different dimensions are enough to characterize a subject's energy consumption.

This result makes us reflect on the representativeness of a traditional perfectly controlled driving test (on a simulator) and a fully naturalistic driving test (without controlling route and travel time). While DSQs alone might correlate well with simulated driving behaviors, the increased interaction with other traffic in real-world conditions confounds drivers’ naturalistic driving styles, and therefore the energy consumption estimation requires the integration of different data sources.

While uncontrolled naturalist experiment results are not suitable for comparison study, the semi-naturalistic, real-world test in this paper compensates for the dynamic nature of the interplay between traffic conditions and person-specific driving styles, which is lost in fixed-condition traditional experiments (e.g., driving simulator). Our results imply that traditional DSQs can still add value to EV energy consumption estimation, completing the information not born in revealed driving behavior. The benefit is even more obvious considering that a DSQ is much more easily accessible than CAN-bus data. In this sense, potential EV drivers would be able to get an ex-ante assessment of their EV driving energy efficiency based on their DSQ results. In the near future, researchers and OEMs can make use of both data sources either to generate a person-specific ecodriving feedback or a user-friendly autonomous driving system that values personal driving styles.

### Table 5: Performance of regression model.

| Scenario | Best performance input indicators | MAPE | RMSE | Adjusted R² | R² |
|----------|-----------------------------------|------|------|-------------|----|
| Smooth Traffic | Energy Regeneration+ Variation of Steering Wheel | 3.52% | 4.68 | 0.72 | 0.77 |
| Scenario 2: DSQ scores data | Factor 2+ Factor 3+ Factor 5+ Factor 6+ Factor 7 | 2.93% | 3.44 | 0.85 | 0.91 |
| Scenario 3: Driving behavior data + DSQ scores data | Variation of Steering Wheel+ Factor 2+Factor 5+ Factor 6+ Factor 7 | 2.57% | 2.68 | 0.91 | 0.95 |
| Congested Traffic | Constant Speed Share+ Average Acc+ Average Dec+ Energy Regeneration+ Variation of Steering Wheel | 7.24% | 6.20 | 0.69 | 0.82 |
| Scenario 2: DSQ scores data | Factor 1+ Factor 3+ Factor 5+ Factor 6+ Factor 7+ Factor 8 | 4.06% | 5.92 | 0.72 | 0.86 |
| Scenario 3: Driving behavior + DSQ scores data | Constant Speed Share+ Average Acc+ Variation of Steering Wheel+ Factor 3+ Factor 6+ Factor 8 | 3.17% | 3.00 | 0.90 | 0.94 |

**Note:** The table includes the best performance input indicators for each scenario, along with their corresponding MAPE, RMSE, Adjusted R², and R² values. The indicators are chosen based on their contribution to energy consumption estimation, with a focus on identifying the most effective combination of factors for different traffic conditions.
4. Conclusions

This paper has innovatively designed a more “human-centric” experiment to explore how drivers’ stated driving styles are reflected and correlated with their actual way of driving. The purpose of this study is to contribute to the research gap of the understanding of EV drivers’ driving behaviors and energy efficiency through the integration of experimentation data and questionnaires.

While much of previous research has focused on safety implications of driving behaviors, in the current study we focus on energy efficiency, which has attracted increasing attention within the EV community. Some factors extracted from DSQs are strongly correlated with revealed driving behavior data regardless of external traffic conditions. For example, Factor 1 (self-confidence in driving) is negatively correlated with the idling share in the driving status distribution, and Factor 5 (intersection acceleration behavior) is positively correlated with the constant speed share in both traffic conditions.

During congestion, energy consumption is positively correlated with the average value and share of acceleration, and with variation of steering wheel angle. While in smooth conditions, energy consumption is only strongly correlated (>0.60, significant at the 5% level) with energy regeneration and variation of steering wheel angle. As for DSQ scores, Factor 3 (impatience in driving), Factor 5 (intersection acceleration behavior), and Factor 7 (rude driving) are strongly correlated (all significant at the 5% level) with energy consumption, although the pattern becomes less prominent in congested conditions. Thus, revealed driving parameters serve as better indicators of energy consumption during congested traffic conditions, while DSQ scores perform better during smooth traffic conditions.

Moreover, as demonstrated through our multiple regression results, the two complementary data sources, CAN-based field test data and questionnaires, could be combined to yield a more accurate energy consumption prediction model. Based on each driver’s field test performance and DSQ scores, a personalized feedback for an ecodriving strategy depending on each driver’s unique characteristics can be proposed for different driving scenarios. The framework of the present research opens up new ways that the field test data can be applied in real life. Additionally, our results show that traditional Driving Style Questionnaires could still be of value as more researchers now show interest in modeling the driving behavior of drivers. In the end, any predictor of EV driving energy that will not take into account the human driving style cannot be accurate. As a matter of fact, the prediction model of EV driving energy neglecting human driving style cannot be that accurate.

Nonetheless, it is also important to point out some limitations of this study: the number of participants (N=13) in the field test might not offer a rich enough variety of driving behaviors in comparison with our DSQ database (N=338). Additionally, care needs to be taken when deciphering our regression model since small sample size could potentially cause sampling errors. Further research could compensate for the defect by involving more drivers with sufficient demographic backgrounds as well as a wider range of EV models in the field tests.

In conclusion, this study has provided with preliminary evidence on the validity of the combinational strategy with both field test data and questionnaires in analyzing EV driving behavior, especially when focusing on the energy efficiency perspective. The relationship between self-stated driving style and observed driving behavior under different traffic conditions has been identified, and our understanding of EV users’ energy efficiency in real-world driving scenarios has been advanced.

Appendix

Driving Style Questionnaire
(Translated from Chinese)

Please fill in your basic information.

1) Gender

(2) Age

3) Do you have a driving license?

4) How long have you had the driving license?

Please choose the answer that applies to you.

1) I feel nervous when driving.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

2) I find it is easy to remain a proper distance with the front vehicle.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

3) I pay attention to the street scenery when driving.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

4) I talk to my passengers when driving.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(5) I accelerate when approaching and crossing a yellow light when there is only one vehicle in front and it is accelerating.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(6) I am worried about a traffic accident when driving.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(7) I change lanes during congestion.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(8) I follow the front vehicle closely in congested condition.

(A) Strongly disagree
(B) Disagree
(C) Agree
(D) Strongly agree

(9) I am skillful in backing and parking.

(A) Strongly disagree
(B) Disagree
(C) Agree
(D) Strongly agree

(10) I maintain a close distance to the vehicle in front.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(11) I feel annoyed when following heavy-duty vehicles like buses and vans.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(12) I adjust my vehicle in advance when entering into a queue.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(13) I feel uncomfortable when others want to cut into my lane.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(14) I can drive normally in harsh weather (windy, foggy, rainy, and snowy).

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(15) I often clean my own vehicle.

(A) Strongly disagree
(B) Disagree
(C) Agree
(D) Strongly agree

(16) I accelerate when approaching and crossing a yellow light when there is no vehicle in front.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(17) I give way to other vehicles if they merge into my lane.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(18) I honk the horn to the vehicle in front in congestion.

(A) No
(B) Seldom
(C) Sometimes
(D) Always

(19) I check my phone/iPad during the red traffic signal period.

(A) No
(B) Seldom
(C) Sometimes
(D) Always
(20) I pay attention to my mobile phone during driving.
   (A) No                (28) I observe the traffic light patterns from a distance.
   (B) Seldom
   (C) Sometimes
   (D) Always
   (A) Strongly disagree
   (B) Disagree
   (C) Agree
   (D) Strongly agree

(21) I enjoy driving.
   (A) No                (29) I change to the expected lane early in preparation for
   (B) Seldom
   (C) Sometimes
   (D) Always
   the next intersection.
   (A) No
   (B) Seldom
   (C) Sometimes
   (D) Always

(22) I can repair a vehicle by myself.
   (A) Strongly disagree
   (B) Disagree
   (C) Agree
   (D) Strongly agree

(23) I drive fast.
   (A) No                (30) I can drive safely under complicated traffic conditions.
   (B) Seldom
   (C) Sometimes
   (D) Always
   (A) Strongly disagree
   (B) Disagree
   (C) Agree
   (D) Strongly agree

(24) I brake hard when I decelerate
   (A) No                (31) I pay attention to fuel consumption during driving.
   (B) Seldom
   (C) Sometimes
   (D) Always
   (A) Strongly disagree
   (B) Disagree
   (C) Agree
   (D) Strongly agree

(25) I can respond reasonably to unexpected events.
   (A) Strongly disagree
   (B) Disagree
   (C) Agree
   (D) Strongly agree

(26) I obey and have faith in traffic rules.
   (A) Strongly disagree
   (B) Disagree
   (C) Agree
   (D) Strongly agree

(27) I can respond reasonably to unexpected events.
   (A) Strongly disagree
   (B) Disagree
   (C) Agree
   (D) Strongly agree

(32) I have confidence in teaching newcomers to drive.
   (A) Strongly disagree
   (B) Disagree
   (C) Agree
   (D) Strongly agree

(33) I answer the phone when driving.
   (A) No
   (B) Seldom
   (C) Sometimes
   (D) Always

(34) I watch car racing TV shows.
   (A) No
   (B) Seldom
   (C) Sometimes
   (D) Always

(35) I use the vehicle even when there are other alternatives.
   (A) No
   (B) Seldom
   (C) Sometimes
   (D) Always
(36) I stick to my accustomed route even the road is congested.
   (A) No
   (B) Seldom
   (C) Sometimes
   (D) Always

(37) I concentrate during driving and always ignore what others say.
   (A) No
   (B) Seldom
   (C) Sometimes
   (D) Always

(38) I feel upset during congestion.
   (A) No
   (B) Seldom
   (C) Sometimes
   (D) Always

(39) You pay attention to the vehicles nearby when following the front vehicle.
   (A) No
   (B) Seldom
   (C) Sometimes
   (D) Always

(40) I have faith in myself to drive steadily.
   (A) No
   (B) Seldom
   (C) Sometimes
   (D) Always

Data Availability

The data generated during the current study are owned by Future Transport Research Center, Tsinghua University, and are not publicly available. Please contact the corresponding author for details.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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