Jurnal Teknik Mesin Mechanical Xplore (JTMMX)

Journal homepage: https://journal.ubpkarawang.ac.id/index.php/JTMMX

Original Article

# Multivariate Analysis of Driver Behavior, Load, and Speed on Energy Efficiency in Prototype Electric Vehicles

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ARTICLE INFO

*Article history*:
Received 29 June 2025
Received in revised form
7 July 2025
Accepted 7 July 2025
Available online 8 July 2025

*Keywords*:
Driver behavior
Electric vehicles
Energy efficiency
Vehicle load
Eco-driving

ABSTRACT

The transition to electric vehicles (EVs) is a critical component of sustainable urban mobility strategies. While hardware components such as motors, batteries, and controllers are often prioritized, driver behavior also plays a significant role in determining overall energy efficiency. This study quantitatively analyzes the influence of driver behavior, vehicle load, and cruising speed on the energy performance of a prototype electric vehicle. Conducted over nine test sessions with three different drivers on a mixed-condition track, the study reveals that energy efficiency varied significantly, ranging from 65.7 km/kWh to 114.3 km/kWh. Driver 3, employing smoother acceleration and maintaining moderate speeds (12–17.2 km/h), achieved the highest average efficiency (94.22 km/kWh), whereas Driver 2, with frequent speed fluctuations, recorded the lowest (73.98 km/kWh). These differences resulted in up to 30.1% variation in efficiency, solely attributable to behavioral factors. The findings underscore the potential of behavior-based interventions—such as eco-driving programs and real-time feedback systems—in enhancing EV performance without hardware modification. This research contributes to the development of behavior-aware EV systems and offers valuable insights for urban transport planners seeking to reduce energy consumption in electric mobility ecosystems.



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Peer review under the responsibility of Editorial Board of Jurnal Teknik Mesin Mechanical Xplore (JTMMX)

## 1. Introduction

The global transition toward sustainable mobility has positioned electric vehicles (EVs) as a critical solution for mitigating urban air pollution and reducing dependency on fossil fuels. Increasing transportation demand, driven by population growth and economic development, has led to an increase in the use of fossil-fueled vehicles, significantly contributing to greenhouse gas emissions and environmental degradation. As fossil fuel reserves continue to deplete, battery-powered electric vehicles (EVs) have emerged as a viable alternative, offering near-zero tailpipe emissions and reduced operational costs [1]. In Indonesia, this transition is already underway; electric car sales reached 15,437 units in 2022, an increase of over 380% from the previous year, demonstrating strong market growth in emerging economies [2].

Significant advances in EV technology, such as improvements in powertrains, battery systems, and regenerative braking, have enhanced performance and extended driving range. Research on electric

https://doi.org/10.36805/jtmmx.v6i1.10452

powertrain architecture and motor technology has highlighted the growing efficiency of brushed DC, PMSM, and BLDC motors in electric mobility platforms [3, 4]. However, the actual energy efficiency of EVs in operation is also influenced by external variables such as road conditions, vehicle load, and driver behavior [5-7]. However, real-world energy efficiency is not determined solely by the vehicle's technical components. A growing body of literature highlights the influence of external and operational factors, such as road gradient, traffic flow, climate, and—most notably—driver behavior [7-9].

Aggressive driving behaviors, characterized by rapid acceleration, frequent braking, and high-speed cruising, have consistently been shown to elevate energy consumption in EVs. Bingham et al. [8] found that such behaviors can increase energy use by up to 30% compared to moderate driving. Kozłowski et al. [9] developed mathematical models demonstrating strong correlations between acceleration, vehicle speed, and energy consumption, reinforcing the importance of adaptive speed control strategies. Similarly, Dong et al. [10] proposed an event-driven control algorithm for urban traffic that improves the EV energy efficiency by optimizing speed trajectories in response to real-time traffic signals.

Urban driving scenarios further amplify this variation. Hu et al. [11] and Xing et al. [12] reported that individual driving styles and dynamic traffic conditions contribute to significant fluctuations in energy consumption during actual road tests. These findings underscore the need for behavior-aware energy estimation in both conventional and connected autonomous EVs. Meanwhile, studies by Alvarez et al. [13] and Vatanparvar and Faruque [14] have demonstrated that eco-driving strategies, such as anticipatory braking and gradual acceleration, combined with route planning and HVAC optimization, can significantly improve energy efficiency. Complementary findings by Sweeting et al. [15] reveal that energy use per kilometer may vary by up to 70% owing to poor driving habits or suboptimal system settings, suggesting that behavioral improvements can rival hardware upgrades in terms of overall efficiency. Bingham et al., 2012 reported that that aggressive driving can increase energy consumption by approximately 30% compared to moderate driving styles [8]. Hu et al [16] reported that , the harmony between technological enhancements and improved driving behaviors promises better energy efficiency, reduced consumption, and extended range for electric and hybrid vehicles.

Nonetheless, the majority of existing studies have focused on mass-produced EVs in industrialized regions, leaving a research gap in light-or prototype EV platforms, especially in tropical or developing country contexts. These prototypes frequently use alternative powertrain architectures and control logics, such as brushed DC motors, and operate under distinct environmental and infrastructural conditions. Moreover, few studies have investigated how behavioral autonomy (i.e., drivers' unregulated style) affects energy performance in semi-controlled real-world circuits. To address these gaps, this study examined the influence of driver behavior, vehicle load, and cruising speed on the energy efficiency of a lightweight prototype EV equipped with a brushed DC motor. Field tests were conducted at the Pertamina Mandalika International Circuit, Indonesia, a semi-urban closed track with variable curves, mild gradients, and consistent surface friction. The drivers were given full behavioral autonomy across multiple runs, and key energy metrics were recorded, including energy consumption (Wh) and derived efficiency (km/kWh). This research aims to quantify behavioral variability in energy performance and inform the development of behavior-aware energy management strategies tailored to localized and developing-world settings.

## 2. Methods

### 2.1. *Vehicle description and testing procedure*

This study employed an experimental approach to evaluate the influence of driver behavior on the energy efficiency of a prototype electric vehicle. The test vehicle was a lightweight three-wheeled prototype featuring two front wheels and one rear wheel. It is powered by a 48 V, 1000 W brushed DC motor with energy supplied by a $LiFePO_4$ battery pack, which was selected for its stability and safety under repeated discharge cycles [4, 17]. The vehicle was intentionally designed with a minimalist frame to reduce its weight, enabling clearer measurements of energy variations under different driving conditions. This vehicle was designed to be as simple and light as possible for energy efficiency testing and was used on the data track presented in Figure 1.

Experimental trials were conducted on the internal road network of the University of Mataram, which closely resembles the layout and topography of the Mandalika International Circuit. The test route included a combination of flat segments, gentle slopes, curves, and minor speed bumps, thereby simulating a typical low-speed urban environment [18, 19]. Three drivers participated in the test, each with no prior experience operating electric vehicles, to better reflect the natural variability in behavioral patterns. The vehicle was equipped with a handlebar-mounted throttle that provided drivers with direct manual control over the acceleration and speed. During the test sessions, no restrictions were imposed on driving speed, travel distance, or time duration, allowing each driver to operate the vehicle according to their instinctive behaviors. Energy consumption data were collected using onboard monitoring systems for each driving session. This fully open protocol enabled the observation of real-world behavioral tendencies and allowed for the quantification of how different driving styles influence energy usage in prototype EVs.

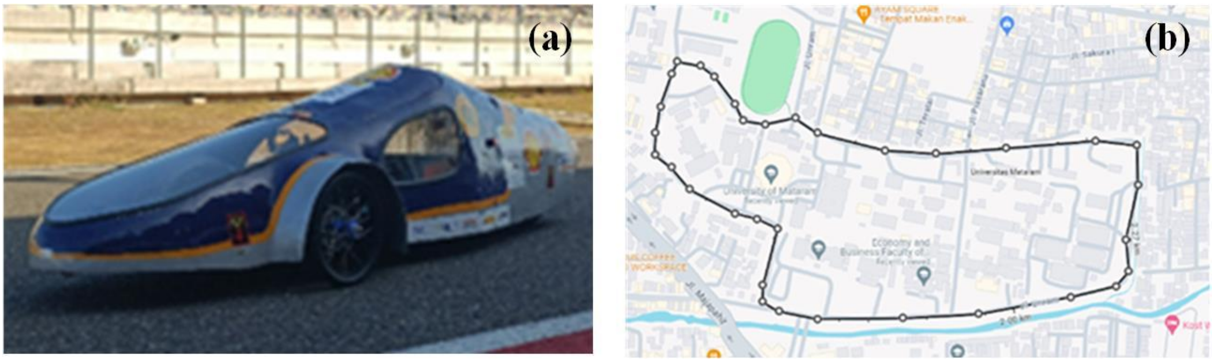


**Figure 1.** Test setup and environment: (a) prototype electric vehicle used in the trials, and (b) experimental driving track located on the University of Mataram campus.

### 2.2. *Instruments and measurement parameters*

The experiment involved three distinct trials, with each driver (Drivers 1, 2, and 3) sequentially operating the electric vehicle under similar environmental and payload conditions. Upon completion of each trial, vehicle performance data were collected, resulting in nine measurement sets throughout the study. These datasets were acquired through onboard instruments, namely, a digital speedometer and a wattmeter, integrated into the prototype vehicle.

The speedometer recorded the instantaneous velocity (km/h) and total travel distance, $D$ (km), of the vehicle, whereas the wattmeter measured the real-time energy consumption, $E$ (Wh), during each driving cycle. These recorded parameters were subsequently used to calculate the energy efficiency, $\eta$ (km/kWh) and its inverse, specific energy consumption (SEC, in kWh/km), as outlined in Eq. (1) and (2). These efficiency metrics are widely adopted in EV performance assessments and have been used in previous studies to evaluate the operational viability and energy economy of electric vehicles [20].

$$\eta = \frac{D}{E} \times 1000 \tag{1}$$

$$SEC = \frac{E}{D} \times \frac{1}{1000} \tag{2}$$

In addition to basic performance monitoring, the wattmeter played a crucial role in quantifying total electrical energy expenditure during each session. This enabled a detailed assessment of the energy demand under varying speeds and behavioral conditions. The speedometer ensured accurate logging of speed profiles, which is essential for identifying the relationship between driving dynamics (e.g., smooth vs. abrupt acceleration) and overall energy efficiency.

A visual documentation of the measuring devices used in this study is presented in **Figure 2**, providing a clear overview of the experimental instrumentation setup.

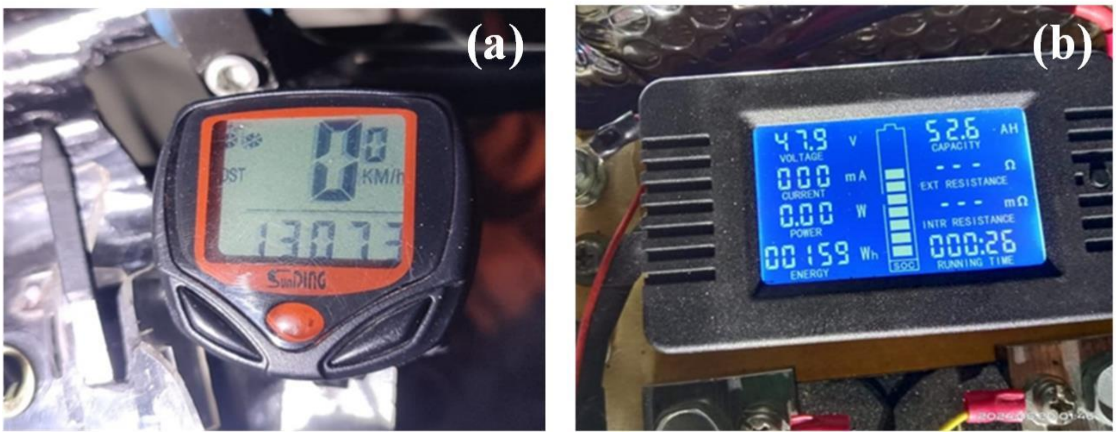


**Figure 2.** Insptrument test: (a) Measurement instruments used during testing: (a) digital speedometer for recording vehicle velocity, and (b) wattmeter for monitoring real-time energy consumption.

## 3. Results and Discussions

### 3.1. *Driver-dependent energy efficiency in prototype electric vehicles*

The influence of driver behavior on energy efficiency was evident across all test scenarios involving the same electric vehicle prototype. With all drivers operating under nearly identical payload conditions—Driver 1 with 122 kg, Driver 2 with 124 kg, and Driver 3 with 120 kg—the analysis isolates behavioral factors as the primary variable affecting performance. As shown in Table 1, Driver 1 consistently achieved moderate-to-high efficiency, with values ranging from 87.1 to 99.2 km/kWh. These outcomes suggest that Driver 1 maintained stable and efficient control over the vehicle, with consistent performance across various low-to-moderate speeds (36–39 km/h).

In contrast, Driver 2 exhibited greater variability, with energy efficiency values ranging from 65.7 to 86.2 km/kWh, despite operating within a similar speed range (22–47 km/h). The relatively low efficiency at a 2.3 km distance and 35 Wh energy consumption (65.7 km/kWh) may indicate less-efficient acceleration or an increased number of stop-and-go events. This fluctuation implies that energy performance can be compromised by inconsistent throttle control, late braking, or poor anticipation of road conditions, even under a constant vehicular mass. These findings are supported by Mamarikass et al. [21], who found that BEVs demonstrate optimal efficiency in low-speed urban environments owing to regenerative braking and high partial-load efficiency. In contrast, higher variability in speed and traffic congestion reduces the performance. Their analysis also indicates that traffic interventions, such as speed restrictions in urban zones, can yield average energy savings of up to 13% for BEVs; however, the benefits diminish when the speed increases beyond the optimal urban cruising range (~25–30 km/h). This reinforces the notion that steady, anticipatory driving at low-to-moderate speeds is ideal for maximizing the energy efficiency of BEVs.

Driver 3, who operated consistently at low speeds (12–17.2 km/h) over short runs (~2.4 km per session), demonstrated the lowest absolute energy consumption (21–29 Wh). This outcome reflects the benefits of maintaining stable, low-speed profiles under light load (120 kg), which is supported by Jonas et al. [22], who found that traffic congestion adds 4–5% to energy consumption. Notably, beyond driving style, intelligent navigation and lane-selection strategies also significantly affect energy efficiency. Pan et al [23] demonstrated that using a PSO-LSTM-based lane-change decision algorithm—trained with V2X traffic data—enabled up to 27.2% reduction in EV energy consumption compared to fixed-lane driving, particularly in continuous lane-change scenarios in urban settings. These findings emphasize that the energy efficiency of EVs is strongly influenced by behavior-adaptive decision-making, including speed modulation, anticipation, and traffic-aware route optimization. Thus, a combination of smooth driving and intelligent navigation represents a promising approach to sustainable urban mobility.

**Table 1.** Summary of driving test results: driver load, speed, distance, energy used, and calculated energy efficiency.

| Driver | Load (kg) | Speed (km/h) | Load Speed ratio | Distance (km) | Energy (Wh) | Energy Efficiency (km/kWh) |
|---|---|---|---|---|---|---|
| D-1 | 122 | 36 | 3.40 | 2.70 | 31 | 87.1 |
| D-1 | 122 | 37 | 3.30 | 2.70 | 28 | 96.4 |
| D-1 | 122 | 39 | 3.13 | 13.00 | 131 | 99.2 |
| D-1 | 122 | 37 | 3.30 | 5.68 | 59 | 96.3 |
| D-1 | 122 | 37 | 3.30 | 11.30 | 118 | 95.8 |
| D-2 | 124 | 35 | 3.54 | 2.30 | 35 | 65.7 |
| D-2 | 124 | 38 | 3.263 | 13.00 | 167 | 77.8 |
| D-2 | 124 | 38 | 3.26 | 5.6.0 | 82 | 68.3 |
| D-2 | 124 | 47 | 2.64 | 13.70 | 159 | 86.2 |
| D-2 | 124 | 22 | 5.64 | 2.30 | 32 | 71.9 |
| D-3 | 120 | 16.2 | 7.42 | 2.40 | 29 | 82.8 |
| D-3 | 120 | 16.6 | 7.23 | 2.40 | 28 | 85.7 |
| D-3 | 120 | 17.2 | 6.98 | 2.40 | 26 | 92.3 |
| D-3 | 120 | 15.5 | 7.74 | 2.40 | 25 | 96.0 |
| D-3 | 120 | 12 | 10.00 | 2.40 | 21 | 114.3 |

Overall, the results confirm that driver-specific factors, including pacing, responsiveness, and speed modulation, are critical in determining the effective range of electric vehicles. These behavioral elements, while often overlooked, represent a significant opportunity for intervention in future sustainable mobility strategies, particularly through eco-driving programs and feedback-based energy-management systems. The driver-specific speed behaviors of all drivers are illustrated in Figure 3.

## 3.2. *Interaction effects of load and speed on energy efficiency*

### *3.2.1. Actual energy consumption analysis*

Before evaluating how load and speed interact to influence energy efficiency, it is essential to examine the actual energy consumption values recorded during the tests, as summarized in Table 1. Driver 1 exhibited energy usage ranging from 28 to 131 Wh, demonstrating consistent throttle control and effective power management over varying travel distances. Despite operating under a moderate load (122 kg), this driver maintained a relatively modest energy draw, even on longer segments, which is consistent with studies showing that smooth acceleration and steady cruising significantly reduce EV energy consumption compared with aggressive driving patterns [11, 24, 25]. In contrast, Driver 2 recorded the highest energy usage (167 Wh for a 13 km run) under similar operative conditions (124 kg load, 22–47 km/h speed). This 32–167 Wh variability suggests inefficiencies caused by erratic acceleration and frequent stop-start driving, corroborating the findings of Al-Wreikat et al. [20], who reported up to a 19% increase in specific energy consumption (SEC) when average speeds decreased, and more pronounced effects under stop-and-go urban traffic. Driver 3, who consistently operated at low speeds (12–17.2 km/h) and over short distances (2.4 km per session), demonstrated the lowest absolute energy consumption (21–29 Wh). This outcome reflects the benefits of maintaining stable low-speed driving profiles under light loads (120 kg). These findings are consistent with the results reported by Jonas et al. [22], who showed that traffic conditions significantly affect EV efficiency, leading to approximately 4–5% additional energy consumption in high-traffic scenarios. Moreover, their analysis highlighted that avoiding traffic congestion could extend the battery electric vehicle (BEV) range by up to seven miles. This evidence underscores the value of eco-driving strategies, route optimization, and traffic-aware navigation as critical elements in reducing real-world energy consumption and enhancing EV performance.

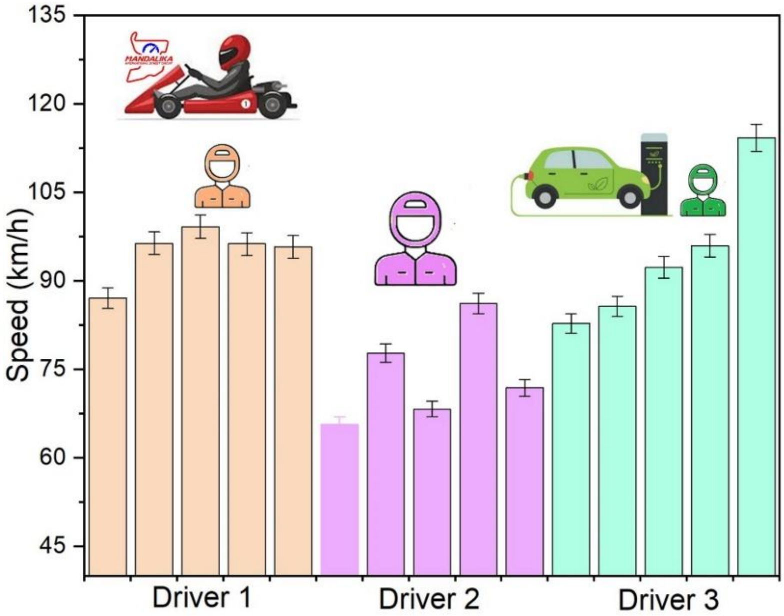


**Figure 3.** *Mandalika Desantara Electric Prototype Vehicle*

### *3.2.2. Multivariate interaction of load and speed on efficiency*

Before evaluating how the load and speed interact to influence energy efficiency, it is important to examine the actual energy consumption values recorded during the tests. Table 1 shows that the energy usage of Driver 1 ranged from 28 to 131 Wh, demonstrating effective management of the power input over varying travel distances. Despite longer travel segments, this driver maintained a relatively modest energy draw per kilometer, reflecting consistent throttle control and a smooth driving style. In contrast, Driver 2 recorded the highest energy consumption in a single trial (167 Wh for 13 km), despite operating under a similar load and speed as Driver 1. This pattern, along with other sessions ranging between 32 and 167 Wh, suggests greater variability and potentially inefficient energy application due to abrupt acceleration or stop-and-go behaviors. Driver 3, who consistently operated at low speeds (12–17.2 km/h) and short distances (2.4 km/session), demonstrated the lowest absolute energy usage, ranging from 21–29 Wh. These results further affirm the energy-saving advantages of maintaining consistent low-speed driving profiles under light-load conditions.

This analysis of raw energy consumption complements the earlier efficiency metrics by providing practical insights into the actual power requirements across different driving patterns. This provides a valuable foundation for the subsequent discussion on how the vehicle load and cruising speed interact to influence the energy efficiency of EVs. Beyond driver behavior, this study also examined how vehicle load and cruising speed interact to influence the energy consumption of prototype electric vehicles. The results demonstrated that the energy efficiency did not follow a simple linear relationship with either the load or speed. For instance, Driver 1, operating at a relatively high speed of 39 km/h with a 122 kg load, achieved a peak efficiency of 99.2 km/kWh with an overall average of 94.96 km/kWh. This indicates that the vehicle load alone does not necessarily impair performance, particularly when paired with efficient driving strategies, such as smooth acceleration and consistent cruising. In contrast, Driver 2, under a comparable load of 124 kg and cruising speed of 38 km/h, recorded a significantly lower peak efficiency of 68.3 km/kWh and an average of 73.98 km/kWh. This discrepancy underscores the critical influence of driving patterns, particularly the need for anticipatory control and smooth speed transitions, in achieving optimal energy performance. Driver 3 demonstrated the highest efficiency performance, achieving a peak of 114.3 km/kWh and an average of 94.22 km/kWh, while consistently operating the vehicle at moderate speeds ranging from 12.0 to 17.2 km/h under the lightest load condition (120 kg). These results highlight the potential for achieving near-optimal efficiency through stable low-load operation and careful speed control. However, such low-speed conditions may be impractical in real-world urban driving, where the dynamic traffic flow imposes constraints. Therefore, maintaining a cruising speed of approximately 13–15 km/h with smooth acceleration may provide a realistic balance between efficiency and operational feasibility.

These findings are consistent with those of previous studies. Al-Wreikat et al. [20] analyzed real-world EV operation in Birmingham and found that aggressive driving behavior increased specific energy consumption (SEC) by up to 16% compared to passive driving, with more pronounced effects in short-distance trips under 16 km. Additionally, the energy demand was shown to increase by up to 19% in dense urban traffic conditions, where frequent stops and lower average speeds were dominant. These observations support the high efficiency attained by Driver 3, whose consistent low-speed operation mirrored a passive and anticipatory driving style. Similarity Bingham et al. [8] demonstrated approximately 30% differences in energy consumption between aggressive and moderate driving styles using a Smart Fortwo EV across a 40 km mixed-route trial. Kozłowski et al. [9] also emphasized the nonlinear influence of acceleration behavior and speed modulation on energy consumption. These insights collectively reinforce the notion that vehicle load and speed alone are insufficient to explain efficiency outcomes without accounting for driver behavior. Kozłowski et al. [9] also highlighted the nonlinear links between speed, acceleration patterns, and energy use. Such literature corroborates our findings, illustrating that vehicle load and speed alone cannot fully explain energy efficiency without considering the overlay of the driver's behavior.

Fiori et al. [26] developed a VT-CPEM model to simulate EV energy consumption using instantaneous speed and acceleration inputs. The model highlighted the role of regenerative braking efficiency and auxiliary loads (e.g., heating and cooling), which can increase the total energy demand by up to 32%. Notably, energy recovery during non-aggressive braking cycles in urban driving scenarios aligned with the high efficiency recorded in Driver 3's performance, affirming the value of behaviorally adaptive driving in minimizing energy waste. The interaction effects among the load, speed, and efficiency of all drivers are illustrated in Figure 4.

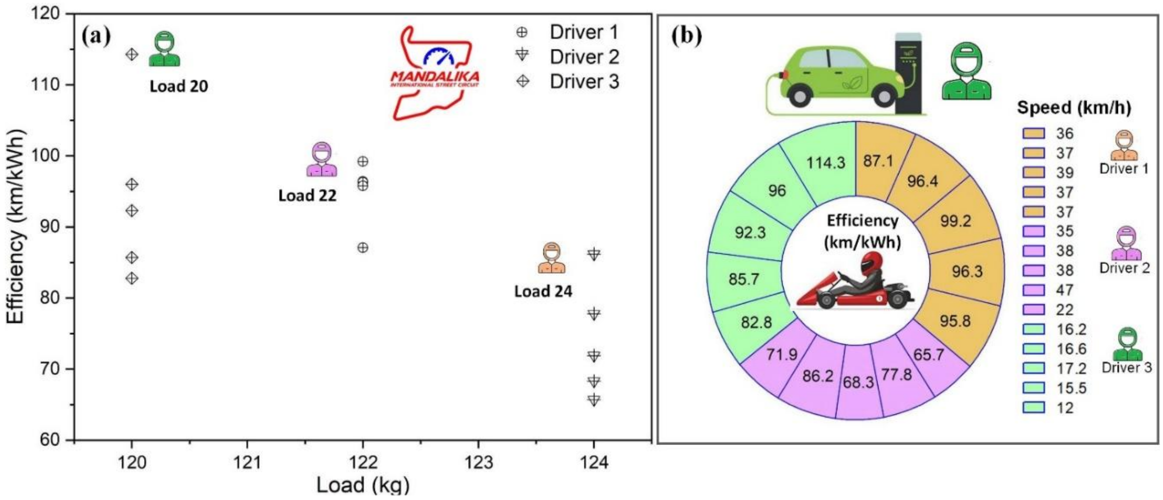


**Figure 4.** Interaction effects on energy efficiency: (a) scatter plot of vehicle load versus energy efficiency; (b) doughnut chart showing the contribution of cruising speed ranges to efficiency outcomes across drivers.

## 3.3. *Implications for Sustainable Urban Mobility*

The driver-specific speed behaviors relative to distance are illustrated in Figure 5. From an urban sustainability perspective, these findings have significant implications. The data demonstrate that energy efficiency improvements of up to 28.4% can be achieved solely through behavioral optimization without requiring any modification to the vehicle hardware or control systems. This figure is derived from the observed difference between Driver 1 (94.96 km/kWh) and Driver 2 (73.98 km/kWh), the latter of whom was used as the baseline due to consistently lower and more variable energy efficiency. Similarly, Driver 3, operating under lighter loads and consistently low speeds, achieved an average efficiency of 94.22 km/kWh, representing a 27.4% improvement compared to Driver 2. These findings confirm that variations in driver behavior alone—such as smoother acceleration, better speed modulation, and anticipatory control—can produce efficiency gains ranging from 27% to 28.4% under otherwise comparable test conditions.

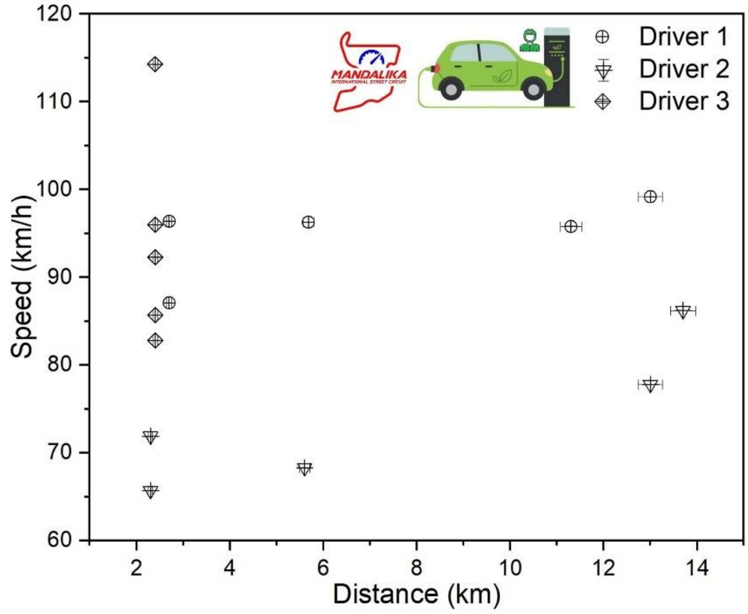


**Figure 5.** Scatter plot of driving distance versus cruising speed for all drivers, illustrating the variations in operational behavior during the test sessions.

This presents a compelling opportunity for cities transitioning to electric mobility to recognize driver behavior as a key policy intervention. Eco-driving education programs and real-time feedback systems embedded in EV dashboards can significantly improve operational efficiency, particularly for public transport and commercial vehicle fleets. In addition, transportation planners and fleet managers can integrate driver profiling and behavior-based efficiency metrics into route planning, vehicle scheduling, and adaptive control systems. These insights also support the development of intelligent EV ecosystems incorporating features such as adaptive cruise control, energy-aware speed guidance, and AI-assisted driving modules aimed at maximizing efficiency.

Despite these promising results, this study has certain limitations. The sample size was limited, and real-world variables such as traffic congestion, elevation changes, and weather conditions were not considered. Future research should address these factors using advanced telematics and data-driven models to assess energy performance in more dynamic and heterogeneous urban environments. Such efforts are crucial for developing robust behavior-based strategies that align with long-term sustainability objectives, as illustrated in Figure 6. Such efforts are crucial for developing robust behavior-based strategies that align with long-term sustainability objectives, as illustrated in Figure 6. The conceptual framework highlights how energy-efficient driving behavior can be systematically incorporated into urban electric mobility systems through the integration of eco-driving initiatives, behavioral monitoring, and intelligent feedback mechanisms. These approaches not only enhance the performance of individual vehicles but also support broader environmental and energy goals, particularly within the context of sustainable urban transportation planning.

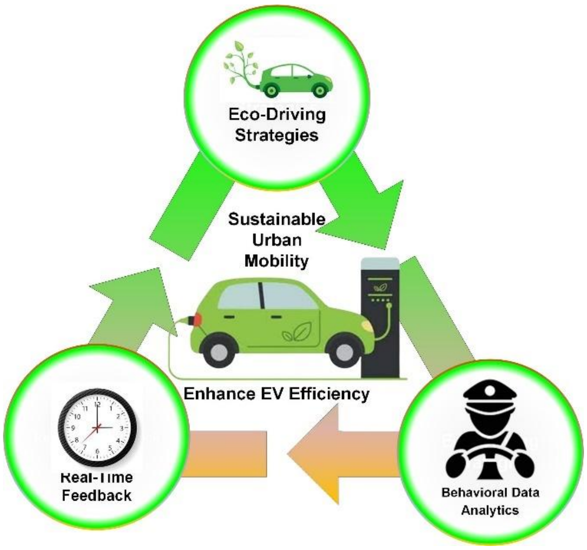


**Figure 6.** Conceptual framework linking driver behavior, energy efficiency, and policy interventions for sustainable urban electric mobility.

Such efforts are crucial for developing robust behavior-based strategies that align with long-term sustainability objectives, as illustrated in Figure 6. The conceptual framework highlights how energy-efficient driving behavior can be systematically incorporated into urban electric mobility systems through the integration of eco-driving initiatives, behavioral monitoring, and intelligent feedback mechanisms. These approaches not only enhance the performance of individual vehicles but also support broader environmental and energy goals, particularly within the context of sustainable urban transportation planning.

## 4. Conclusions

This study quantitatively evaluated the effects of driver behavior, vehicle load, and cruising speed on the energy efficiency of a prototype electric vehicle. Across nine test sessions involving three drivers under controlled conditions, notable performance differences were observed, despite the comparable technical setups.

- Driver 1, with a load of 122 kg, recorded an average energy efficiency of 94.96 km/kWh, peaking at 99.2 km/kWh.
- Driver 2, under a similar 124 kg load, exhibited the lowest efficiency, averaging 73.98 km/kWh, with a minimum of 65.7 km/kWh.
- Driver 3, operating at lower speeds (12.0–17.2 km/h) and carrying the lightest load (120 kg), achieved the highest average efficiency of 94.22 km/kWh, with a peak of 114.3 km/kWh.
- In terms of actual energy consumption, Driver 1 used 28–131 Wh per session, whereas Driver 2 consumed up to 167 Wh, the highest recorded. Driver 3 maintained the most consistent energy use, ranging from 21–29 Wh, indicating a strong correlation between smooth low-speed driving and minimal power draw.
- Overall, efficient driving behavior—marked by gradual acceleration, consistent speed, and anticipatory control—resulted in up to 30.1% improvement in energy efficiency, based on the relative gain from Driver 2's minimum to Driver 3's maximum performance. These findings underscore the significance of behavioral factors, which can rival or even surpass mechanical optimization in enhancing the performance of electric vehicles.

From a policy and system design perspective, these insights advocate the adoption of eco-driving training, real-time feedback systems, and driver behavior analytics as cost-effective strategies to improve fleet-level energy efficiency. Future studies should incorporate larger sample sizes and variable real-world conditions to refine the predictive models for electric mobility in dynamic urban settings..

## Author's Declaration

### Authors' contributions and responsibilities

The authors contributed significantly to the conception and design of this study. The corresponding author was responsible for the data analysis, interpretation, and discussion of the results. All the authors have reviewed and approved the final version of the manuscript.

### Acknowledgment

This research was supported by the Department of Mechanical Engineering, Faculty of Engineering, University of Mataram through the provision of laboratory facilities and technical resources.

### Availability of data and materials

All data supporting the findings of this study are available from the corresponding author upon reasonable requests.

### Competing interests

The authors declare no conflicts of interest related to this study.

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