Article

Quantifying the Impact of Traffic on Electric Vehicle Efficiency

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Abstract: While the influence of several factors on battery electric vehicle (BEV) efficiency has been investigated in the past, their impact on traffic is not yet fully understood, especially when driving in a natural environment. This paper investigates the influence of driving in intense traffic conditions while considering the ambient temperature and driving behavior on BEV energy efficiency in a field study. A total of 30 BEV inexperienced drivers test drove a 2017 Volkswagen eGolf on a route with various road types in two different traffic intensity scenarios: During morning commute hours with higher traffic congestion and lower congestion hours throughout the middle of the day. Results support the hypothesis that traffic conditions significantly impact the vehicle's efficiency, with additional consumption of approximately 4–5% in the high traffic scenario. By creating and comparing driving in traffic to an underlying base case scenario, the additional range potential by avoiding traffic for this particular vehicle can be quantified as up to seven miles. New patterns of BEV efficiencies emerged, which can help stakeholders understand how eco-driving can be strategically improved by selecting trip times and routes that avoid high traffic intensity.

Keywords: battery electric vehicle; traffic; driving behavior; eco-driving; efficiency

1. Introduction

The increasing popularity of electric-powered vehicles is a promising sign for achieving more sustainable transportation systems. Within the past few years, United States (U.S.) sales of electric vehicles (EVs), including battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), have proliferated, reaching over 295,000 units in 2020 [1]. Meanwhile, BEVs have become increasingly important, representing 78% of the 2020 U.S. EV sales [1]. Although commonly seen as a low-carbon and environmentally friendly option, BEVs have noteworthy drawbacks, such as limited battery capacities and driving range, leading to 'range anxiety'. This phenomenon describes the fear of running out of energy before reaching a charging station [2,3]. Along with insufficient charging infrastructure [4], the limited range of BEVs represents a significant barrier for a comprehensive transition to BEVs [5–8].

One way of overcoming BEV drawbacks associated with a limited driving range and 'range anxiety' is to apply eco-driving strategies. Eco-driving on an operational level can improve the vehicle's fuel economy through behavioral adjustments (e.g., speed, idling, cruise control, heating, ventilation, and air conditioning) [9,10]. While eco-driving strategies for internal combustion engine vehicles (ICEVs) are widely known, they do not necessarily apply to BEVs due to fundamental differences in their drivetrain and their characteristics (e.g., source of force, the ability of recuperation). These differences also account for changes in the energy consumption behavior of BEVs in traffic. Understanding how traffic intensities (i.e., high traffic intensity correlates with high congestion, high variation in acceleration, and high variation in jerk) impact BEV efficiency is crucial to deriving specific and successful

eco-driving strategies, creating opportunities for eco-routing, and, finally, facilitating the widespread adoption of BEVs.

Different factors influencing the energy consumption of BEVs have been explored in the past. For example, Sivak and Schoettle [10], and Arend and Franke [11] found that the application of eco-driving strategies, including route selection and, thus, the consideration of traffic, can extend the range of BEVs. In addition, driving behavior, external and technical factors influence BEV efficiency. While the initial state of charge (SOC) of the battery was not found to impact BEV efficiency significantly [12], the ambient temperature [12–18], and the use of auxiliaries (e.g., ventilation, air conditioning, and cruise control) do correlate significantly with the energy consumption of BEVs [13,16,17,19–23]. For example, Bartels et al. [12] found in their field study that there was no relationship found between the initial SOC at the beginning of a drive and the energy consumed. Instead, their results indicated a significant direct impact of the ambient temperature on the SOC consumed [12]. In addition to the direct impact, temperature can increase the need for additional charging through heating and cooling. For example, Kambly and Bradley [13] modeled differences in cabin thermal comfort conditioning loads across the United States based on the 2009 National Household Transportation Survey. The authors stated that air conditioning, which is more likely used in warmer regions, increased the energy consumption of EVs significantly. Furthermore, Yuksel and Michalek [17] used the same survey data and supported findings in [12,13]. The authors posited that BEV energy consumption was higher in colder regions of the United States and that air conditioning and heating negatively impact efficiency. In Badin et al. [19], a simulation-based approach was used to analyze EV energy consumption influencing factors. The study revealed that the additional load of auxiliaries (e.g., cruise control and air conditioning) could increase the energy consumption while the impact varies with the vehicle speed. Another study by Johnson [21] supported evidence of the effect of air conditioning on a vehicle's efficiency through simulations. By analyzing actual driving cycles, Bingham et al. [23] found that additional loads through heating and air conditioning require consideration in travel planning and user behavior due to their decreasing effect on achievable ranges of BEVs. Additionally, Haworth and Simmons [22] posited that the use of cruise control and constant travel speed could increase the efficiency of vehicles.

So far, literature exploring the impact of traffic has focused on ICEV fuel. However, traffic can ultimately impact EV efficiency through its influence on vehicles' speed profile. While existing studies have derived conclusions about the impact of traffic on BEVs from related findings (e.g., speed, acceleration, travel time), the current literature lacks a comprehensive study aiming to explore the impact of traffic on BEV efficiency in a naturalistic environment. For example, Agrawal et al. [24] found that BEVs used less energy at lower speeds and, thus, inferred that BEVs are more efficient in traffic. The authors investigated three categories, including four speed levels, changes in speed during traffic (e.g., stop-and-go-traffic), and potential energy loss. The authors use simulation models to compare costs for ICEVs and BEVs while using different cost functions for the two types of vehicles. The authors conclude that BEVs choose low-speed routes to reduce energy consumption and range anxiety. Fiori et al. [25] supported these findings through their simulation models. However, both studies disregard the human element of driving and the impact of other factors, such as temperature and traffic. Instead, another study [26] found that their EV conversion was more efficient during in-city driving than freeway driving and derived a positive relationship between higher traffic intensities in cities and BEV energy efficiency. The authors did not account for actual traffic intensities, differences in road characteristics between freeways and local roads, or speed profiles. Furthermore, in [26], data were collected based on a single driver, disregarding variation in driving styles and potential aggressiveness between individuals. In [27], a freeway network aiming to optimize BEV driving paths and charging procedures was modeled. The authors considered different factors while minimizing travel time in their objective function. The study found that higher traffic volume leads to an increase in route options, which reduce travel time while

increasing energy consumption. Galvin's model was considered in [27], describing the relationship between speed and BEV energy consumption through regression models [28]. The model describes the minimum energy consumption of BEVs at approximately 38 miles per hour under consistent acceleration [28]. Logically, an increase in acceleration requires more power, leading to lower efficiency per unit distance [28].

Based on the studies mentioned above and the speed–energy relationship described by Galvin's model, it is questionable whether a difference in BEV energy consumption can be found on the same route with different traffic intensities. To the best of our knowledge, no study has yet focused on exploring this question. Therefore, there is a gap in investigating the influence of traffic on BEV energy consumption based on a sophisticated field study with a variegated sample of drivers. This study aims to close this gap while considering the attributes of driver behavior and real-world environmental conditions, such as temperature. For this purpose, the scope of this research is to explore whether BEVs are less efficient during commuting hours compared to driving in a less traffic-intense scenario. Furthermore, if the results of this study indicate a significant relationship between traffic and BEV efficiency, a quantification of this effect is intended.

The remainder of the paper will present the methodology, results, discussion, and conclusion. In Section 2, we describe the methodology for our experimental environment, data collection, data processing, and the statistical analysis. In Section 3, the results are evaluated and compared through the different ANOVA models, followed by an overarching discussion in Section 4. We provide concluding remarks in Section 5, summarizing key results, limitations, and potential areas for future research.

2. Materials and Methods

In a naturalistic driving experiment with several exogenous variables, it is crucial to mitigate their impact to the extent possible. The design of the experiment and the methods for the analysis were chosen accordingly and are summarized in Figure 1. This chapter will describe them in more detail.
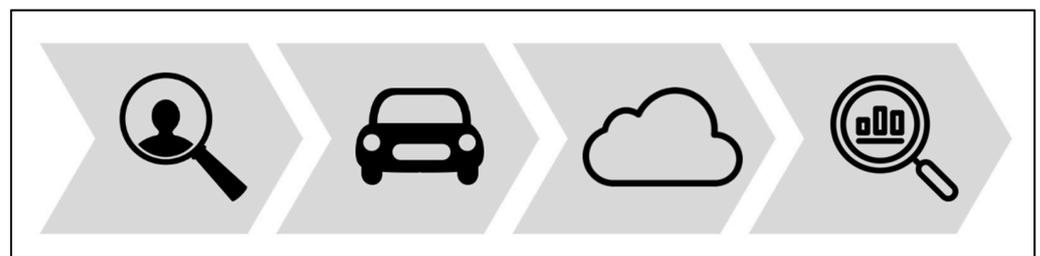

Figure 1. Methodological framework.

2.1. Experimental Design

In this study, BEV driving data were collected from a total of 30 drivers, each driving a 2017 Volkswagen eGolf twice on a predetermined test route. The eGolf is equipped with a 134-horsepower electric motor and a 35.8 kWh battery pack [29]. Like other electric vehicles, the eGolf can recuperate energy while braking, depending on the drive mode chosen. The participants' recruitment was conducted at a midsized research institution and consisted of 12 female and 18 male drivers with an average age of 23.73 years and a standard deviation of 2.56 years. To ensure a homogeneous degree of BEV experience in the sample and mitigate the effect of BEV driving experience on energy efficiency [30,31], only drivers with no previous experience in driving a BEV were selected. The test route was located in Washington County, Rhode Island, and covered different road types (i.e., local roads, collectors, arterials, and freeway/expressway) with a total distance of 27.6 miles [32]. Two scenarios with assumed differences in traffic intensities were constructed to analyze and quantify the impact of traffic on BEV energy consumption. The scenarios were differentiated by controlling the time of the day since commuter patterns impact traffic intensities. Previous

work has found these patterns by focusing on BEV utilization patterns [33,34] and air pollution [35]. Therefore, in scenario 1 (S1), drives were conducted between 7:30 a.m. and 9:00 a.m. during peak traffic intensity. Low-intensity traffic scenario 2 (S2) test drives were not started before 10:00 a.m. and scheduled to be completed before 4:30 PM to exclude the impact of light conditions and afternoon congestion on driving behavior [18]. Furthermore, all drives were conducted on dry roads, during stable weather conditions, and with good visibility; otherwise, they were rescheduled. The data collection period started in early April and ended in early June of 2019. The ambient temperatures were monitored and ranged between 36 °F and 73 °F. Regardless of the ambient temperature, the vehicle's inside temperature was set to 68 °F. Windows always remained closed to keep the aerodynamic drag constant. The 2017 Volkswagen eGolf offers different driving modes (i.e., B, D, D1, D2, and D3) [12], which differ in the intensities of recuperation and acceleration. In this research, the recuperation mode 'D' was used, which recuperated energy only while applying the brakes and was considered closest to driving in a conventional vehicle.

The vehicle's data were extracted through a data logger from the third-party company FleetCarma, which was plugged into the On-Board Diagnostics port (OBD-ll) system. The data were accessed and downloaded from the FleetCarma website and used for further calculations. The tracking rate was mainly at 1 Hz. Data included the timestamp, the speed, the GPS location, the battery current, the battery voltage, the initial SOC, and the ambient temperature.

2.2. Data Processing

Data processing was automated through a project-specific code using the *Pandas* [36] and *Matplotlib* [37] packages in *Python*. In the first step, the data were cleaned to ensure equal starting and ending points and exclude noise. To this end, rows of data before the uniform starting coordinates and after the uniform ending coordinates were removed for each drive. During the period of data collection, road construction occurred on the test route. Because of impacts on the speed profiles of the trials, the respective stretch of approximately 2.1 miles between the construction starting point (N 41° 25′ 55.654″, W 71° 36′ 26.071″) and ending point (N 41° 25′ 45.394″, W 71° 34′ 5.883″) had to be removed from the data sets. The total net distance of the cleaned drives considered for the analysis was approximately 25.5 miles. Different variables were calculated for each test drive (i.e., energy consumption per mile, average variation of speed, average variation of acceleration, average variation of jerk, and average ambient temperature). Table 1 summarizes the computed variables, the respective units, and a description of the computation procedure.

Table 1. Target measures and explanation of computation.

Measure	Unit	Methodology of Calculation
Total energy consumption	kWh	Transform wattage and voltage information provided at 1 Hz intervals to kWh using power-law and energy equation.
Total distance	miles	Sum of speed information (miles/hr) provided at 1 Hz intervals is divided by the total duration of the drive.
Average consumption per mile	kWh/mile	Total energy consumption of the drive is divided by the total distance.
Mean variation in speed	miles/s	Overall standard deviation of speed for the drive.
Mean variation in acceleration	miles/s^2	Acceleration is derived from speed at a frequency of 1 Hz. Then the standard deviation is computed for each drive.
Mean variation in jerk	miles/s^3	Jerk is derived from acceleration at a frequency of 1 Hz. Then the standard deviation is computed for each drive.
Mean ambient temperature	°F	Average of ambient temperature information at 1 Hz.

As previously mentioned, most data were tracked at a rate of 1 Hz. By applying the power-law and the electrical energy equation, the total energy consumption in kWh could be calculated for each drive. Each trial's total distance was calculated using the vehicle's

speed for every second. GPS data were not accurate enough since they were refreshed at a rate of 4 Hz. Finally, the average consumption per mile [kWh/mile] could be derived by dividing the total absolute difference in the SOC or ΔSOC [kWh] by each drive's total distance. Therefore, the average consumption can also be denoted as average ΔSOC/mile. The variation in speed was calculated as the standard deviation of speed for each trial. The vehicle's acceleration could be derived from the vehicle's speed at a rate of 1 Hz and its standard deviation computed for each drive. The same procedure was undertaken for variation in jerk, which describes the difference in acceleration over the difference in time. Each test drive's ambient temperature was calculated as the mean temperature over the total duration of a drive.

2.3. Statistical Methods

This research evaluates differences in energy consumption due to different traffic intensity scenarios while including important factors about the driver and ambient temperature. Statistical tests were performed in *R* [38] using the packages *glm2* [39], *olsrr* [40], and *tidyverse* [41]. For all regression models in this study, a Bonferroni corrected confidence interval was calculated and used to reduce the possibility of Type I error (i.e., a false-positive result) [42]. Following the sample size, a significance level of $\alpha = 0.10$ was chosen for the Bonferroni correction in all statistical tests [43].

Initially, all trials were split into subsamples based on the scenario. To test these subsamples for differences in means of average ΔSOC/mile, a paired sample *t*-test was used. Under consideration of the subsample sizes ($n = 30$), normality tests were carried out to meet conditions for applying a *t*-test using the Shapiro–Wilk test [44]. Differences in traffic intensities between the two scenarios were investigated accordingly. Traffic flow data were not available for the test route. Hence, measures based on speed (i.e., variation in speed, acceleration, and jerk) could be used to provide potential evidence for differences in traffic intensities between the test scenarios. Especially variation in acceleration and jerk have a high effect on traffic movement and vice versa [45]. While the subsamples were tested for differences in means for all measures, the standard deviation of jerk is a reliable proxy to represent traffic intensities. Whether the subsamples differed in the ambient temperature was investigated using an unpaired *t*-test as the ambient temperature is independent of the participants' behavior.

For the purpose of this field study with several exogenous factors, a multiple linear regression was considered appropriate [46]. In [12], this method was previously applied successfully. The average energy consumption ΔSOC/mile was the dependent variable in this study. Dummy variables were constructed to analyze factors of a categorical nature (i.e., driver and traffic scenario). For example, the two scenarios were treated as binary dummy variables, where '1' represents driving in a more congested traffic scenario (S1) and '0' in a less congested traffic scenario (S2). The factor scenario was considered an ordered factor since the traffic intensity of S2 was lower than the one in S1. The same approach was applied to the factor driver. '1' indicates that the individual is driving, and '0' that the individual is not driving. In contrast to the factor scenario, the factor driver was treated as an unordered factor. Finally, all critical assumptions of the multiple linear regressions were assessed. An analysis of variance (ANOVA) for the regression model was carried out to test dependent variables for significance. Furthermore, a stepwise regression was applied to find a potentially better fitting model. Two additional regression models were created to test potential interaction effects. One accounted for the interaction between driver and scenario, and the other for the interaction between ambient temperature and scenario. To assess all regression models and compare their goodness of fit, the coefficient of determination (R^2_{adj}) was evaluated according to the guidelines described in [47] for models with endogenous latent variables. Cohen [47] distinguishes between a weak explanation of variance ($0.02 \leq R^2 < 0.13$), a moderate explanation of variance ($0.13 \leq R^2 < 0.26$), and a strong explanation of variance ($R^2 \geq 0.26$).

To identify the range impact of driving in a more traffic intense scenario, the achievable range of driving in a traffic intense scenario S1 was compared to an underlying base case. This base case consisted of the less-traffic-intense scenario S2 and the driver whose average consumption was closest to the sample's overall average in both scenarios. The base case's ambient temperature was set as 68 °F since this represents the battery service life optimal ambient temperature [48,49].

3. Results

Before carrying out the regression analysis, the two scenarios had to be investigated for differences in the vehicle's mean average energy consumption and ambient temperature. The dependent continuous measure average ΔSOC/mile of both subsamples was approximately normally distributed based on the Shapiro–Wilk test. Table 2 summarizes the descriptive statistics for the average energy consumption per mile of both scenarios. It shows that all measures of central tendency and the quartiles, the minimum, and the maximum consumption were higher in the presumably more traffic-intense scenario S1. Driving in S2 was related to a higher standard deviation than driving in S2. In S1, the vehicle had an average energy consumption of 0.2330 kWh with a standard deviation of 0.1600 kWh and a median of 0.2327 kWh. In S2, lower energy consumption with an overall average of 0.2172 kWh, a standard deviation of 0.0126 kWh, and a median of 0.2181 kWh could be observed.

Table 2. Descriptive statistics of the average consumption per mile for both scenarios.

Scenario	N	Mean	St. Dev.	Minimum	Q25	Median	Q75	Maximum
S1	30	0.2330	0.0160	0.1966	0.2214	0.2327	0.2433	0.2632
S2	30	0.2172	0.0126	0.1893	0.2104	0.2181	0.2255	0.2379

Figure 2 displays boxplots for the vehicle's consumption in each scenario and supports the mentioned differences visually. The paired two-sided *t*-test ($p = 0.000$) did further indicate a difference in means of the average ΔSOC/mile.
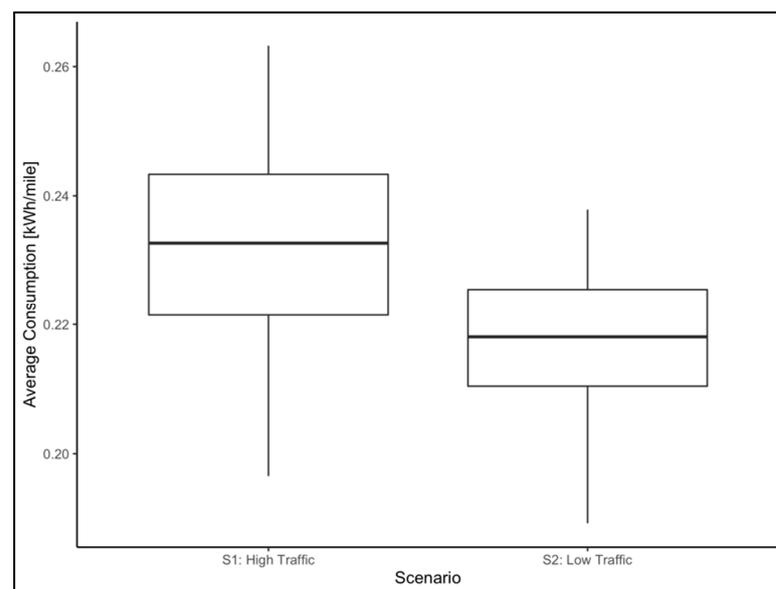

Figure 2. Boxplots of average energy consumption per mile for the respective scenario.

The two scenarios were investigated regarding the differences in ambient temperature means and the following traffic measures: Average variation in speed, acceleration, and jerk. All measures of both subsets were found to be approximately normally distributed according to the Shapiro–Wilk test. An unpaired *t*-test showed that the means of ambient

temperature between the scenarios differed significantly ($p = 0.002$). While there was no evidence that the means of variation in speed did differ significantly between the subsets ($p = 0.873$), the other two traffic measures (i.e., variation in acceleration and variation in jerk) did show a significant difference between the scenarios with higher means in S1 ($p = 0.068$; $p = 0.063$).

A linear relationship between the independent numeric variables (i.e., ambient temperature) and the numeric dependent variable (i.e., ΔSOC/mile) is a sine qua non condition for applying linear regression models. A linear regression analysis was carried out with only ambient temperature as the independent variable to test this relationship's existence. A significant regression ($p = 0.000$; $R^2 = 0.296$) demonstrated that the BEV's kWh/mile decreases with an increase in ambient temperature.

Another regression model was carried out with the explanatory variables scenario, driver, and ambient temperature. The predicted energy consumption equals 0.230 + 0.010 (Scenario) − 0.001 (Temperature) + β_i (Driver *i*), where the scenario is coded as 0 = No traffic, 1 = Traffic, the temperature is measured in Fahrenheit, and the driver is coded as 0 = Driver was not driving, 1 = Driver was driving for all 30 drivers. Table 3 contains the results of the ANOVA. For testing all three factors for their significance, the Bonferroni-corrected significance level was $\alpha = 0.0333$. The two independent variables, scenario ($p = 0.0083$) and ambient temperature ($p = 0.0027$), showed statistical significance for the dependent variable, average ΔSOC/mile. The factor driver did not appear to be statistically significant ($p = 0.1311$). The model's adjusted coefficient of determination (R^2_{adj}) was 0.5219. The Shapiro–Wilk test showed that the residuals followed a normal distribution ($p = 0.9373$). Following this model, the base case would lead to an average energy consumption of 0.2181 kWh/mile when driving in S2 at 68 °F. Instead, driving in S1 with a higher traffic intensity would increase consumption by approximately 4.5% and end up in an average of 0.2279 kWh/mile.

Table 3. ANOVA for initial multiple linear regression.

Source	df	SS	F Value	Pr (>F)
(Intercept)	1	0.0166	130.1294	0.0000 ***
S1	1	0.0098	8.0568	0.0083 **
Temperature	1	0.0014	10.8679	0.0027 **
Driver	29	0.0057	1.5322	0.1311
Residuals	28	0.0086		

Note. ** $p \leq 0.01$, *** $p \leq 0.001$.

A stepwise regression was performed to explore the potential of a better-fitting model. This regression model removed the driver from the initial model and led to a predicted energy consumption of 0.272 + 0.011 (Scenario) - 0.001 (Temperature). With two remaining factors, the significance criteria were given a Bonferroni corrected significance level of $\alpha = 0.05$. The ANOVA, as summarized in Table 4, shows that both variables, scenario ($p = 0.0023$) and ambient temperature ($p = 0.0001$), remain significant. This regression model had an R^2 of 0.4130 and R^2_{adj} of 0.3924. The Shapiro–Wilk test for normality showed that the residuals are normally distributed ($p = 0.9274$). This model led to an average consumption in the underlying base case of 0.2043 kWh/mile. This consumption increases by approximately 5.4% to 0.2154 kWh/mile when driving in S1.

Table 4. ANOVA for stepwise regression model.

Source	df	SS	F Value	Pr (>F)
(Intercept)	1	0.0649	399.2361	0.0000 ***
S1	1	0.0017	10.1915	0.0023 **
Temperature	1	0.0027	16.8666	0.0001 ***
Residuals	57	0.0093		

Note. ** $p \leq 0.01$, *** $p \leq 0.001$.

Two more regression models were created to account for interactions between driver and scenario, or temperature and scenario. When accounting for the interaction between the factors scenario and driver, the predicted energy consumption equals 0.244 + β_i (Driver$_i$:Scenario) − 0.001 (Temperature). Table 5 contains the results of the ANOVA with a Bonferroni corrected significance level of α = 0.05. No factor was found statistically significant, nor did the residuals follow a normal distribution (p = 0.000). The model had a coefficient of determination of 0.424.

Table 5. ANOVA for regression model with driver–scenario interaction.

Source	df	SS	F Value	Pr (>F)
(Intercept)	1	0.0259	167.9696	0.0000 ***
Driver:S1	30	0.0066	1.4298	0.1723
Temperature	1	0.0003	2.0526	0.1630
Residuals	28	0.0043		

Note. *** $p \leq 0.001$.

According to the last model accounting for the interaction effect between the factors ambient temperature and scenario, the predicted energy consumption equals 0.244 + 0.000 (Temperature:Scenario) + β_i (Driver$_i$). Table 6 summarizes the ANOVA of this regression analysis. There was evidence of a significance of the interaction effect between temperature and scenario for the average energy consumption of the vehicle (p = 0.000). However, the factor driver did not show statistical significance for the outcome of the dependent variable. The model had an R^2_{adj} of 0.2688, and the residuals followed a normal distribution according to the Shapiro–Wilk test for normality (p = 0.6685).

Table 6. ANOVA for regression model with temperature–scenario interaction.

Source	df	SS	F Value	Pr (>F)
(Intercept)	1	0.0913	466.7415	0.0000 ***
Driver	29	0.0076	1.3442	0.2153
Temperature:S1	1	0.0031	15.7264	0.0004 ***
Residuals	29	0.0057		

Note. *** $p \leq 0.001$.

4. Discussion

This section discusses the findings of this study and its implications for the operation and improvement of BEVs. First and foremost, the finding concerning the latter supported previous research results on the existence of higher levels of traffic intensity or congestion outcome during morning commutes [45]. Higher variations in acceleration and jerk appear more frequently in the morning (S1) than in the afternoon (S2), providing evidence that differences in traffic intensities exist between the scenarios. These results align with EV commuter patterns previously found in [33–35]. However, future research should consider real-time traffic data and use a higher tracking frequency than 1 Hz. Real-time traffic data would improve the granularity of the data while allowing the analysis of traffic intensities as a continuous variable. Neither traffic data nor a higher tracking frequency were available for this study.

Second, a paired two-sided *t*-test was performed and provided evidence that mean consumptions indeed differed. More specifically, higher consumptions were found when driving in the more traffic-intense scenario S1, which supports Galvin's model [28]. To explore whether lower means in efficiency in S1 were caused by differences in the traffic intensities between the two scenarios or another considered factor, multiple linear regression analyses were performed and compared by their goodness of fit. The initial regression model considered the factors ambient temperature, driver, and scenario separately. While the traffic scenario and ambient temperature were significant for the vehicle's energy efficiency, the factor driver was not. Driving in a more intense traffic scenario decreased BEV

efficiency. Ambient temperature was negatively related to the vehicle's average ΔSOC/mile. With a coefficient of determination of R^2_{adj} = 0.522, the model had a robust explanation of variance. A stepwise regression led to a model that no longer included the factor driver. While the factors ambient temperature and scenario were again significant for the outcome of the dependent variable, the stepwise regression did not lead to a better-fitting model. In other words, R^2_{adj} = 0.3924 was strong but lower than the initial model.

Two further multiple linear regression analyses were carried out to assess potential interaction effects between the scenario and one of the remaining two factors. An interaction effect between driver and traffic scenario was not found. This model's residuals did not follow a normal distribution and, therefore, violated a fundamental assumption of the linear regression analysis. Instead, a model with the interaction effect between ambient temperature and traffic scenario showed normally distributed residuals. This model gave evidence of the significance of a temperature–scenario interaction for BEV efficiency. Although an R^2_{adj} of 0.2688 can still be considered a strong explanation of variance, it was half of the initial model's explanation rate. Therefore, the first model, which considered all factors separately, explained the highest percentage of variance and, hence, had the highest goodness of fit.

In summary, the regression models' results have provided evidence that traffic significantly impacts BEVs' energy consumption. While a negative relationship between ambient temperature and a BEV's energy consumption was expected and aligned with previous findings in the literature [12–18], novel findings emerged about the efficiency behavior of BEVs in traffic. Previous studies focusing on BEV in-traffic behavior were either based on simulation models [24,25,27], leaving out the human element of driving, or were focusing on speed profiles to derive energy consumption behavior in traffic [26]. However, different speeds can have similar flow rates, offering the potential for endogeneity. This study provides evidence that traffic decreases BEV efficiency while using a different approach to analyze BEV consumption behavior associated with traffic in a field study with a sample of human drivers. However, the driver's insignificance should be treated carefully since the literature has shown the impact of driving behavior in the past [10,11]. A potential reason for this outcome could be similarities in the participants' driving behavior. Therefore, future studies should include a broader and more diverse sample of drivers to capture differences in driving styles and BEV experience. A diverse sample could contribute to understanding how traffic impacts BEV efficiency in correlation with different driving styles.

The initial regression model was used to quantify the range implications of driving in traffic, which predicted the average consumption most accurately. Accordingly, driving in a scenario with higher traffic intensity increased the energy consumption by approximately 4.5%. This supports the notion that driving during times with less traffic (S2) would increase the achievable range of a fully charged test vehicle with a battery capacity of 35.8 kWh by more than seven miles. It should be mentioned that the range potential varies among vehicles, battery capacities, drivers, ambient temperatures, and traffic intensities.

5. Conclusions

This study provides an approach to analyzing the impact of traffic on electric vehicles' energy consumption while considering the human element of individual driving behaviors. To this end, two scenarios were differentiated by their traffic intensity based on the time of the day. The results demonstrate by applying a multiple linear regression that driving in a more traffic-intense scenario decreases BEV efficiency. More specifically, the road tests revealed that the test vehicle's average energy consumption per mile was significantly higher during typical commuting hours in the morning. While this was already acquainted with ICEVs, the study discovered that this effect applies to BEVs, contradicting previous findings derived solely from the analysis of speed profiles. Despite having the capability to recuperate energy, a higher variation in speed during in-traffic driving seems to cause energy losses that significantly reduce BEV efficiency. Thus, this work adds to the exist-

ing literature by extending the body of knowledge about BEV energy consumption in a naturalistic setting that can facilitate operation and adoption.

In the future, more priority should be given to understanding the range implications of traffic and other factors on BEV energy consumption in a natural environment. To this end, this study could be extended by including a more diverse sample of drivers with different levels of driving experience and real-time traffic flow data to better account for differences in driving behavior and traffic intensities. However, the findings here can be considered a good starting point for systematically understanding BEVs' energy consumption behavior in different traffic situations under real-world conditions. The results offer opportunities for more precise BEV range estimations, which can increase public confidence in the performance of EVs. Furthermore, considering traffic in eco-driving strategies allows BEV users to improve their achievable ranges and reduce range anxiety. Moreover, the results and their consideration could mitigate current adoption barriers and generally facilitate BEV ownership, thus supporting the electrification of national and global transportation systems.

Abbreviations

B	Braking Energy Recuperation: Very High
BEV	Battery Electric Vehicle
D	Conventional Braking Setting
D1	Braking Energy Recuperation: Light
D2	Braking Energy Recuperation: Medium
D3	Braking Energy Recuperation: High
EV	Electric Vehicle
GPS	Global Positioning System
ICEV	Internal Combustion Engine Vehicle
OBD-II	On-Board Diagnostics Port-II
PHEV	Plug-in Hybrid Electric Vehicle
S1	Scenario 1: Peak traffic intensity
S2	Scenario 2: Low-intensity traffic
SOC	State of Charge
U.S.	United States

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