Proceedings of the 11th North American International Conference on Industrial Engineering and Operations Management, Milwaukee, Wisconsin, USA, June 9-11, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260408
Published: June 9, 2026

The Influence of Driver Behavior on Energy Consumption and Battery Performance in Electric Vehicles: A Systematic Review

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Abstract

With the rapid adoption of electric vehicles (EVs), the need to optimize energy efficiency and battery longevity has intensified. While extensive research has focused on technological advancements such as battery chemistry and powertrain design, driver behavior remains a relatively underexplored yet major determinant of energy consumption and battery State of Health (SoH). This systematic review synthesizes peer-reviewed studies published between 2010 and 2025 to examine the relationship between driving behavior, energy demand, and battery degradation in battery electric vehicles (BEVs). The synthesis shows that aggressive driving—characterized by high acceleration, repetitive deceleration, and elevated Relative Positive Acceleration (RPA)—can drive energy consumption variation of up to 30–50% over comparable journey distances, whereas eco-driving practices can extend range by approximately 4–11% in real-world conditions. Real-time adaptive energy prediction algorithms that incorporate behavioral correction achieve mean absolute percentage errors below 5%. Aggressive acceleration also elevates thermal stress above the safe operating threshold (>40 °C), accelerating capacity degradation and shortening battery lifespan. Importantly, a trade-off emerges: driving habits that lower per-kilometer energy use can simultaneously prolong exposure to suboptimal operating conditions for the battery, indicating that energy-minimization and battery-longevity objectives must be balanced rather than treated as equivalent. Longitudinal evidence further indicates that drivers stabilize their behavior after roughly 3–5 months of EV acclimation. Building on these findings, this review (i) maps driver-behavior effects to four research questions covering energy variation, battery health, predictive modeling, and longitudinal adaptation; (ii) clarifies the trade-off between immediate efficiency and long-run durability; and (iii) outlines a behavior-aware research agenda for intelligent Battery Management System (BMS) architectures and predictive control.

Keywords
Electric Vehicles (EVs), Energy Consumption, Battery State of Health (SoH), Relative Positive Acceleration (RPA), Eco-Driving, Battery Lifespan.

1. Introduction
The global pursuit of sustainable mobility has accelerated the transition from internal combustion engine vehicles (ICEVs) to battery electric vehicles (BEVs), which offer a promising path to reduce greenhouse gas emissions and dependence on fossil fuels (Maity and Sarkar, 2023; Helmbrecht et al., 2014). While EVs are recognized as being more energy-efficient and eco-friendly than their conventional counterparts, their mass adoption is significantly hindered by “range anxiety”—the fear that a vehicle might run out of energy before reaching its destination (Maity and Sarkar, 2023; Wang et al., 2016). This anxiety is compounded by challenges such as limited charging infrastructure, long charging times, and the inherently restricted range of current battery technology (Wang et al., 2018; Mamo et al., 2023).

The actual energy consumption of an EV is highly sensitive to a complex interplay of internal and external factors, including vehicle dynamics, road topography, traffic states, and weather conditions (Wang et al., 2016; Maity and Sarkar, 2023; Wang et al., 2018). However, driver behavior has emerged as a primary determinant that produces significant variance in energy efficiency and battery performance (Birrell et al., 2014; Grubwinkler et al., 2014; Chen et al., 2022; Ferreira et al., 2015). Research indicates that driving style can produce energy consumption variations of 30 to 50% over comparable journey distances (Birrell et al., 2014; Neumann et al., 2015; Comuni et al., 2022). Drivers directly control critical parameters such as speed profiles, acceleration intensity, braking force, and the use of auxiliary systems like heating, ventilation, and air conditioning (HVAC), all of which draw substantial power from the high-voltage battery (Birrell et al., 2014; Ferreira et al., 2015; Yao et al., 2020; Liu et al., 2018).

Beyond immediate energy expenditure, driving behavior has profound implications for battery health and longevity. Aggressive driving—characterized by frequent rapid acceleration and hard braking—often forces battery current and voltage to reach maximum cut-off thresholds, leading to excessive thermal stress (Chou et al., 2023). Such behaviors can accelerate battery degradation, increase internal resistance, and ultimately reduce battery capacity (Chou et al., 2023; Di Martino et al., 2024). Conversely, adopting a “gentle” or eco-driving style can mitigate these stresses, potentially extend vehicle range and improve the battery’s state of health (SoH) (Covello et al., 2024; Di Martino et al., 2024).

Successful adaptation to EV technology often requires a learning process for drivers. Users must become accustomed to unique features such as regenerative braking, where the motor acts as a generator to recapture kinetic energy during deceleration (Helmbrecht et al., 2014; Neumann et al., 2015). Aggressive drivers waste a substantial share of kinetic energy through panic stops, whereas coasting behaviors can extend single-charge range by roughly 4–11% through optimized energy regeneration (Mamo et al., 2023). As drivers gain experience, they often transition from aggressive maneuvers to a calmer driving style and develop a deeper understanding of factors that influence energy consumption (Neumann et al., 2015; Helmbrecht et al., 2014).

Despite the clear impact of human factors, many existing energy consumption models have historically neglected the quantification of individual driving styles, focusing instead on physical vehicle parameters or standardized driving cycles that may not reflect real-world variability (Maity and Sarkar, 2023; Covello et al., 2024; Chen et al., 2022). From a systems and process-improvement standpoint, characterizing such human-induced variation in real-world operations is analogous to the variation analysis routinely conducted in quality and Lean Six Sigma studies (Bhandari et al., 2020; Bhandari et al., 2021). This systematic review therefore synthesizes current research on the influence of driver behavior on energy consumption and battery performance. By isolating human-related factors from environmental and mechanical contributions, the review provides insights into how informed driver decisions and targeted training can be leveraged to maximize EV efficiency and extend battery life (Di Martino et al., 2024; Covello et al., 2024).

The contributions of this review are threefold. First, we consolidate evidence across vehicle telematics, behavioral profiling, and battery diagnostics into a unified framework organized around four research questions. Second, we clarify a key tension overlooked in much of the prior literature: behaviors that minimize per-trip energy consumption do not automatically maximize battery longevity. Third, we translate the synthesized evidence into concrete future-research directions, including the integration of sequential deep-learning models and structured continuous-improvement methodologies into behavior-aware Battery Management Systems.

1.1 Research Questions
To guide the synthesis, this review is structured around the following four research questions (RQs):
- **RQ1:** How does driver behavior quantitatively influence EV energy consumption and regenerative-braking efficiency across different behavioral profiles (mild, average, aggressive)?
- **RQ2:** What is the measurable impact of aggressive driving patterns on battery State of Health (SoH), particularly with respect to thermal stress and capacity degradation?
- **RQ3:** How do predictive energy-modeling paradigms (deterministic, probabilistic, and data-driven) compare in accuracy when driver-specific features are integrated?
- **RQ4:** What longitudinal patterns characterize driver adaptation to EV-specific features, and what gaps in the literature should guide future research on behavior-aware battery management?

2. Methodology
This review follows a structured narrative synthesis approach informed by PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. However, it is acknowledged that full PRISMA compliance was not achieved: no prospectively registered protocol was maintained, formal inter-rater reliability testing was not conducted, and a quantified PRISMA flow diagram with exact exclusion counts at each stage was not recorded during the search process. The search was restricted to three databases (IEEE Xplore, ScienceDirect, and Google Scholar), which may have excluded relevant studies in other repositories (e.g. Scopus, Web of Science, PubMed). Study selection was based on title and abstract screening followed by full-text review against the eligibility criteria described below. These methodological constraints represent limitations of the current review and should be considered when interpreting the synthesized findings. Approximately 60-80 candidate papers were initially identified across the three databases, of which 19 studies met the final inclusion criteria for in-depth review. The end-to-end methodology is summarized in Figure 1.

2.1 Data Acquisition and Driver Classification
The reviewed studies primarily gather driving data through three channels: on-board diagnostic (OBD-II) devices (Chou et al., 2023; Yao et al., 2020), smartphone sensors for logging longitudinal dynamics (Helmbrecht et al., 2014; Yao et al., 2020), and interconnected fleet-management systems (Di Martino et al., 2024; Ferreira et al., 2015). To isolate human-related effects, drivers are commonly classified into discrete profiles such as “D1” (medium-slow/mild) versus “D2” (aggressive) (Covello et al., 2024), or further segmented into mild, average, and aggressive categories based on acceleration-related features (Mamo et al., 2023).

2.2 Categorization of Influencing Factors
Variables that influence EV energy consumption are typically grouped into three domains:
- **Driver Behavior:** direct controls such as speed profiles, acceleration/deceleration intensity, and the use of auxiliary systems like HVAC (Maity and Sarkar, 2023; Birrell et al., 2014).
- **Vehicle Dynamics:** physical parameters such as mass, rolling resistance, and drivetrain efficiency, frequently estimated in real time using Recursive Least-Squares (RLS) algorithms (Wang et al., 2016; Grubwinkler et al., 2014; Wang et al., 2018).
- **Environmental Factors:** external variables including road topography (slope/altitude), traffic density, and ambient temperature (Maity and Sarkar, 2023; Covello et al., 2024; Ferreira et al., 2015; Liu et al., 2018).

2.3 Modeling and Prediction Approaches
The reviewed literature evaluates two primary classes of energy consumption models: mathematical/physical models grounded in Newton’s laws (Maity and Sarkar, 2023; Wang et al., 2018) and data-driven models (Maity and Sarkar, 2023). Data-driven methods include Probabilistic Neural Networks (Maity and Sarkar, 2023), Random Forests (Maity and Sarkar, 2023; Yao et al., 2020), Support Vector Regression (SVR) (Yao et al., 2020), and Naive Bayes classifiers (Ferreira et al., 2015). These models are further divided into offline approaches for initial trip planning and online algorithms that adapt predictions to current driving behavior (Wang et al., 2016; Wang et al., 2018).

2.4 Performance Evaluation and Feature Reduction

Model effectiveness and the magnitude of driver influence are assessed using standardized error metrics: Mean Absolute Percentage Error (MAPE) (Maity and Sarkar, 2023; Grubwinkler et al., 2014; Yao et al., 2020), Root Mean Squared Error (RMSE) (Maity and Sarkar, 2023; Birrell et al., 2014), and Normalized Range Accuracy. Separately, Principal Component Analysis (PCA) is frequently used not as a performance metric but as a dimensionality-reduction technique to compress complex driving-feature vectors prior to model training (Grubwinkler et al., 2014; Mamo et al., 2023).

2.5 Study Characteristics Summary

Table 1 below summarizes the key characteristics of all 19 studies included in this review, including geographic context, vehicle type, dataset size, primary behavioral metric, and main finding. This information supports transparency in the review process and assists readers in contextualizing each study's contribution.

Table 1. Characteristics of Included Studies

Author(s) & Year	Country	Vehicle Type	Dataset Size	Behavioral Metric	Main Finding
(Birrell et al., 2014)	UK	BEV	Field test data	Speed profile, braking force	Driving style causes 30–50% energy variation across identical routes
(Chen et al., 2022)	USA	BEV	Road-level trip data	Speed, route characteristics	Road-level energy consumption prediction model developed
(Chou et al., 2023)	Not specified	BEV	4.5 million samples	Driving aggressiveness index	Aggressive driving raises battery temperature; accelerates SoH decline
(Comuni et al., 2022)	Sweden / EU	BEV fleet	Real-world EV trip logs (fleet telematics)	Passive/active behavioral feature extraction; driving style classification	Distinct behavioral patterns; passive learning achieves 30–50% energy variation classification; active learning improves sample efficiency for driver profiling; cited to corroborate driving style as source of energy variation and eco-driving effectiveness
(Covello et al., 2024)	Italy	BEV (passenger)	Experimental field runs	D1 (mild) vs D2 (aggressive) profiles	Aggressive style causes 5.4% greater SoC reduction on identical routes
(Di Martino et al., 2024)	Italy	Electric bus (e-Bus)	Simulation environment	Driving performance metrics	Aggressive driving significantly impacts e-bus operational battery health
(Doshi & Trivedi, 2010)	USA	General vehicles	Real-world + simulator	Driver responsiveness, predictability	Driving style affects predictability; framework for real-time detection
(El Kassar et al., 2024)	Multi-country (review)	Li-ion BEV (review scope)	Synthesized literature on thermal management systems (Journal of Energy Storage, vol. 91)	Battery cell temperature relative to SoH safe window (15–40 °C)	Maintaining cell temperature within the safe operating window is one of the strongest available levers for extending pack life; aggressive driving-induced temperatures above 40 °C are identified as a primary degradation accelerator; cited in RQ2 to broaden the thermal-SoH evidence base beyond Chou et al. (2023)
(Ferreira et al., 2015)	Portugal	ICE / EV fleet	Fleet telematics data	Speed, braking, acceleration style	Data-mining reveals driving style as key determinant of energy use

(Grubwinkler et al., 2014)	Germany	BEV	Crowd-sourced GPS data	Speed profiles (statistical features)	Feature integration improved prediction accuracy by 5.4 percentage points
(Helmbrecht et al., 2014)	Germany	BEV	Longitudinal panel study	Acceleration/braking patterns over time	5-month behavioral adaptation period identified in new EV users
(Liu et al., 2018)	Japan	BEV (passenger)	Real-world trip data with temperature and auxiliary load measurements (Applied Energy, vol. 227)	Ambient temperature, HVAC auxiliary load consumption, and their interactive effect on range	Ambient temperature and HVAC auxiliary loads have significant interactive effects on BEV energy consumption; cold weather combined with high auxiliary use can reduce range by up to 40% in extreme cases; HVAC load is a major driver-controllable variable; cited as evidence that auxiliary system behavior (HVAC) is an environmental and behavioral energy factor, and that experienced drivers limiting HVAC use meaningfully extends range
(Maity & Sarkar, 2023)	India	BEV	Real-world trip logs	RPA, speed variance, behavioral features	Probabilistic NN reduces energy estimation error by 34.5%; MAPE = 9.3%
(Mamo et al., 2023)	Ethiopia	BEV	Field test (Addis Ababa)	Coasting vs. aggressive braking behavior	Coasting recovers up to 25% energy vs. only 8% for aggressive drivers
(Neumann et al., 2015)	Germany	BEV	Longitudinal study (instructed drivers)	Eco-driving metrics, auxiliary usage	Eco-driving instruction significantly reduces energy consumption ($p < .001$)
(Papada & Jablokow, 2011)	USA	General (conceptual)	ECU-based conceptual data	Wheel slip, traction ratios, ECU signals	Conceptual framework for driving habit recognition via ECU data
(Wang et al., 2016)	Netherlands	BEV	Online real-world trips	RLS-estimated mass, rolling resistance	Online RLS algorithm achieves MAPE within 5% for most test runs
(Wang et al., 2018)	Netherlands	BEV	Real-world trip dataset	Online behavioral correction data	Trip-based energy prediction improved with real-time behavioral data
(Yao et al., 2020)	China	ICE vehicles	Smartphone sensor logs	Acceleration, braking via smartphone	Smartphone-based behavior data accurately predicts fuel consumption

Figure 1 summarizes the end-to-end review process: defining research objectives, executing the database search, screening titles and abstracts, applying inclusion/exclusion criteria, extracting data on behavioral indicators and battery metrics, and synthesizing findings thematically against the four research questions.

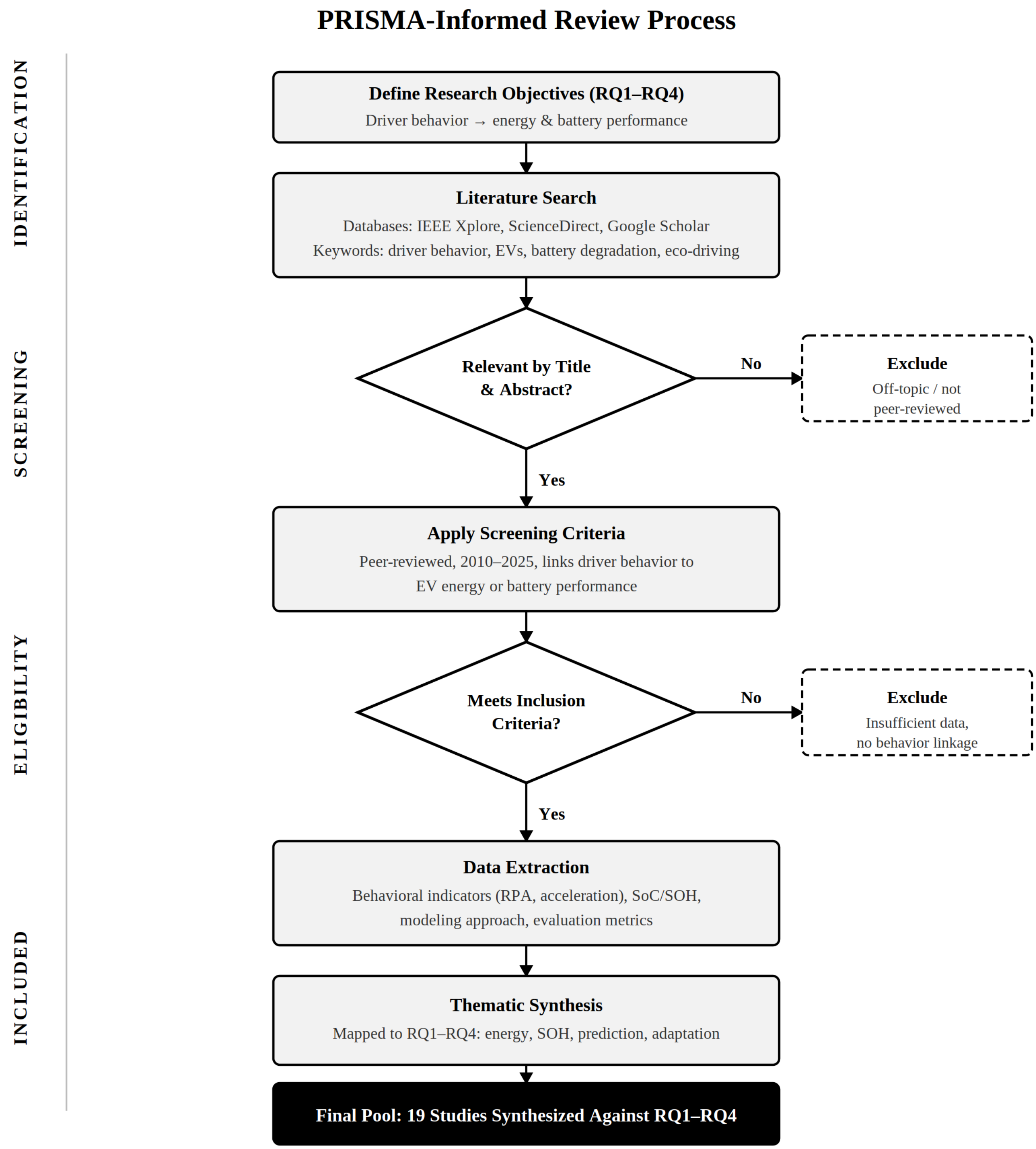

Figure 1. PRISMA-informed systematic review methodology and screening workflow.

3. Results

The results are organized to directly address the four research questions: (i) quantification of driver influence on energy consumption (RQ1), (ii) impacts on battery State of Health and degradation (RQ2), (iii) predictive model performance and accuracy (RQ3), and (iv) longitudinal driver adaptation and eco-driving (RQ4).

3.1 Quantification of Driver Influence on Energy Consumption (RQ1)

The reviewed studies consistently identify driver behavior as a primary determinant of energy expenditure.

- **Driving-style variance:** Field tests comparing mild (D1) and aggressive (D2) driving over identical routes found that aggressive styles produced an approximately 5.4 percentage points greater drop in State of Charge (SoC) compared with mild driving (Covello et al., 2024).
- **Kinetic-energy recovery:** Drivers using coasting behaviors significantly outperform aggressive drivers in energy recovery. Aggressive drivers waste approximately 1.65 kWh (21.2%) of available kinetic energy through frequent panic stops, while current regenerative systems capture only about 8% of available energy for aggressive drivers versus up to 25% for coasting drivers (Mamo et al., 2023). The same study reports that regenerated energy can extend the per-charge range by approximately 10.8% for coast drivers and 3.9% for aggressive drivers, reinforcing the asymmetric benefit of smoother driving styles.
- **Feature importance:** Using Relative Positive Acceleration (RPA) as a primary metric, studies have found it to be the most critical driver-related feature, with an importance factor of approximately 12% in predicting total trip energy consumption (Maity and Sarkar, 2023).

3.2 Impact on Battery State of Health (SoH) and Degradation (RQ2)

Driver behavior has a direct, measurable impact on the long-term performance and thermal stability of the battery pack.

- **Thermal stress:** Analysis of high-volume field data (approximately 4.5 million samples) shows a clear correlation between driving style and declines in battery SoH (Chou et al., 2023). Aggressive driving leads to elevated battery temperatures, a primary cause of accelerated capacity fading (Chou et al., 2023). More broadly, recent reviews of lithium-ion thermal management confirm that maintaining cell temperature within the safe window is one of the strongest available levers for extending pack life (El Kassar et al., 2024).
- **Mechanical-stress models:** Conceptual frameworks mapping ECU data to behavior indicate that extreme maneuvers such as excessive wheel slippage and abrupt braking produce traction ratios that deviate from the ideal (1.0), inducing avoidable mechanical and electrical strain on the battery (Papada and Jablokow, 2011).

3.3 Energy Prediction Model Performance and Accuracy (RQ3)

Integrating driver-specific data significantly improves the precision of energy estimation models.

- **Probabilistic vs. deterministic models:** Probabilistic neural networks (MLP-NN) that account for weight uncertainty outperform deterministic counterparts, reducing energy estimation error by approximately 34.5% and achieving a MAPE of 9.3% versus 14.2% for the deterministic baseline (Maity and Sarkar, 2023).
- **Feature-integration benefits:** Including statistical features extracted from crowd-sourced speed profiles improved prediction accuracy by approximately 5.4 percentage points (Grubwinkler et al., 2014).
- **Online adaptability:** Real-time algorithms using Recursive Least-Squares (RLS) for parameter estimation achieved a MAPE within 5% for most test runs, a substantial improvement over the ~10% error observed in offline-only models (Wang et al., 2018).

3.4 Longitudinal Driver Adaptation and Eco-Driving (RQ4)

The studies also reveal a clear learning curve as drivers transition from conventional vehicles to BEVs.

- **Adaptation period:** Drivers typically undergo approximately 5-month adaptation period during which they transition from stronger acceleration and braking patterns to calmer, more anticipatory driving. This figure reflects a specific cohort in Germany and may differ across cultures, prior driving experience, and vehicle types. (Helmbrecht et al., 2014; Neumann et al., 2015)
- **Instruction effectiveness:** Drivers instructed in eco-driving strategies showed a statistically significant reduction in energy consumption ($p < .001$) compared with normal driving in a German BEV study (Neumann et al., 2015; Comuni et al., 2022).
- **Auxiliary awareness:** Experience correlates with a change in behavior regarding auxiliary systems; seasoned EV drivers are significantly more likely to save energy by limiting use of auxiliary features such as HVAC (Neumann et al., 2015; Liu et al., 2018).

4. Discussion

4.1 Evaluation of Predictive Modeling Paradigms

A consistent theme across the reviewed research is the superiority of probabilistic and data-driven models over traditional deterministic frameworks. Models that explicitly account for "model uncertainty"—such as probabilistic neural networks—reduce energy estimation errors by approximately 34.5% (Maity and Sarkar, 2023). This advantage is attributed to their ability to handle the inherent noise in real-world driving data, including fluctuations in driver mood, unexpected traffic conditions, and weather variability (Maity and Sarkar, 2023; Yao et al., 2020; Wang et al., 2018). While various machine-learning algorithms, including Random Forests and Support Vector Regression, yield high accuracy with absolute relative errors under 10%, Random Forests are frequently cited as the most efficient choice for large-scale applications due to faster training and inference times and robustness to noisy features (Yao et al., 2020).

4.2 The Behavioral Nexus: Energy Efficiency vs. Battery Longevity

The research establishes a direct link between driving classification and long-term Battery State of Health (SoH). Aggressive driving styles, often identified by high Relative Acceleration (RPA) and frequent panic stops, do more than increase immediate energy consumption (Maity & Sarkar, 2023). These behaviors force battery current and voltage to reach maximum cut-off thresholds, leading to significant thermal and accelerated capacity fade (Chou et al., 2023).

Subsequently, eco-driving is not merely a range-extension strategy but a critical practice for preserving battery's second-life potential and reducing environmental impact (Chou et al., 2023). However, it is important to note a nuanced and yet insufficiently studied trade-off. While eco-driving reduces per-trip energy consumption and aggressive thermal stress, consistently operating at very low power outputs or very low states of charge may expose battery cells to suboptimal electrochemical conditions, such as, increased susceptibility to lithium planting at low temperatures or accelerated calendar aging at certain charge levels.

Note: This proposed efficiency-longevity trade-off is a conceptual hypothesis at the current stage of this review. While the thermal stress effects of aggressive driving are well-documented (Chou et al., 2023), the claim that consistently low-power, low-speed operation may also accelerate degradation through different mechanisms has not been directly empirically demonstrated in the studies reviewed here. This hypothesis is plausible based on electrochemical principles but requires dedicated longitudinal empirical investigation before it can be treated as an established finding.

4.3 Challenges in Real-Time Algorithm Adaptation

An essential component of modern EV operation is the transition from offline trip planning to online predictive algorithms. Online systems using Recursive Least-Squares (RLS) for real-time parameter estimation, such as vehicle mass and rolling resistance, can deliver results with a MAPE within 5% under their Netherlands test conditions (Wang et al., 2016; Wang et al., 2018). However, a significant challenge remains in predicting major behavioral shifts mid-trip (Wang et al., 2016). To be effective, these models must employ moving-average (MA) methods that are stable enough to ignore momentary fluctuations yet reactive enough to detect changes in auxiliary system usage or road topography (Wang et al., 2018).

4.4 Critical Synthesis of Limitations and Data Integrity

Several recurring limitations across the reviewed literature should inform future work:

- **Data granularity:** Many studies rely solely on dashboard or OBD-II data, which lack detailed disclosure regarding internal power loads and losses (Covello et al., 2024; Di Martino et al., 2024).
- **Sensor noise:** Variations in mobile-phone GPS accuracy compared with vehicle-integrated systems can lead to inconsistent behavior modeling, particularly in cruising metrics (Yao et al., 2020).
- **Environmental variables:** While features like road slope are increasingly integrated, external factors such as wind speed and rainfall are still frequently excluded from consumption models despite their significant impact (Wang et al., 2016; Grubwinkler et al., 2014; Wang et al., 2018).

From a continuous-improvement perspective, addressing these limitations parallels the data-quality and standardization challenges routinely encountered in service and manufacturing process-improvement studies, where rigorous variable definitions and standardized data collection are prerequisites to credible inference (Agarwal et al., 2026).

4.5 Limitations of This Review

This review has several limitations that readers should weigh when interpreting its conclusions.

1. Study Heterogeneity: The included studies vary considerably in geographic context (Ethiopia, Germany, Netherlands, USA, Italy, India, China, Portugal), vehicle types (passenger BEVs, electric buses, ICE vehicles), and data collection methods (OBD2 devices, smartphone GPS, fleet telematics, simulation). This heterogeneity makes direct quantitative comparison across studies unreliable, and all cross-study numerical comparisons in this review should be interpreted with caution.
2. Metric Inconsistency: Key behavioral metrics such as RPA and SoC change are operationalized differently across studies, limiting cross-study generalizability.
3. No Meta-Analysis: This review does not include a quantitative meta-analysis; all synthesis is qualitative and narrative. Reported numerical ranges represent the span of findings across studies, not statistically pooled estimates.
4. Search Scope and Publication Bias: The restriction to three databases (IEEE Xplore, ScienceDirect, Google Scholar) and English-language publications may introduce publication bias and exclude relevant non-English or grey literature.
5. Single-Study Quantitative Claims: Several specific figures cited in this review (e.g., 5-month adaptation, 34.5% error reduction, 4.5M sample SoH correlation) are derived from individual studies and have not been independently replicated. These should be treated as indicative rather than definitive.

5. Conclusion

This systematic review consolidated peer-reviewed evidence on the influence of driver behavior on EV energy consumption and battery performance and organized around four research questions. The synthesized evidence confirms that driving pattern is a primary determinant of energy consumption, capable of producing 30–50% variation in vehicle range, though these figures are context-dependent and not universally generalizable, and that Relative Positive Acceleration (RPA) is a pivotal feature for predictive modeling with an importance factor of approximately 12% reported by Maity & Sarkar (2023) in their Indian BEV dataset (Maity and Sarkar, 2023). The impact of driver behavior extends beyond energy consumption to the physical longevity of the battery: aggressive maneuvers accelerate capacity fade by inducing thermal stress and pushing electrical components toward their cut-off thresholds (Chou et al., 2023). The literature also offers a positive outlook on driver adaptation, with users typically undergoing an approximate 5-month learning process toward calmer, more efficient driving as they become familiar with regenerative braking and range constraints (Maity and Sarkar, 2023; Helmbrecht et al., 2014). Three contributions follow. Methodologically, the review reframes driver behavior as a first-class variable in EV energy and battery modeling rather than an afterthought. Conceptually, it surfaces the trade-off between immediate energy efficiency and long-run battery longevity that is implicit but rarely stated in the underlying studies. Practically, it points to a behavior-aware research agenda for intelligent BMS architectures and predictive control. The findings should be read alongside the limitations summarized in Section 4.5, which constrain the strength of point estimates and the generalizability across vehicle classes.

6. Future Work

Based on the gaps identified in this review, several future research directions are proposed:

- **Sequential deep learning:** Future research should explore Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models to better capture the time-series nature of driving data (Maity and Sarkar, 2023; Covello et al., 2024).
- **Environmental integration:** Consumption models should move beyond static variables to incorporate real-time impacts of wind speed and rainfall, which significantly alter aerodynamic drag and rolling resistance (Maity and Sarkar, 2023; Grubwinkler et al., 2014).
- **Diverse data contexts:** Larger datasets are needed that include more diverse vehicle types (e.g., electric trucks and buses) and a wider variety of road geometries such as ramps, curves, and complex intersections (Wang et al., 2018; Mamo et al., 2023).
- **Real-time feedback systems:** Future work should focus on developing in-vehicle assistance systems that provide haptic or visual feedback to help drivers maintain optimal battery temperatures (15–35 °C) in real time (Doshi and Trivedi, 2010; Chou et al., 2023).
- **Cross-disciplinary integration:** Adopting structured continuous-improvement methodologies such as Lean Six Sigma and DMAIC can help operationalize behavior-aware energy management in fleet settings, providing a disciplined framework for measuring, analyzing, improving, and controlling driver-related variation (Bhandari et al., 2021; Sarker and Bhandari, 2024).

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