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Cross-temporal framework for driving behavior impact on electric vehicle battery health

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ABSTRACT: Driving behavior significantly impacts battery health. Existing research mainly improves battery health through powertrain and vehicle control. However, they rarely isolate and quantify the contribution of driving behaviors, which may lead to overestimating theoretical gains and underperformance in practice. To address this gap, this paper introduces an integrated framework that links daily driving behavior to long-term battery health. The framework establishes a multi-scale dynamic driving environment that integrates battery cell processes, powertrain systems, and vehicle-level driving behavior, enabling the estimation of real-time battery health influenced by driving behavior. Moreover, the problem formulation of the battery health-aware framework extends beyond traditional fixed driving cycles to dynamic driving scenarios that incorporate energy efficiency, battery health, and safety. Furthermore, second-level driving behaviors are linked to year-to-year battery health. Experiments across different travel demands and regions demonstrate that more stable driving behavior decreases energy consumption by 15.7% and reduces battery degradation by 10% over 10 years, with equivalent degradation occurring in 5 years under intensive travel. This work provides a cross-temporal quantitative framework that reveals the independent impact of driving behavior on battery degradation, supporting next-generation eco-driving and policy design.

Key words: battery health, travel demand, energy efficiency, driving behavior, electric vehicle

1 Introduction

Electric vehicles (EVs) are gaining widespread adoption owing to their ability to reduce reliance on fossil fuels and mitigate environmental impacts (Liu et al., 2023; Pei et al., 2023). However, EVs still face significant challenges, such as range anxiety (F. Liu et al., 2024) and battery degradation (Saba et al., 2024), which limit their practicality and consumer acceptance. In this context, utilizing route information for speed control, trajectory planning, and energy management to enhance energy efficiency and battery health has become a crucial objective in advancing energy conservation, carbon emission reduction, and transportation electrification (Z. Li et al., 2024). This objective has consistently attracted attention from both the research community and industrial corporations.

Some research on energy efficiency and battery health optimization has been proposed over the years. They typically utilize energy consumption and battery aging costs as evaluation criteria, encompassing both powertrain-level (from tank to wheel) and vehicle-level (from wheel to distance) considerations (J. Li et al., 2024). Accordingly, research can be roughly categorized into three types: powertrain-level, vehicle-level, and coordinated powertrain-vehicle level. Powertrain-level refers to the Energy Management System (EMS) in EVs, which aims to improve energy consumption and battery health while meeting driving power demands (Wang and Lin, 2020). EMS can adjust the energy distribution among the powertrain components, such as the electric motor and battery, based on driving demands (He et al., 2024). Nevertheless, the frequency with which these cycling conditions occur in real-world scenarios remains unclear (Schreiber et al., 2025). In most cases, total power demand is primarily determined by dynamic external driving environments, including driving patterns, slopes, and other external factors. All factors are influenced by driving behaviors at any given time, regardless of the EMS. Vehicle-level refers to the optimization of velocity management and driving behaviors. The former aims to

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improve energy consumption and battery health across different driving cycles by optimizing the speed profile without accounting for driving behavior (Wang et al., 2024). The latter aims to optimize driving behavior for a specific route to minimize energy consumption (W. Li et al., 2024). They often obtain information about the states of surrounding vehicles, pedestrians, traffic signals, and route conditions to meet driving demands and improve energy efficiency (Zamanpour et al., 2025). Typically, the energy consumption associated with vehicle motion is estimated using energy-flow models (Ji et al., 2022), which calculate power flow based on current-voltage or torque-speed relationships while neglecting battery degradation and thermal dynamics (Wu et al., 2023). Powertrain-vehicle Level refers to the co-optimization of powertrain control and speed management. They often incorporate powertrain characteristics into the speed optimization process. Energy efficiency and battery health are co-optimized within a hierarchical framework, with the upper layer focusing on speed planning and the lower layer on powertrain control (Hu et al., 2020). The complex modeling required for co-optimization makes it rare for vehicle control to simultaneously consider both lateral and longitudinal driving behaviors (C. Liu et al., 2024), which limits their applicability in dynamic driving environments (Guo et al., 2022).

Generally, existing studies have addressed energy efficiency and battery health primarily through powertrain management and vehicle control, with cycling aging tests typically conducted under specific driving cycles or single longitudinal car-following scenarios. The simulation of factors influencing battery health is often simplified to varying degrees, thereby overlooking the contribution of driving behavior to battery health under real driving conditions, which limits the applicability of these studies. (Gore et al., 2024). The challenge here is threefold. First, estimating real-time battery health requires careful integration of multiple real-world factors, such as slope and temperature, and validation to ensure consistency with physical laws. Second, incorporating real-world factors and battery health dynamics into driving behavior is challenging, as it requires simultaneously considering energy efficiency, battery health, and safety. Third, the strong coupling among these factors and driving behaviors makes it difficult to isolate the impact of driving behavior on long-term battery health.

Considering the above research gaps, this study proposes a novel cross-temporal framework to assess the contribution of daily driving behavior to long-term battery health under real-world conditions. Unlike previous studies that address battery health (Table 1), the framework first develops a multiscale driving environment that enables real-time estimation of battery health influenced by driving behaviors. It further incorporates external factors, such as temperature and slope, together with the powertrain and battery subsystems that are directly affected by them. This approach overcomes the limitations of fixed driving cycles. Additionally, the framework proposes the problem formulation that integrates battery states and information from surrounding traffic participants into the observation space, considering both lateral and longitudinal behaviors as control variables to optimize driving behaviors for energy efficiency, battery health, and safety in dynamic driving environments. This formulation broadens the scope of battery health-aware studies under real-world driving conditions. Moreover, the framework introduces a cross-temporal battery degradation experimental design that incorporates both calendar aging and cycling aging, with the latter generated from driving cycles derived from diverse travel demands, regional characteristics and driving behaviors. The framework bridges temporal scales from driving behavior to year-to-year battery health assessment. Experiments with privately owned vehicles in Los Angeles and New England, as well as ride-hailing vehicles in Guangzhou, demonstrate the applicability of this framework across various travel demands and driving conditions. The results reveal that more stable driving behavior may lead to a 15.7% decrease in energy consumption and 10% reduction in long-term battery degradation. The quantification results offer valuable insights for technological development, insurance design, and practical deployment of battery health-aware research.

The rest of the paper is organized as follows. Section 2 summarizes the methodologies for energy efficiency and battery health at different levels. Section 3 elucidates the construction of dynamic driving environments and the optimization of driving behavior in the proposed framework. Section 4 presents an assessment of the impact of independent driving behavior on battery health based on long-term driving cycles across different travel scenarios. This paper concludes in Section 5 with additional discussions.

2 Related work

Depending on the system component targeted for energy consumption and battery health, existing optimization research, as mentioned before, can be categorized into powertrain-level, vehicle-level, and powertrain-vehicle level. This paper reviews these studies according to Fig. 1, covering research published from 2018 to 2015.

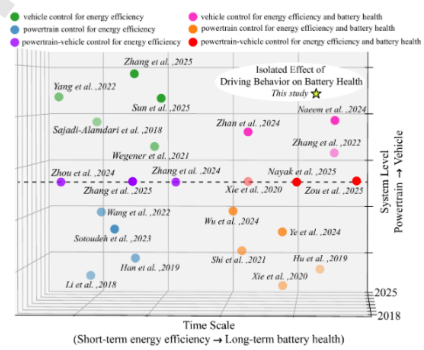

Fig. 1. Literature Review. (2018-2025)

2.1. Powertrain-level

A key feature of powertrain-level research is that it often focuses on optimizing internal components, such as battery management, torque control, and gear selection, to improve energy efficiency and battery health (Peng et al., 2023). The driving costs may occur over different periods. From this perspective, powertrain-level research can be categorized into two main areas: short-term energy efficiency optimization and those that consider both short-term energy efficiency and long-term battery health. Short-term powertrain-level optimization often utilizes online algorithms to enable real-time interaction. Early optimization methods were primarily model-driven, relying on predefined models and rule-based logic. For instance, Li and Görges used heuristic dynamic programming to manage gear shifting and power splitting in real-time (Li and Görges, 2018). Wang et al. used Model Predictive Control (MPC) at the powertrain level for real-time energy allocation based on driving style-aware advisory speeds (Wang et al., 2022). With advances in learning-based technologies, data-driven methods have been introduced to improve adaptability and performance under complex driving conditions. Han et al. employed double deep Q-learning to optimize the power split between the engine and dual motors in a hybrid electric tracked vehicle (Han et al., 2019). Sotoudeh and HomChaudhuri proposed a deep neural

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Table 1. Studies on battery health-aware frameworks

Reference	Observation	Control	Factors	Scenario	Aging type	Results
(Liu et al., 2025)	SOC, Power	Current	-	Driving cycles	Cycling aging	5.1%~12.4% battery health improvement
(Guan et al., 2025)	SOC, Current	Current	-	Driving cycles	Cycling aging	5.3%~10.2% battery health improvement
(Y. Wu et al., 2024)	Battery temperature	Power	Temperature	Driving cycles	Cycling aging	2.34%~3.06% battery health improvement
(Naeem et al., 2024)	Front vehicle, Traffic signals, Battery states	Longitudinal control	Road grade	Car-following	Cycling aging	16%~25% battery health improvement
(Li et al., 2025)	Front vehicle, Ambient temperature, Road grade	Battery temperature, Speed	Road grade, Temperature	Car-following	Cycling aging	22% battery health improvement
Ours	**Battery states, Road grade, Traffic participants**	**Driving behavior includes both lateral and longitudinal control**	**Road grade, Temperature**	**Dynamic driving environments and driving cycles**	**Calendar aging, Cycling aging**	**More stable driving behavior leads to 10% improvement in battery health over 10 years under real travel demands and driving conditions**

network (DNN)-based predictive controller to optimize power spilt (Sotoudeh and HomChaudhuri, 2023). While short-term optimization focuses on the immediate energy efficiency of the powertrain, the long-term hidden costs of battery degradation must also be considered, given their significant impact on vehicle ownership cost and performance. Hu et al. and Y. Xie et al. employed MPC to optimize energy consumption while accounting for long-term degradation of batteries and fuel cells, aiming to balance driving efficiency and component lifespan in electrified powertrains (Hu et al., 2019; Y. Xie et al., 2020). Ye et al. employed a digital twin model to improve the performance of the energy management system in real-time control (Ye et al., 2024). Shi et al. further extended this line of work by proposing a cyber- physical-energy system framework that jointly manages energy consumption and battery degradation (Shi et al., 2021). C. Wu et al. introduced a soft actor-critic (SAC)-based energy management strategy with memory function to jointly minimize energy consumption and battery degradation in a dual-motor, two-speed battery electric vehicle (C. Wu et al., 2024).

2.2. *Vehicle-level*

While powertrain-level research focuses on power split and internal energy optimization, vehicle-level strategies aim to improve energy efficiency and battery health by optimizing speed planning and driving behavior. These strategies can be categorized into single-vehicle and multi-vehicle scenarios depending on the deployment context. For single-vehicle scenarios, the goal is to improve energy efficiency by optimizing driving speed and behaviors under dynamic driving conditions. Sajadi-Alamdari et al. developed a nonlinear MPC-based strategy to optimize cruising speed under stochastic traffic conditions, improving real-time efficiency (Sajadi-Alamdari et al., 2018). Wegener et al. proposed a DRL-based driving strategy that enables efficient driving in urban scenarios with limited traffic information by learning optimal speed control policies (Wegener et al., 2021). Zhang et al. and Zhan et al. introduced battery health management into a real-time control framework through speed planning (Zhang et al., 2022; Zhan et al., 2024). Naeem et al. further extended the application of vehicle control for improving battery health to longitudinal control under uncertain environmental conditions (Naeem et al., 2024). For multi-vehicle scenarios, driving strategies further account for vehicle interactions and cooperative behavior to enhance system-level efficiency. Yang et al. introduced an optimization framework for general mixed platoons of connected and autonomous vehicles (CAVs) and human-driven vehicles (HDVs), integrating offline speed planning with real-time MPC-based tracking (Yang et al., 2022). To further enhance practical applicability, recent studies have integrated safety considerations and real-world deployment. Y. Zhang et al. combined predictive cruise control with a cost-guided neural EMS and validated its fuel-saving benefits and real-time feasibility through scenario- and hardware-in-the-loop experiments (Y. Zhang et al., 2025). Sun et al. designed a DRL-based framework with risk prediction and dynamic modeling to ensure safe and efficient driving in heterogeneous platoons (Sun et al., 2025).

2.3. *Vehicle-powertrain level*

Cooperative control can provide energy efficiency improvements by jointly optimizing powertrain and speed management (J. Li et al., 2024). For single-vehicle scenarios, Zhou et al. developed a multi-layer predictive control strategy to coordinate powertrain energy management and velocity management, thereby enhancing both short-term fuel economy and computational efficiency (Zhou et al., 2024). F. Zhang et al. developed a Pontryagin's minimum principle (PMP)-based co-optimization framework integrating ecological adaptive cruise control (eco-ACC) and energy control under signal phase and timing (SPaT) constraints (F. Zhang et al., 2025). To improve practicality in real-world applications, multi-vehicle scenarios are introduced based on connected technology. S. Xie et al. introduced a real-time energy management strategy that co-optimizes velocity planning and battery depth of discharge (DOD) to mitigate long-term battery degradation in connected plug-in hybrid electric vehicles (S. Xie et al., 2020). Zhang et al. proposed a hierarchical eco-driving control framework that coordinates predictive velocity planning and energy management to improve short-term fuel economy for connected fuel cell hybrid vehicles (Zhang et al., 2024). Nayak and Satpathy proposed an artificial neural network (ANN)-based adaptive strategy for plug-in hybrid vehicles that integrates real-time speed profiles and battery discharge optimization to reduce cost and account for degradation (Nayak and Satpathy, 2025). Zou et al. further attempted to employ co-optimization for energy consumption and battery health in online operation to validate deployment (Zou et al., 2025).

For battery health considerations, existing studies mainly aims to achieve optimal performance through powertrain control, vehicle control, or their cooperation. While these advanced technologies can improve battery health to some extent, their effectiveness in real-world scenarios remains limited. Dynamic driving environments with diverse driving behaviors, comprehensive battery health factors (e.g., slope and temperature), and system components (e.g., battery thermal management) must also be considered. Therefore, it is necessary to establish a comprehensive framework that incorporates battery health factor modeling, problem formulation, and long-term evaluation design.

3 System overview

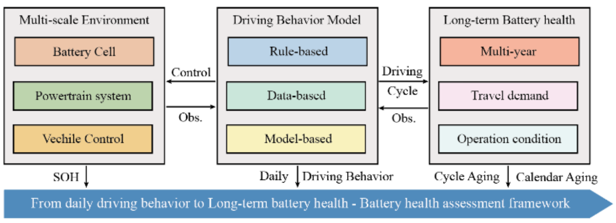


Fig. 2. Overview of the cross-temporal framework.

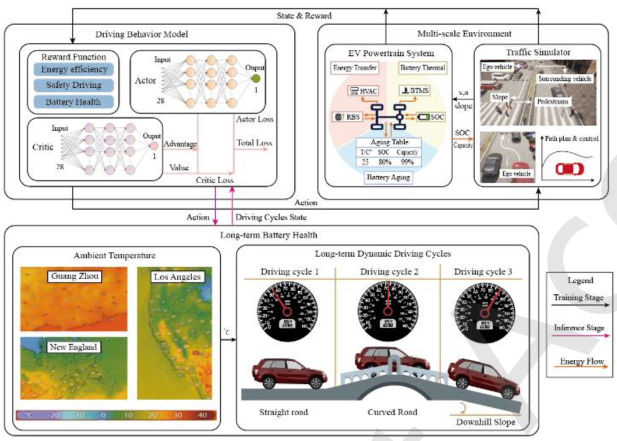


Fig. 3. The implementation of the cross-temporal framework.

To enable analysis of how daily driving behavior impacts long-term battery health, this study proposes a cross-temporal framework that integrates multiscale environmental factors and a dynamic driving behavior model for long-term battery health assessment. The structure of the proposed "Drive2Battery" (D2B) framework is illustrated in Fig. 2. The framework develops a multi-scale environment that incorporates top-down modeling at the vehicle, powertrain, and battery cell levels. The environment estimates real-time battery states, including energy consumption and battery health, influenced by driving behavior. Second, the driving behavior model can be constructed to represent optimized real-world driving behavior within a specific modeling paradigm, with respect to safety, energy efficiency, and battery health. Third, the driving behavior model serves as a long-term driving pattern for battery health assessment based on travel demands under different operating conditions and time spans. Fig. 3 further illustrates the implementation of the proposed framework. The multi-scale environment integrates the EV powertrain system with a traffic simulator to estimate battery states based on dynamic driving behavior. In a multiscale environment, the driving behavior model performs multi-objective optimization using deep reinforcement learning to represent different driving styles and to optimize long-term driving patterns. The driving behavior model estimates multi-year battery degradation using driving cycles generated from travel demand, incorporating geographical information, temperature variations, and vehicle dynamics. In doing so, the proposed cross-temporal framework can yield clear results that quantify the impact of daily driving behavior on battery health over the coming years, supporting insurance design, technological improvements, and user behavior optimization.

3.1. *Multi-scale environment*

Although battery health estimation has been widely studied, there is still no clear, numerical quantification of the impact of driving behavior on battery health from a holistic, interpretable perspective. To address this gap, the multi-scale environment requires a model-based approach from micro- to macro-level modeling that can integrate the battery, powertrain, and vehicle control systems. The multi-scale environment integrates a physics-based EV powertrain system with a traffic simulator (Dosovitskiy et al., 2017), enabling interpretable estimation of real-time fluctuations in battery health induced by dynamic driving behaviors. The longitudinal and lateral driving behaviors are translated into control demands through the vehicle control system and executed in the traffic simulator to generate diverse maneuvers and interactive traffic responses. The resulting traffic states, such as speed, acceleration, and slope, are then fed into the EV powertrain system to estimate the state of charge (SOC) and battery health indicators. These traffic and battery states jointly constitute the observation space of the driving behavior model inputs, while the action space corresponds to longitudinal and lateral driving behaviors.

The vehicle control in the traffic simulator consists of a motion planning module that generates paths based on following or lane-changing behavior, and a trajectory-tracking module that ensures the vehicle follows the planned trajectory at the expected speed demand for the corresponding behavior. The EV powertrain system encompasses the motion power demand and the battery cell processes, including: (1) Energy transfer module, which calculates traction power, auxiliary power consumption such as heating, ventilation, and air-conditioning (HVAC) system and regenerative braking energy such as the regenerative braking system (RBS); (2) Battery aging module, which estimates thermal aging and calendar aging for available battery capacity; (3) Battery thermal module, which handles state of charge (SOC) estimation and temperature regulation based on battery thermal management system (BTMS). The parameters of the modules in the powertrain system can be adjusted based on the vehicle type and operating conditions. Additional information on the physics-based powertrain system, its battery-state modeling, and vehicle control mechanisms can be found in Supplementary Table 1 and Supplementary Notes 1, 3.

3.2. *Driving behavior model*

The driving behavior model needs to learn a driving strategy that balances energy efficiency and battery health while ensuring safety in a multi-scale environment, which can be viewed as a sequential decision-making (SDM) problem. This paper follows the RL paradigm to introduce the driving behavior optimization (Kaelbling et al., 1996). Typically, SDM problems are formalized as a Markov decision process (MDP), defined by a five-tuple $M :< S, A, R, P, \gamma >$, where S is the state space, A is the action space, $S : S \times A \rightarrow \mathrm{R}$ is the reward function, P: $S \times A \rightarrow \Delta(S')$ is the state transition probability, and $\gamma \in [0,1]$ is the reward discount factor.

Table 2. Inputs and outputs of the driving behavior models

Input/Output	Category	Variable name	Description	Variable type	Value
Input	Ego vehicle	Velocity	Velocity of the ego vehicle (m/s)	Float	0.00 to 14.00
Input	Ego vehicle	Acceleration	Acceleration of the ego vehicle (ratio)	Float	-0.30 to 0.75
Input	Ego vehicle	Capacity	The remaining battery capacity of the ego vehicle (Ah)	Float	158.50 to 198.50
Input	Ego vehicle	SOC	The state of charge of the ego vehicle (ratio)	Float	0.10 to 0.80
Input	Traffic conditions	Slope	The slope of the driving road (ratio)	Float	0.00 to 0.04
Input	Traffic conditions	Signal	Whether there is a red light affecting the ego vehicle lane	Bool	True, False
Input	Surrounding traffic	Surrounding vehicles	Speed, acceleration, and relative distance of 7 surrounding vehicles to the ego vehicle	Hybrid	Hybrid
Input	Pedestrians	Pedestrians	Whether there are pedestrians within the safety range of 30m	Bool	True, False
Output	Driving behavior control	Lateral and longitudinal vehicle control	1. Five discrete high-level driving intentions and their corresponding speed: A_1 Eq. (1) 2. Categorical behavior + continuous speed ratio: A_2 Eq. (2)	1. Discrete 2. Hybrid	1. $a \in A_1$ 2. $a = (x_1, x_2) \in A_2$

Here, P is implicitly determined by the traffic simulator and physics-based powertrain system. The state space S is designed to comprehensively reflect both the vehicle's energy states and its dynamic surrounding environment states, which are essential for making energy-aware and safe driving decisions. Therefore, the inputs of the DRL-based driving behavior models consist of two parts: (1) the ego vehicle state, including battery system states, speed, and acceleration; (2) the surrounding traffic environment, including the positions and behaviors of traffic participants. Both battery system states and traffic-related states can be extracted from the multi-scale environment, as described in Section 3.1. These features are integrated as the state inputs to the decision-making process. To better capture the long-term impact of driving behaviors on energy consumption and battery health, this study adopts a high-level discrete action space rather than low-level control signals such as steering angle or pedal positions. High-level decisions, such as adjusting speed and changing lanes, exhibit a more direct and interpretable relationship with energy consumption and battery health. Low-level actions often influence battery degradation through multiple indirect pathways spanning multiple physical layers. In contrast, high-level driving behaviors, as vehicle-level responses, provide a more stable and learnable strategy. Therefore, two action space designs based on high-level intentions are considered for the driving behavior model as shown in Eq. (1) and Eq. (2):

$$A_1 = \{(a^{acc}, 1+\delta), (a^{brk}, 1-\delta), (a^{keep}, 1), (a^{lcl}, 1+\delta), (a^{lcr}, 1+\delta)\} \quad (1)$$
$$\delta \in \{0.1, 0.2, 0.3\}$$

$$A_2 = \{(x_1, x_2) \mid x_1 \in \{a^{following}, a^{lcl}, a^{lcr}\}, x_2 \in [0.8, 1.2]\} \quad (2)$$

The first is a discrete action space consisting of five high-level intentional behaviors: accelerating, braking, maintaining speed, and lane changing to the left or right, together with their corresponding discrete speed adjustment factors δ. The second is a hybrid action space defined as $\{x_1, x_2\}$, where $x_1 \in \{0,1,2\}$ indicates car following or lane changing to the left or right, and $x_2 \in [0.8, 1.2]$ represents a continuous speed adjustment ratio. Details of the input state space and the output action space are demonstrated in Table 2. It is noted that although the action space allows speed changes, the ego vehicle is always restricted to within [0%~130%] of the road speed limit. This is because real-world physical constraints and traffic regulations prevent vehicle speeds from exceeding 130% of the road speed limit under normal conditions. Such overspeed cases typically involve critical safety situations that fall outside the scope of typical daily driving. Additionally, even if a larger speed range were allowed, the throttle would still be limited by the physical controller, whose output is bounded by its maximum allowable value. For example, in high-speed scenarios, an excessively large speed adjustment factor would cause unrealistically abrupt velocity changes, violating physical plausibility and requiring more than a few time steps. In the driving environment, complex maneuvers such as overtaking and lane-changing can be performed through sequential decision-making across multiple time steps. Therefore, the action space with such discrete or hybrid settings can represent real-world driving behaviors and satisfy practical travel demands.

The objective function of RL is to learn a policy $\pi(a \mid s)$ that maximizes the expected cumulative discounted reward, as shown in Eq. (3):

$$J(\pi) = E[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)] \quad (3)$$

The advanced DRL algorithm, proximal policy optimization (PPO), is employed in this study (Schulman et al., 2017). The training objective of the driving model can be defined as Eq. (4):

$$L = L_A(\theta) + 0.5 L_V(\phi) \quad (4)$$

Here, the $L_A(\theta)$ represents the loss of the policy network and $L_V(\phi)$ is the loss of the value network. More details about the learning process are provided in Supplementary Note 2.

In real-world dynamic driving conditions, the driver needs to ensure both safety and eco-driving performance. The goal of driving behavior optimization needs to balance both short-term energy efficiency and long-term battery health while ensuring driving safety, making the problem a multi-objective optimization. Therefore, the reward function can be defined as Eq. (5):

$$R = R_{\text{safe}} + R_{\text{speed}} + R_{\text{eco}} + b \tag{5}$$

where R_{safe} represents the penalty for potential risks and collisions, R_{speed} is the penalty for the cost of undermining traffic efficiency, and R_{eco} is the cost associated with driving behavior, reflecting both energy consumption and battery health, as evaluated by the physics-based powertrain system. b is a bias term introduced to prevent the model being discouraged by negative rewards at the beginning of training.

Specifically, R_{safe} is defined as Eq. (6):

$$R_{\text{safe}} \begin{cases} -10 & \text{, collision} \\ -0.02 \cdot clip(5 - \| p_{\text{ego}} - p_{\text{target}} \|_2 \text{, } 0, 5), & \text{otherwise} \end{cases} \tag{6}$$

The vectors p_{ego} and p_{target} represent the positions of the ego vehicle and the target vehicle in the considered driving scenario, respectively. The *clip* function constrains the value to remain between 0 and 5, and $\| \cdot \|_2$ is the Euclidean distance.

The speed-related reward function R_{speed} penalizes deviations from a target speed predefined by the CARLA simulator based on the specific road segment, guiding the ego vehicle toward efficient driving, which can be defined as Eq. (7):

$$R_{\text{speed}} = -10^{-3} \, | v_{\text{ego}} - v_{\text{target}} | \tag{7}$$

The energy-related reward function considers both energy efficiency and battery health, which can be expressed as Eq. (8):

$$R_{\text{eco}} = R_{\text{energy efficiency}} + 10^{-5} R_{\text{battery health}} \tag{8}$$

The reward $R_{\text{battery health}}$ penalizes battery degradation based on the rated initial battery capacity $C_{\text{bat,ini}}$ and remaining battery capacity $C_{\text{bat,r}}$, and is formulated as Eq. (9):

$$R_{\text{battery health}} = -\eta (C_{\text{bat,ini}} - C_{\text{bat,r}}) \tag{9}$$

The reward $R_{\text{energy efficiency}}$ penalizes energy consumption compared to the initial state of charge SOC_{ini} and the remaining state of charge SOC_r, as shown in Eq. (10):

$$R_{\text{energy efficiency}} = -\mu (\text{SOC}_{\text{ini}} - \text{SOC}_r) \tag{10}$$

where η and μ are economic-related cost coefficients derived from current market prices. In particular, η represents the hidden cost of battery health degradation and is set at 150 CNY/Ah, based on the average market price of batteries in 2024 (Reuters, 2024). The coefficient μ is set to 0.59 CNY/kWh, reflecting the electricity price gathered from charging stations provided by Amap.

3.3. Long term battery health assessment

Long-term battery health testing scenarios face challenges such as missing data, difficulties in quantification, and the intersection of multiple factors. First, there are no available datasets that include both driving conditions and behaviors over a period longer than one year. Second, assessing the impact of driving behaviors on battery health is slow, as both calendar and thermal aging require long-term observation. Third, several intersecting factors, including travel demands, driving patterns, and environmental conditions, will impact long-term battery health. To address these gaps, this section introduces the proposed assessment process of cross-temporal long-term battery health. The assessment process is designed to quantify the impact of daily driving behavior on multi-year battery health. Building on the foundation of the multi-scale environment and the driving behavior model, the assessment process explicitly accounts for factors such as complex driving conditions, travel demand, and driving behavior, thereby supporting a holistic, long-term and interaction-aware evaluation.

The assessment construction follows a structured, three-stage workflow: data collection, scenario generation, and scenario simulation. Fig. 4 illustrates the workflow schema. During data collection, driving cycles and travel demand data are transformed into structured inputs suitable for the driving behavior model. Next, the driving behavior model can generate daily driving cycles based on the travel demand, which represent daily travel scenarios. Finally, the daily driving cycles are simulated within the physics-based powertrain system, day by day, to estimate multi-year battery health. The results reflect the impact of daily driving behaviors on long-term battery health, considering real travel demands and driving conditions.

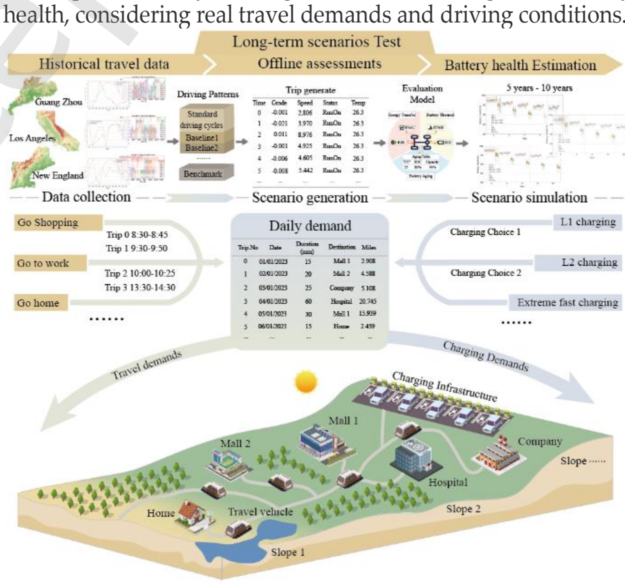


Fig. 4. Schema of cross-temporal battery health assessment.

3.3.1. Data collection

In the proposed cross-temporal framework, driving cycles and travel demand are utilized. The daily travel demand includes trip No., time, destination, duration, and mileage, which are used to construct the dynamic travel scenario. The driving cycles include time step, slope, speed, acceleration, temperature, and running status, where running status indicates the vehicle's operational state ("On" for driving, "Off" for parking) and time step represents the sampling frequency. The variables in the driving cycle are sampled at the same frequency as the time step (1sec), while the temperature is sampled once per hour. Given that subsequent scenario generation in this study needs to reflect changes in battery health across real-world user travel scenarios, the mileage specified in the travel demand must serve as the daily vehicle miles traveled (VMT) target when generating each daily driving cycle based on the driving behavior model. It is noted that only the ego vehicle's driving cycle is considered. The trajectories of surrounding vehicles and other V2X information are not modeled in the long-term scenarios, which are padded with zeros to satisfy the input shape of the driving behavior model. To demonstrate the effectiveness of the proposed framework, the data collection includes driving cycles from three regions: Guangzhou, Los Angeles, and New England, which exhibit distinct temperature and slope characteristics, as well as driving patterns and travel demand from different vehicle usage types. The detailed datasets are described in section 4.1.

3.3.2. Scenario generation

Scenario generation needs to account for all end-user factors that influence EV battery health. In general, these factors include charging behavior and driving behavior, both of which expose the battery to different cycling patterns and consequently affect battery health. Driving behavior models with varying parameter settings represent various long-term driving patterns of real-world EV users. Each model receives historical driving cycles as inputs and outputs optimized driving cycles that correspond to specific driving patterns. These driving cycle segments are accumulated until the upper bound of the real-world daily travel mileage is reached, thereby achieving the daily travel scenario. Additionally, standard driving cycles such as Urban Dynamometer Driving Schedule (UDDS) and Highway Fuel Economy Test (HWFET) are utilized to match travel demands using the same method as the driving behavior model (Jaafar and Rahman, 2020; Ou, 2023). They serve as benchmark driving patterns for comparison with different user driving behavior models. After completing a full day of travel, the charging behavior is applied using the same charging type across all scenarios to ensure consistency and avoid voltage or power variations that may arise from different charging types, thereby preserving the validity of battery health comparisons across scenarios and regions. In this study, we assume sufficient charging time is available during the night to guarantee a fully charged battery. Therefore, Level 1 charging is consistently used as the daily energy replenishment choice. The impact of charging behavior on battery health is calculated in the same manner as the energy transfer module described in Supplementary Note 1.

3.3.3. Scenario simulation

Most battery health benchmarking approaches are based on accelerated cycling tests conducted under laboratory conditions, which do not account for the cross-temporal impacts of real-world user behaviors. To address this issue, scenario simulation needs to estimate multi-year battery health, including cross-temporal calendar aging and cycling aging driven by user behaviors. This process is implemented by running the daily driving cycles constructed based on travel demand and the driving behavior model. Specifically, the driving cycles are repeatedly incorporated into the physics-based powertrain system to accumulate battery health loss over the multi-year horizon. The scenario simulation results demonstrate the long-term evolution of battery health for a BEV over its full usage lifecycle, accounting for both environmental conditions and user-related factors over future multi-year periods. Different driving behavior models yield distinct cross-temporal fluctuations in battery health degradation under the same travel demand and regional conditions. The fluctuations are based on the physics-based powertrain system in Supplementary Note 1, providing strong interpretability of how driving behaviors cumulatively affect battery degradation over time. These results serve as an important reference and validation protocol for comparing and analyzing the impact of driving behaviors on long-term battery health.

4 Experiment analysis

To rigorously validate the effectiveness of the proposed framework in assessing the independent contribution of driving behavior optimization to long-term battery health, this study conducts comparative experiments with three principal objectives:

(1) To assess the effectiveness of the proposed framework in optimizing driving behaviors while remaining comparable to benchmarks;

(2) To provide quantitative results on the independent impact of driving behavior optimization on long-term battery health;

(3) To evaluate the effectiveness and generalizability of this general framework across different regions and travel demands.

4.1. Experiment setup

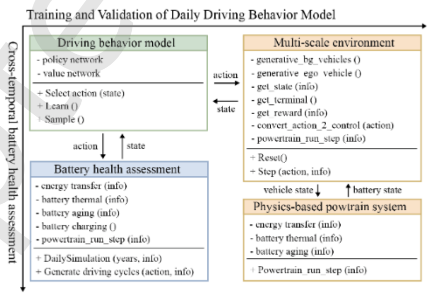


Fig. 5. Logic flow of the experiments.

The experiments are conducted in multi-scale driving environments and long-term driving cycles. The experimental logic flow is illustrated in Fig. 5. This study employs a hierarchical class design to perform the simulation. The driving behavior model is trained in a multi-scale environment that integrates a physics-based powertrain system and traffic simulation. The long-term driving cycles accumulated from daily simulations based on the driving behavior model are utilized for battery health assessment. In the multi-scale environment with dynamic daily driving scenarios (Fig. 6), energy efficiency and driving safety are the primary evaluation metrics that can be directly estimated over a few time steps within the simulation. These scenarios are conducted in the CARLA simulator on a bidirectional four-lane road network (Town15 map) featuring traffic signals and a roundabout. The ego vehicle is equipped with CARLA's default perception and control modules. At the same time, a rule-based action checker is introduced to ensure basic safety. Surrounding vehicles and pedestrians are controlled by CARLA's built-in modules. Specifically, background vehicles are generated using CARLA's three categories of behavior agents, which can be broadly classified as cautious, normal, and aggressive types. These settings enable the simulation of lane-changing and car-following interactions in realistic and diverse traffic conditions. The constructed scenarios mainly include basic driving behaviors such as car following, lane changing, and lane keeping, which represent the majority of typical driving cycles. This paper did not design many adversarial scenarios, as such scenarios would lead to frequent abrupt changes in driving behavior, making it very difficult to optimize energy efficiency and battery health.

This study utilizes one-year historical trip data collected from three geographically diverse regions. Los Angeles (USA),

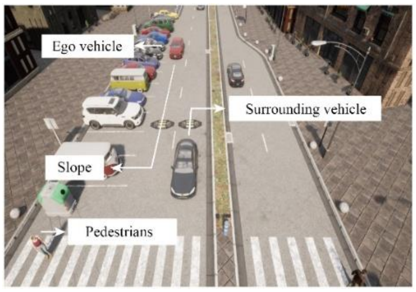


Fig. 6. Dynamic driving scenarios.

the New England area (USA), and Guangzhou (China). The dataset incorporates comprehensive driving parameters, including elevation profiles, road gradient information, travel patterns, and ambient temperature variations, as illustrated in Fig. 7. These locations were strategically selected to represent substantially different climatic conditions, topographical features, and mobility patterns, thereby providing a robust validation for evaluating the proposed framework under heterogeneous real-world conditions. Key regional characteristics include:

(1) The New England area serves as a high-latitude test case, featuring frequent sub-zero temperatures that enable rigorous performance evaluation under extreme thermal variations. Los Angeles, characterized by a warm, dry climate and moderate topographical diversity, provides a representative low-latitude benchmark for assessing framework performance in typical temperate conditions. Guangzhou, situated in a humid subtropical zone, offers an ideal test case for evaluating the framework's robustness in high-temperature, high-humidity environments.

(2) Guangzhou's dataset, derived from taxi fleet operations, exhibits substantially higher daily travel distances compared to private vehicle patterns in Los Angeles and New England, facilitating assessment of distance-dependent framework effectiveness.

(3) The inclusion of both North American and Asian urban contexts ensures cross-regional validation of the framework's adaptability to different driving behaviors and infrastructure characteristics.

The comparative analysis of these distinct operational scenarios allows for comprehensive verification of the framework's robustness against: (i) climatic extremes, (ii) varying usage patterns, and (iii) diverse topological challenges. The atmospheric temperature data for these regions are obtained from the National Oceanic and Atmospheric Administration (National Centers for Environmental Information (NCEI), NOAA, 2025), and slope data are collected from the United States Geological Survey (United States Geological Survey (USGS), 2025). Travel distance and driving behavior data for Los Angeles and New England are obtained from the National Household Travel Survey (https://nhts.ornl.gov/). Jing et al. provide the travel data for Guangzhou (Jing et al., 2025).

To evaluate the effectiveness and generalizability of the proposed framework, this paper employs eight baseline methods for comparative analysis. First, three discrete-action PPO implementations with different discretization levels are used to validate the framework's effectiveness in handling varying driving behavior patterns. The fourth baseline is designed for sensitivity analysis of reward weights. In addition,

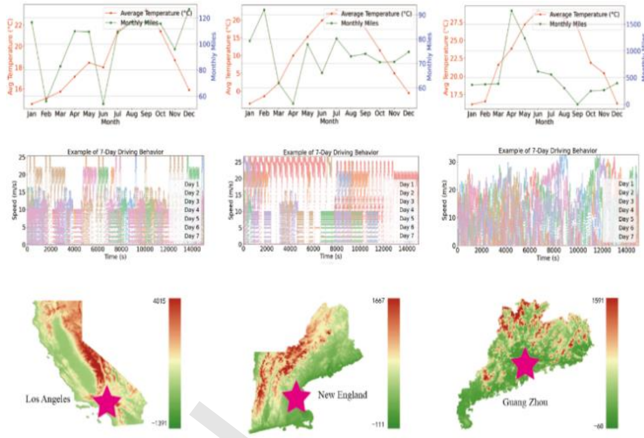


Fig. 7. Travel data in Los Angeles, New England, Guangzhou.

a hybrid-action PPO (HPPO) is included to assess the impact of combining continuous and discrete controls. Furthermore, a baseline is introduced that excludes battery health considerations to quantify the independent contribution of driving behavior optimization to long-term battery health. Finally, standard driving cycles and imitation learning are used as reference baselines to assess the potential feasibility of the learned strategy across different regional travel demands. It is noted that these standard driving cycles are used only in long-term battery health-aware scenarios, since dynamic driving environments require explicit consideration of driving safety, which is often not addressed in standard driving cycles. Major differences between the baselines are illustrated in Table 3. All training processes for representative driving behaviors are conducted in the multi-scale driving environment. Validation is conducted in both daily simulation scenarios and long-term, real-world trip data. The hyperparameters of different driving behavior models are shown in Supplementary Table 2. To measure the performance of energy consumption and battery health, this study adopts 100-kilometer energy consumption (unit: kWh/100km) and state of health (SOH%) as evaluation metrics in the experiments.

Table 3. Description of baseline driving behavior models.

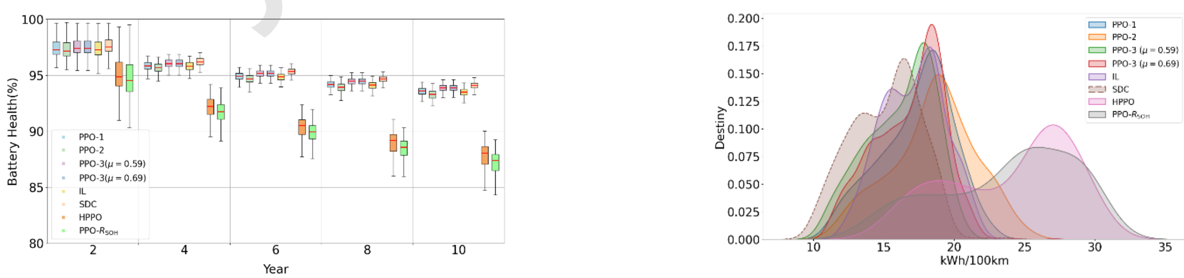
Number	Name	Distinctive Features
Baseline1	PPO-1	Discrete action: $A = A_1, \delta = 0.2$
Baseline2	PPO-2	Discrete action: $A = A_1, \delta = 0.3$
Baseline3	PPO-3 ($\mu = 0.59$)	Discrete action: $A = A_1, \delta = 0.1$
Baseline4	PPO-3 ($\mu = 0.69$)	Discrete action: $A = A_1, \delta = 0.1$
Baseline5	IL	Learn from expert demonstrations
Baseline6	HPPO	Hybrid action: $A = A_2$
Baseline7	PPO- R_{SOH}	Ablate battery health-related objective
Baseline8	Standard Driving cycles (SDC)	Fixed speed profiles from SDC

Table 4. Driving behavior model test results in a multiscale driving environment

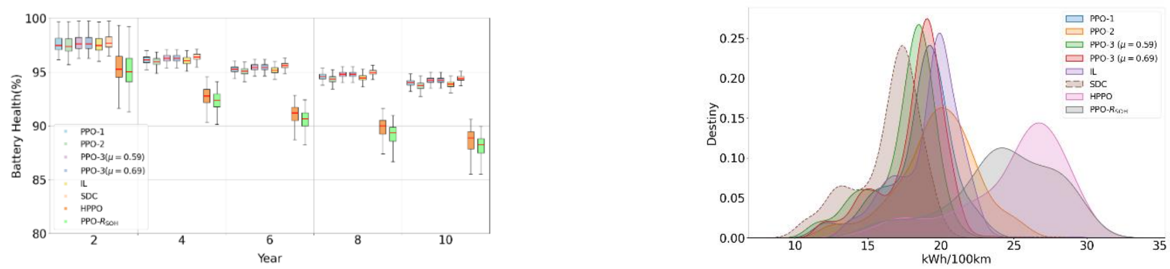
Method	Eval reward	Collision rate (%)	Avespeed (m/s)	EC (kWh/100km)
PPO-1	235.21 ± 4.20	1.00 ± 1.20	9.83 ± 1.10	10.24 ± 2.15
PPO-2	231.35 ± 4.62	1.50 ± 1.00	10.65 ± 0.90	10.50 ± 2.23
PPO-3($\mu = 0.59$)	239.51 ± 4.15	1.10 ± 1.10	9.50 ± 1.15	10.21 ± 1.86
PPO-3($\mu = 0.69$)	243.61 ± 4.59	1.20 ± 1.30	9.72 ± 1.35	10.22 ± 1.98
IL	-	1.60 ± 1.10	9.44 ± 1.22	10.31 ± 1.56
HPPO	219.42 ± 9.35	2.20 ± 1.50	8.52 ± 1.30	14.82 ± 2.62
PPO- R_{SOH}	225.76 ± 5.60	1.40 ± 1.10	9.78 ± 1.02	14.31 ± 2.43

Table 5. Cross-temporal battery health assessment in Los Angeles, New England, and Guangzhou

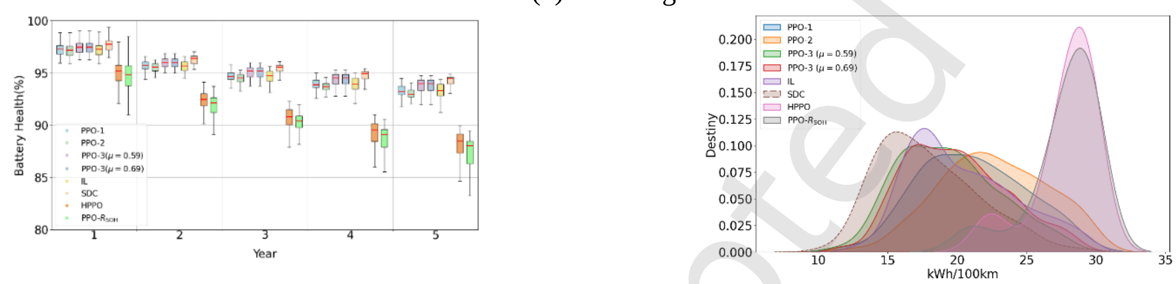
	Method	Times (yr)	Vehicle miles traveled (miles)	Travel complete (%)	Main EC range (kWh/100km)	Battery health (%)
Los Angeles	PPO-1	10 yrs	138224.0 ± 59.5	100	15~20	92.66 ± 0.37
	PPO-2	10 yrs	138225.6 ± 68.2	100	15~20	92.51 ± 0.51
	PPO-3 ($\mu = 0.59$)	10 yrs	138220.7 ± 52.1	100	15~20	94.02 ± 0.32
	PPO-3 ($\mu = 0.69$)	10 yrs	138229.3 ± 62.1	100	15~20	93.86 ± 0.35
	IL	10 yrs	138237.3 ± 72.5	100	15~20	93.78 ± 0.39
	SDC	10 yrs	138219.5 ± 12.3	100	15~20	94.30 ± 0.19
	HPPO	10 yrs	138137.3 ± 75.9	94.7 ± 1.2	25~30	85.65 ± 0.72
	PPO- R_{SOH}	10 yrs	138203.4 ± 72.3	98.6 ± 1.0	25~30	84.91 ± 1.30
New England	PPO-1	10 yrs	110995.3 ± 54.6	100	15~20	92.81 ± 0.38
	PPO-2	10 yrs	110999.6 ± 62.1	100	17~22	92.39 ± 0.56
	PPO-3 ($\mu = 0.59$)	10 yrs	110996.2 ± 49.5	100	15~20	93.20 ± 0.34
	PPO-3 ($\mu = 0.69$)	10 yrs	111003.7 ± 59.6	100	15~20	93.19 ± 0.42
	IL	10 yrs	111014.2 ± 58.2	100	17~22	92.70 ± 0.36
	SDC	10 yrs	110993.6 ± 10.6	100	15~20	93.50 ± 0.20
	HPPO	10 yrs	110832.1 ± 69.6	96.9 ± 1.4	25~30	87.04 ± 1.25
	PPO- R_{SOH}	10 yrs	110976.4 ± 66.5	98.9 ± 1.1	20~25	86.02 ± 1.76
Guang Zhou	PPO-1	5 yrs	121764.0 ± 65.2	100	17~22	92.50 ± 0.41
	PPO-2	5 yrs	121764.7 ± 72.2	100	20~25	92.53 ± 0.57
	PPO-3 ($\mu = 0.59$)	5 yrs	121763.1 ± 60.5	100	15~20	94.04 ± 0.36
	PPO-3 ($\mu = 0.69$)	5 yrs	121763.5 ± 62.7	100	15~20	94.02 ± 0.33
	IL	5 yrs	121762.9 ± 68.4	100	15~20	93.45 ± 0.37
	SDC	5 yrs	121762.4 ± 11.3	100	15~20	94.25 ± 0.21
	HPPO	5 yrs	121595.3 ± 85.9	93.2 ± 2.0	25~30	87.01 ± 1.95
	PPO- R_{SOH}	5 yrs	117914.7 ± 92.3	87.1 ± 2.2	25~30	83.64 ± 2.12



(a) Los Angeles



(b) New England



(c) Guang Zhou

Fig. 9. Annual battery degradation and energy consumption across different driving behavior models.

4.2. Experiment results

This section presents the evaluation results of the proposed framework in quantifying the impacts of driving behavior on battery health. Key factors and temporal fluctuations are examined in detail. Furthermore, the proposed cross-temporal framework is demonstrated.

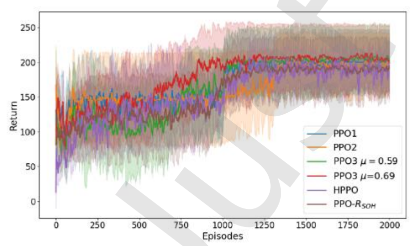


Fig. 8. Training rewards of the driving behavior models.

4.2.1. Framework evaluation

Fig. 8 illustrates the cumulative rewards over the training episodes. Table 4 presents the daily driving scenario test results in the multi-scale environment. Table 5 presents the long-term driving cycle test results from Los Angeles, New England, and Guangzhou. As shown, most driving behavior models exhibit an increase in rewards and remain stable, thanks to a rule-based safety checker that prevents collisions and supports lane-change decisions. After training, PPO-1, PPO-2, and PPO-3 are shown to be comparable to both standard driving cycles (SDC) and expert demonstrations, indicating the framework's ability to optimize driving behaviors under different styles. PPO-3 ($\mu = 0.69$) achieves comparable results to PPO-3 ($\mu = 0.59$). This is because the weight factors are set based on economic value. The change from 0.59 to 0.69 indicates that the increase in charging price does not affect the balance between energy efficiency and battery health. HPPO uses a more complex action space, leading to longer training episodes to achieve stability. As a result, it performs worse compared to the previous discrete setting with the same number of training episodes. In cases where the battery health objective is ignored, PPO- R_{SOH} weakens penalties for unstable driving behaviors, preventing the model from learning stable patterns and leading to higher energy consumption and accelerated long-term battery degradation.

The experiments establish a direct link between daily driving behaviors and long-term battery degradation through multi-scale environments and long-term driving cycle tests. The results reveal that neglecting driving behavior optimization may lead to a 15.7% increase in energy consumption in daily driving scenarios and up to 10% additional capacity loss over 10 years under the same travel demand and regional conditions. They directly quantify the independent contribution of daily driving behavior optimization to long-term battery health. Moreover, long-term driving cycle tests conducted in Los Angeles, New England, and Guangzhou show that the framework produces results that are optimized and comparable to standard driving cycles and expert demonstrations. This demonstrates its strong generalization across diverse regional travel demands and its ability to evaluate the independent impact of daily driving behaviors on long-term battery degradation. Fig. 9 further clarifies the quantitative results reported in Table 5 by illustrating annual battery degradation and energy consumption from daily driving. The battery degradation processes occur nonlinearly, with the aging rate gradually accelerating over time, consistent with known battery aging characteristics. Simultaneously, the distribution does not over-concentrate on extremely low energy values, reflecting that the models do not blindly minimize consumption but instead maintain practical efficiency under realistic constraints.

4.2.2. *Cross-temporal battery health analysis*

Key factors in the cross-temporal framework that influence battery health include driving behavior, travel demand, geographical information, and temperature. For diving behavior, the well-trained models serve as representations of different long-term driving patterns. Among these models, the one that does not incorporate battery health considerations may produce unstable driving patterns, leading to higher daily energy consumption. The increased energy consumption further prevents the vehicle from covering the required daily travel distance, resulting in a decline in the travel-complete metric. Therefore, the model results in 9.1%, 7.17% and 10.4% additional battery capacity degradation across the three long-term tests. Furthermore, the model accounts for nearly 10% of battery health degradation over 10 years. In contrast, real-world battery health typically falls within the 80%~100% range, indicating that driving behavior is a non-negligible factor in long-term battery degradation and normally accounts for more than half of the practically usable battery capacity. The battery health-aware models with different δ , representing driving patterns from conservative to aggressive, exhibit less than 2% variation in both battery health and energy consumption. This indicates that the differences in long-term battery health impact across different driving styles are relatively small after these behaviors are optimized with the same objective. In real-world conditions, differences in long-term battery health caused by driving style may stem from behaviors themselves, such as frequent acceleration and deceleration, rather than simply from driving fast or pressing the accelerator harder.

Travel demand, temperature, and geographical information exhibit distinct characteristics across the three test areas. In Guangzhou taxis, battery health after 5 years is comparable to that observed in Los Angeles and New England after 10 years. This suggests that intensive travel demands and high-frequency usage accelerate battery degradation primarily through cycling aging, which plays a more significant role than calendar aging. Additionally, the battery health gap between different driving behavior models becomes larger, increasing from 9.1% and 7.17% to 10.4%. The influence of driving behavior on battery health increases with the intensity of travel demand. This is because the higher the travel demand intensity, the longer the influence of driving behavior lasts. As a result, the optimization effects and their significance become more substantial. In similar private vehicle usage conditions in Los Angeles and New England, the high-latitude New England region shows battery health comparable to that in Los Angeles. Still, its vehicle-miles-traveled is about 20% lower, indicating the battery ages faster for the same driving distance. In the high-latitude region of New England, temperatures fall below 0 ℃ during certain months. This leads, on the one hand, to reduced battery capacity because the battery's chemical characteristics become less active at low temperatures; on the other hand, the HVAC requires additional energy for heating, further reducing the battery's driving range and, consequently, lowering the daily VMT. In addition, the battery health gap caused by different driving patterns narrows from 9.1% to 7.17% when transitioning from high-temperature to low-temperature conditions. The influence of driving behavior is reduced by temperature effects. This is because the heating energy requirements far exceed the impact caused by vehicle motion. In regions with persistently low temperatures, the influence of driving behavior becomes almost negligible. In Los Angeles, the topography is characterized by moderate topographical variation. The battery health and VMT remain at relatively high levels, indicating that slope variation within a normal range is not a major factor affecting long-term battery health. Therefore, the dominant influences are still driving behavior, temperature, and travel demand.

4.2.3. *Framework application*

The framework provides interpretable and quantitative results on the impact of daily driving behavior on cross-temporal battery health, covering the fundamental EV usage scenarios and the key factors that influence battery health for technology improvement, insurance design, and user understanding. Compared with other data-driven methods, the battery health estimation in this framework is entirely physics-based, offering interpretable, controllable results. The errors occurring on specific dates and at arbitrary time steps can all be traced back to the corresponding physical equations. In real-world applications, the framework first needs to collect the driver's historical travel demand and the regional characteristics of the area in which they drive, including factors such as temperature and road slope, as a basis for analysis. Subsequently, the optimization algorithm designed by engineers is applied to optimize daily driving behavior. The well-trained driving behavior models generate daily EV usage scenarios based on the driver's historical usage patterns. Finally, daily EV usage scenarios are combined to form projected usage scenarios for future years, and the resulting travel scenarios are used to simulate battery health within the cross-temporal framework.

The battery health estimation results can serve as the theoretical optimal values provided by engineers to meet the daily travel scenarios of an individual user or a regional user group. Before purchase, users can understand the potential service life of an EV based on their travel demand, thereby improving their understanding of battery health and increasing their confidence in EV adoption. After purchase, if the actual battery health under the same time period and travel scenarios falls below the theoretical values provided by engineers within this framework, then the insurance provider and manufacturers should assume greater responsibility for the battery health degradation. Additionally, the cross-temporal results of different driving behavior models implemented by engineers are intended for reference. When the improvements from different driving behavior models are relatively similar, the dominant factors of battery health in that usage scenario are more likely to be attributed to external environmental conditions. Accordingly, both insurance policies and technical strategies should be adjusted. Furthermore, the framework provides customizable interfaces. The physics-based powertrain system parameters can be adjusted for the specific vehicle type. The driving behavior models are not limited to reinforcement learning, as long as their input structure is compatible with generating daily travel scenarios within this framework. It is noted that the compatibility and effectiveness of the framework need to be validated when the battery characteristics change.

5 Conclusions

This study develops a cross-temporal framework that systematically links daily driving behavior to long-term battery health under real-world conditions, providing a comprehensive basis for understanding battery health and optimizing daily driving behavior. Specifically, the framework establishes a physics-based multi-scale dynamic environment that integrates electrochemical battery processes, powertrain subsystems, and vehicle-level driving behavior while accounting for external factors such as temperature and slope. This environment enables real-time estimation of battery health fluctuations in an interpretable, scalable manner, ensuring that degradation can be clearly attributed to specific driving behaviors and operating conditions. The framework further formulates a problem that jointly optimizes efficiency, safety, and battery health in dynamic driving environments, broadening the scope of driving behavior studies and supporting sustainable, practically deployable strategies. In addition, a validation protocol with a 10-year horizon is further established to bridge temporal scales by linking second-to-minute driving decisions with month-to-year battery health assessment, providing a unified perspective that integrates daily driving behavior optimization with long-term battery health.

As a case study, the long-term experiments across private vehicles in Los Angeles and New England and taxis in Guangzhou further demonstrate the framework's robustness and generalizability, with performance differences consistently within 2-3% across diverse driving conditions and travel demands. Overlooking driving behavior optimization leads to a 15.7% increase in energy consumption and a 10% decline in long-term battery health. Simultaneously, intensive usage, such as that of the taxis, accelerates degradation to just five years. These findings not only deepen understanding of battery health-aware driving but also demonstrate the framework's practicality as a tool for evaluating and optimizing driving strategies. They provide insights for the development of battery health-aware energy management systems, adaptive warranty strategies, and behavior-based insurance models.

Building upon the current implementation, future work will further refine and expand the framework. The constructed dynamic driving environments mainly include typical behaviors such as car following, lane changing, and lane keeping, which represent common daily driving patterns but do not encompass complex driving scenarios. Future work will expand the scenario library and extend the framework to cover a wider range of driving and environmental conditions. With the progressive establishment of large-scale mobility and vehicle operation data platforms, and subject to user authorization, the proposed framework can be further extended to support application-oriented studies such as insurance-related battery degradation assessment and technology evaluation based on real-world case data. Based on this extended framework, regional benchmarks linking driving behaviors with battery degradation will be established, enabling a deeper understanding of how local traffic characteristics, climate, and driving cultures influence long-term battery health. These efforts will further enhance the framework's robustness and practical value for sustainable electric mobility and behavior-based battery health management.

6 References

Dosovitskiy, A., Ros, G., Codevilla, F., Lopez, A., Koltun, V., 2017. CARLA: An open urban driving simulator, in: Conference on Robot Learning. PMLR, pp. 1–16.

Gore, C., Ranganath, S., Kneifel, J., Fadojutimi, D., Helgeson, J., 2024. Consumer Perspectives on Battery Electric Vehicles: A Literature Review. US Department of Commerce, National Institute of Standards and Technology.

Guan, K., Huang, Z., Gao, Y., Wu, Y., Li, F., Li, H., 2025. Towards adaptive deep reinforcement learning energy management for electric vehicles: An online updating approach. Energy 325, 135996.

Guo, L., Zhang, X., Zou, Y., Han, L., Du, G., Guo, N., Xiang, C., 2022. Co-optimization strategy of unmanned hybrid electric tracked vehicle combining eco-driving and simultaneous energy management. Energy 246, 123309.

Han, X., He, H., Wu, J., Peng, J., Li, Y., 2019. Energy management based on reinforcement learning with double deep Q-learning for a hybrid electric tracked vehicle. Appl. Energy 254, 113708.

He, H., Meng, X., Wang, Y., Khajepour, A., An, X., Wang, R., Sun, F., 2024. Deep reinforcement learning based energy management strategies for electrified vehicles: Recent advances and perspectives. Renew. Sustain. Energy Rev. 192, 114248.

Hu, X., Zhang, X., Tang, X., Lin, X., 2020. Model predictive control of hybrid electric vehicles for fuel economy, emission reductions, and inter-vehicle safety in car-following scenarios. Energy 196, 117101.

Hu, X., Zou, C., Tang, X., Liu, T., Hu, L., 2019. Cost-optimal energy management of hybrid electric vehicles using fuel cell/battery health-aware predictive control. IEEE Trans. Power Electron. 35, 382–392.

Jaafar, A.H., Rahman, A., 2020. EMA-CVT Performance for UDDS and HWFET Cycles with Fuzzy Logic Approach. Test Eng. Manag. 83, 13775–13781.

Ji, J., Bie, Y., Zeng, Z., Wang, L., 2022. Trip energy consumption estimation for electric buses. Commun. Transp. Res. 2, 100069.

Jing, H., Hu, J., Ou, S.S., Lv, Z., Lyu, R., Zhao, J., 2025. Scalable and generalizable deep learning for battery state of health estimation in on-road electric vehicles. J. Energy Chem.

Kaelbling, L.P., Littman, M.L., Moore, A.W., 1996. Reinforcement learning: A survey. J. Artif. Intell. Res. 4, 237–285.

Li, D., Hu, Q., Jiang, W., Dong, H., Song, Z., 2025. Integrated power and thermal management for enhancing energy efficiency and battery life in connected and automated electric vehicles. Appl. Energy 396, 126213.

Li, G., Görges, D., 2018. Ecological adaptive cruise control and energy management strategy for hybrid electric vehicles based on heuristic dynamic programming. IEEE Trans. Intell. Transp. Syst. 20, 3526–3535.

Li, J., Fotouhi, A., Liu, Y., Zhang, Y., Chen, Z., 2024. Review on eco-driving control for connected and automated vehicles. Renew. Sustain. Energy Rev. 189, 114025.

Li, W., Rios-Torres, J., Wang, B., Khattak, Z.H., 2024. Experimental assessment of communication delay's impact on connected automated vehicle speed volatility and energy consumption. Commun. Transp. Res. 4, 100136.

Li, Z., Bian, Z., Chen, Z., Ozbay, K., Zhong, M., 2024. Synthesis of electric vehicle charging data: A real-world data-driven approach. Commun. Transp. Res. 4, 100128.

Liu, C., Chen, Y., Xu, R., Ruan, H., Wang, C., Li, X., 2024. Co-optimization of energy management and eco-driving considering fuel cell degradation via improved hierarchical model predictive control. Green Energy Intell. Transp. 3, 100176.

Liu, F., Shafique, M., Luo, X., 2024. Unveiling the determinants of battery electric vehicle performance: A systematic review and meta-analysis. Commun. Transp. Res. 4, 100148.

Liu, W., Yao, P., Wu, Y., Duan, L., Li, H., Peng, J., 2025. Imitation reinforcement learning energy management for electric vehicles with hybrid energy storage system. Appl. Energy 378, 124832.

Liu, Y., Francis, A., Hollauer, C., Lawson, M.C., Shaikh, O., Cotsman, A., Bhardwaj, K., Banboukian, A., Li, M., Webb, A., others, 2023. Reliability of electric vehicle charging infrastructure: A cross-lingual deep learning approach. Commun. Transp. Res. 3, 100095.

Naeem, H.M.Y., Bhatti, A.I., Butt, Y.A., Ahmed, Q., Bai, X., 2024. Energy efficient solution for connected electric vehicle and battery health management using eco-driving under uncertain environmental conditions. IEEE Trans. Intell. Veh. 9, 4621–4631.

National Centers for Environmental Information (NCEI), NOAA, 2025. Climate Data Online: Dataset Discovery.

Nayak, N., Satpathy, M.A., 2025. An Adaptive Energy Management Strategy for Plug-in Hybrid Electric Vehicles (PHEVs) Utilizing Real-Time Speed Profiles and Optimized Battery Discharge Levels. Energy Storage Sav.

Ou, S., 2023. Estimate long-term impact on battery degradation by considering electric vehicle real-world end-use factors. J. Power Sources 573, 233133.

Pei, M., Zhu, H., Ling, J., Hu, Y., Yao, H., Zhong, L., 2023. Empowering highway network: Optimal deployment and strategy for dynamic wireless charging lanes. Commun. Transp. Res. 3, 100106.

Peng, J., Chen, W., Fan, Y., He, H., Wei, Z., Ma, C., 2023. Ecological driving framework of hybrid electric vehicle based on heterogeneous multi-agent deep reinforcement learning. IEEE Trans. Transp. Electrification 10, 392–406.

Reuters, 2024. Battery cell prices fall to record low in says report. URL https://www.reuters.com/markets/commodities/battery-cell-prices-fall-record-low-september-says-report-2024-10-30

Saba, I., Ullah, M., Tariq, M., 2024. Advancing electric vehicle battery analysis with digital twins in intelligent transportation systems. IEEE Trans. Intell. Transp. Syst. 25, 12141–12150.

Sajadi-Alamdari, S.A., Voos, H., Darouach, M., 2018. Ecological advanced driver assistance system for optimal energy management in electric vehicles. IEEE Intell. Transp. Syst. Mag. 12, 92–109.

Schreiber, M., Lin, Y., Sommer, A., Wassiliadis, N., Torricos, P.M., Rogge, M., Lewerenz, M., Grosu, C., Endisch, C., Jossen, A., others, 2025. Apparent vs. true battery aging: Impact of various load characteristics on accelerated aging tests. J. Energy Storage 127, 116924.

Schulman, J., Wolski, F., Dhariwal, P., Radford, A., Klimov, O., 2017. Proximal policy optimization algorithms. ArXiv Prepr. ArXiv170706347.

Shi, M., He, H., Li, J., Han, M., Jia, C., 2021. Multi-objective tradeoff optimization of predictive adaptive cruising control for autonomous electric buses: A cyber-physical-energy system approach. Appl. Energy 300, 117385.

Sotoudeh, S.M., HomChaudhuri, B., 2023. A deep-learning-based approach to eco-driving-based energy management of hybrid electric vehicles. IEEE Trans. Transp. Electrification 9, 3742–3752.

Sun, X., Lu, Y., Zheng, L., Li, H., Zhang, X., Yang, Q., 2025. A novel eco-driving strategy for heterogeneous vehicle platooning with risk prediction and deep reinforcement learning. Energy 314, 134225.

United States Geological Survey (USGS), 2025. EarthExplorer.

Wang, S., Lin, X., 2020. Eco-driving control of connected and automated hybrid vehicles in mixed driving scenarios. Appl. Energy 271, 115233.

Wang, S., Yu, P., Shi, D., Yu, C., Yin, C., 2022. Research on eco-driving optimization of hybrid electric vehicle queue considering the driving style. J. Clean. Prod. 343, 130985.

Wang, Y., Advani, S.G., Prasad, A.K., 2024. Effects of eco-driving on energy consumption and battery degradation for electric vehicles at signalized intersections. ArXiv Prepr. ArXiv241001685.

Wegener, M., Koch, L., Eisenbarth, M., Andert, J., 2021. Automated eco-driving in urban scenarios using deep reinforcement learning. Transp. Res. Part C Emerg. Technol. 126, 102967.

Wu, C., Peng, J., Chen, J., He, H., Pi, D., Wang, Z., Ma, C., 2024. Battery health-considered energy management strategy for a dual-motor two-speed battery electric vehicle based on a hybrid soft actor-critic algorithm with memory function. Appl. Energy 376, 124306.

Wu, J., Song, Z., Lv, C., 2023. Deep reinforcement learning-based energy-efficient decision-making for autonomous electric vehicle in dynamic traffic environments. IEEE Trans. Transp. Electrification 10, 875–887.

Wu, Y., Huang, Z., Li, D., Li, H., Peng, J., Stroe, D., Song, Z., 2024. Optimal battery thermal management for electric vehicles with battery degradation minimization. Appl. Energy 353, 122090.

Xie, S., Qi, S., Lang, K., Tang, X., Lin, X., 2020. Coordinated management of connected plug-in hybrid electric buses for energy saving, inter-vehicle safety, and battery health. Appl. Energy 268, 115028.

Xie, Y., Wang, C., Hu, X., Lin, X., Zhang, Y., Li, W., 2020. An MPC-based control strategy for electric vehicle battery cooling considering energy saving and battery lifespan. IEEE Trans. Veh. Technol. 69, 14657–14673.

Yang, J., Zhao, D., Lan, J., Xue, S., Zhao, W., Tian, D., Zhou, Q., Song, K., 2022. Eco-driving of general mixed platoons with CAVs and HDVs. IEEE Trans. Intell. Veh. 8, 1190–1203.

Ye, Y., Xu, B., Wang, H., Zhang, J., Lawler, B., Ayalew, B., 2024. Deep reinforcement learning-based energy management system enhancement using digital twin for electric vehicles. Energy 312, 133384.

Zamanpour, M., He, S., Levin, M.W., Sun, Z., 2025. Incorporating lane-change prediction into energy-efficient speed control of connected autonomous vehicles at intersections. Transp. Res. Part C Emerg. Technol. 171, 104968.

Zhan, S., Liu, C., Yin, Y., Yu, C., Zhao, C., 2024. Eco-driving strategy for fuel cell vehicles in car-following scenarios considering stack heat and durability based on SAC. Energy Convers. Manag. 315, 118744.

Zhang, F., Qi, Z., Xiao, L., Coskun, S., Xie, S., Liu, Y., Li, J., Song, Z., 2025. Co-optimization on ecological adaptive cruise control and energy management of automated hybrid electric vehicles. Energy 314, 133542.

Zhang, Y., Qu, X., Tong, L., 2022. Optimal eco-driving control of autonomous and electric trucks in adaptation to highway topography: Energy minimization and battery life extension. IEEE Trans. Transp. Electrification 8, 2149–2163.

Zhang, Y., Wei, Z., Wang, Z., Tian, Y., Wang, J., Tian, Z., Xu, F., Jiao, X., Li, L., Wen, G., 2024. Hierarchical eco-driving control strategy for connected automated fuel cell hybrid vehicles and scenario-/hardware-in-the loop validation. Energy 292, 130592.

Zhang, Y., You, X., Song, Y., Zhao, Y., Wei, Z., Jiao, X., 2025. Hierarchical eco-driving of connected hybrid electric vehicles: Integrating predictive cruise control and cost-to-go approximation-guided energy management. Energy 319, 134579.

Zhou, Q., Du, C., Yan, Y., 2024. A multi-layer predictive energy management strategy for intelligent hybrid electric trucks collaborated with eco-driving control. Energy 308, 132848.

Zou, Y., Yang, Y., Zhang, Y., Tang, X., 2025. Aging-aware real-time multi-layer co-optimization approach for hybrid vehicles: across configuration, parameters, and control. Energy Convers. Manag. 332, 119748.

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Replication and data sharing

The datasets and codes used in this study is partially available published on https://doi.org/10.26599/ETSD.2025.9190054.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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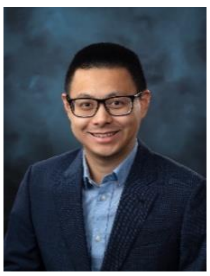

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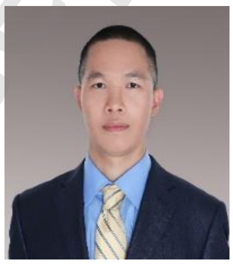

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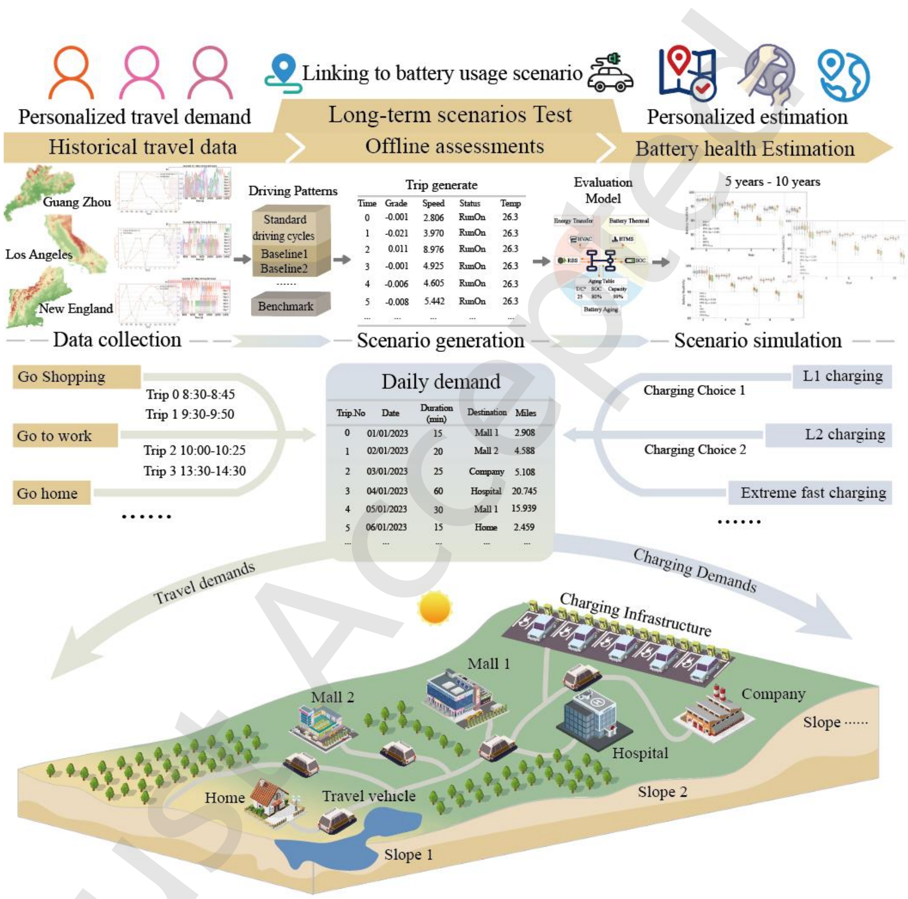
Graphical abstract and highlights

- A systematic framework linking daily driving behavior with long-term battery health.
- A multi-scale environment integrating cell processes, powertrain, and driving behavior.
- Goes beyond fixed driving cycles to consider efficiency, battery health, and safety.
- More stable driving behavior decreases battery degradation 10% in 10 years.
- Provides evidence for eco-driving, adaptive warranty, and behavior-based insurance.



The cross-temporal framework links personalized travel demand to battery usage scenarios to construct a personalized battery health estimation based on driving behavior. The quantitative results provide references for consumers' understanding of daily usage scenarios, as well as for the design of personalized insurance and eco-driving strategies.