

A Brief Discussion on AI-Driven Technological Innovation in Electric Vehicles: Focus on Intelligent Cockpit and Battery Thermal Safety

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Abstract. The new energy vehicle industry is in a stage of rapid development, where intelligent cockpits and Battery Management Systems serve as key technologies determining its core competitiveness. The technical system of traditional electric vehicles has obvious performance bottlenecks, including passive and simplistic cockpit interaction modes, insufficient accuracy in battery state estimation, and delayed thermal safety early warnings. These issues not only limit the service life of power batteries but also pose potential driving safety risks. Addressing the above industry pain points, this paper systematically reviews the technological evolution and application innovations of artificial intelligence in the fields of intelligent cockpits and battery thermal safety management for electric vehicles. The research shows that AI technology reduces the annual capacity decay rate of power batteries by 43%, advances the thermal runaway early warning time to 3.9 seconds, and raises the gesture recognition accuracy of intelligent cockpits to 98.3%, significantly improving the safety, endurance, and user interaction experience of electric vehicles. Meanwhile, this paper points out the core challenges faced by current AI applications, such as decreased perception accuracy in complex environments, the black-box nature of high-precision models, and the high cost of high-quality training data, and prospects future development directions including lightweight design, explainable artificial intelligence, and federated learning.

Keywords: Artificial intelligence, Electric vehicles, Intelligent cockpit, Battery management system

1. Introduction

New energy vehicles are developing rapidly at present, with intelligent cockpits and battery management (BMS) serving as key technologies. AI can significantly improve safety, range and user experience, making relevant research highly necessary. The technological system of traditional electric vehicles has obvious performance bottlenecks. The interaction of traditional cockpits is not natural enough, battery early warning is not timely, and the effect of multi-sensor fusion is poor, meaning existing solutions can hardly meet high safety requirements. These problems not only restrict the service life of power batteries but also pose hidden dangers to driving safety. In response to the above industry pain points, this paper summarizes the applications of AI in intelligent cockpits

and battery management, analyzes performance improvements, key algorithms and practical effects. By summarizing cutting-edge research progress including adaptive gamma preprocessing, cockpit-Llama large model, and physics-empowered deep learning, this paper aims to clarify the technological development context of artificial intelligence empowering electric vehicles. This paper can provide theoretical support and directional guidance for the future development of intelligent electric vehicles with high safety, high comfort and long cruising range.

2. Technology trends of AI in EVs

2.1. AI in intelligent cockpit of EVs

2.1.1. Comparison of AI applications in interactive paradigms and input channels of intelligent cockpits

The traditional intelligent cockpit uses close touch and physical buttons within about 30 cm of the central control screen as the core interaction model; As shown in Figure 1 [1], the new generation of cockpit has achieved remote pointing interaction of more than 80 cm. Meanwhile, it expands diversified human-vehicle input approaches by integrating gesture perception, natural voice interaction, and mobile phone-based remote control operation [2].

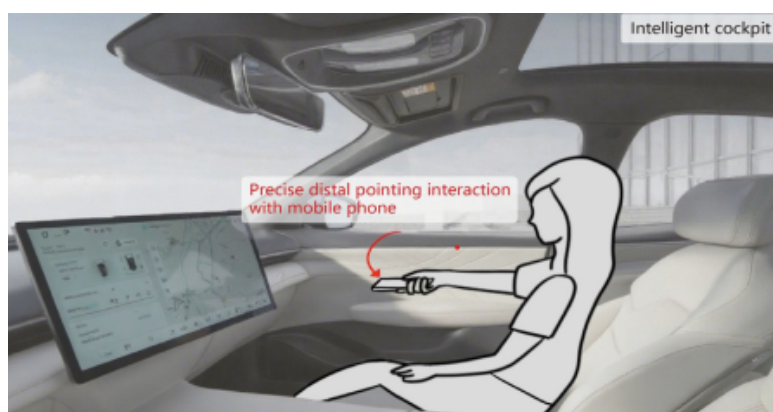


Figure 1. An example of distal pointing interaction in intelligent cockpit [1]

From the above cases, it is not difficult to find that AI has transformed automotive cockpits from passively responsive modes to actively cognitive ones. In other words, the system no longer merely waits for clear user instructions to perform tasks. Instead, it proactively perceives and understands the user's state and intentions, provides personalized services before the user puts forward demands, and realizes the shift from people adapting to vehicles to vehicles adapting to people.

These perception and input channels include voice, gestures, eye movement and physiological signal interfaces. In terms of voice interaction, traditional vehicle cabins can only recognize fixed and simple voice commands and passively respond to occupants' needs. In contrast, new intelligent vehicle cabins integrated with large language models, such as ChatGPT, enable more natural conversations and more complex intent understanding. For instance, according to Gao et. al, BMW's Intelligent Personal Assistant and Mercedes-Benz's MBUX Voice Assistant can not only accurately recognize and execute drivers' commands to control basic in-vehicle functions including navigation, entertainment and communication, but also facilitate vehicle-to-vehicle communication by collaborating with other voice assistants [3]. In addition, the gesture recognition function of the traditional smart cockpit is easily affected by changes in the light in the car, and can only rely on an

ordinary color camera to judge the driver's movements. According to Hao et al, as a model adopting an adaptive Gamma image enhancement preprocessing method based on Retinex theory, Bi-YOLOv5s constructs a novel bi-directional feature pyramid structure to reduce information loss in the feature fusion network and improve the recognition accuracy of small-scale gestures. Experimental results show that the recognition accuracy of this model reaches 98.3%. At the same time, AI also makes it possible to directly control music playback, switch tracks and perform other functions through specific gestures [2]. The new cockpit can also monitor eyelid closure, blink frequency and gaze direction in real time through cameras to determine whether the driver is fatigued or distracted [4]. It can then actively intervene in vehicle control, greatly improving driving safety. Meanwhile, as shown in Figure 2 and Figure 3, the new generation of AI-powered intelligent cockpit also integrates ECG monitoring sensors in the seats, heart rate monitoring sensors on the steering wheel, and is equipped with millimeter-wave radar, thermal imaging and other equipment that can be monitored without contact, which can simultaneously collect the driver's ECG, skin electricity, heart rate and other physiological data. According to Table 1, this provides early warning of sudden cardiovascular diseases and other diseases that the driver may encounter, and it also establishes an exclusive personal health record for the driver, which fundamentally improves the safety and security of the driving process [4].

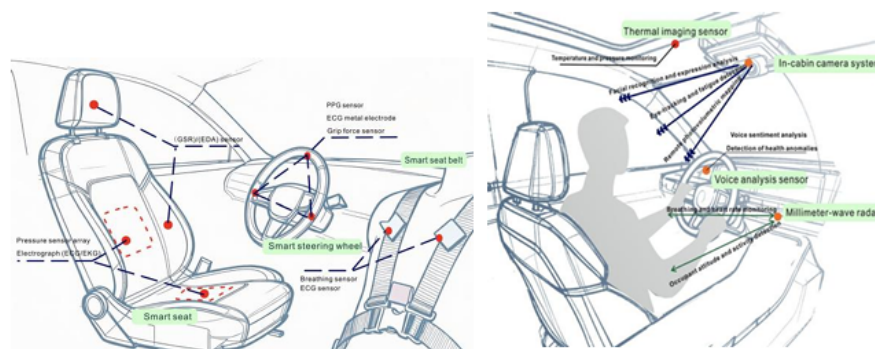


Figure 2. (a) Schematic diagram of contact sensor distribution in the intelligent cockpit of a car. (b) Schematic diagram of non-contact sensor distribution in the intelligent cockpit of automobiles [4]

Table 1. Typical sudden illness and accident types [4]

Sudden Illness	Symptoms	Resulting Accident Types
Cardiovascular diseases (myocardial infarction, arrhythmia, heart failure)	Sudden chest pain, loss of consciousness, sudden cardiac arrest	Loss of braking/steering control, leading to straight-line collisions, rollovers, or rear-end collisions
Cerebrovascular diseases (cerebral infarction, cerebral hemorrhage, subarachnoid hemorrhage)	Sudden dizziness, hemiplegia, confusion	Vehicle drift out of lane, collisions with roadside facilities

On this basis, the cockpit's perception ability also breaks through the limitations of the interior space, combining the driver status data monitored in the car with the road conditions, traffic signals and other information to achieve a full range of perception coverage of driving status inside the car + traffic environment outside the vehicle [3].

2.1.2. Comparison of AI models and multimodal data processing systems in intelligent cockpits

Traditional intelligent cockpits rely on machine learning algorithms such as Support Vector Machines, Decision Trees, Random Forests, and Logistic Regression. Such models are usually trained on fixed datasets and designed for single-scenario tasks. They cannot be updated after deployment, making it difficult for them to adapt to complex driving environments [4]. With the rise of large language models (LLMs), in-cabin AI has achieved a qualitative leap. They can not only predict drivers' subsequent behaviors through intent prediction but also perform commonsense reasoning, enabling collaborative multi-task processing. At the same time, many AI models today can form a closed loop through driver feedback and continuously optimize themselves [3].

As shown in Figure 3, Y. Chen et al. proposed a novel language model named Cockpit-Llama specifically designed for predicting drivers' behavioral intentions. Cockpit-Llama is capable of forecasting driver intentions based on current driver operations, historical interactions, and the correlations between drivers and cockpit environmental states, thereby supporting further proactive interactive decision-making. The model can package driving scenarios into textual form and feed them to Llama3, a general LLM trained on massive data. Most importantly, the model undergoes LoRA fine-tuning with targeted training on just a small amount of data, and ultimately outputs driver intentions in natural language. As can be seen from Table 2, the cockpit-dedicated Llama model significantly outperforms general large models such as GPT-4 and ChatGLM-3 across all evaluation metrics. However, constrained by the limited dataset scale, only approximately 60,000 samples were used for fine-tuning Cockpit-Llama, and its inference latency is relatively high, making it difficult to meet the real-time requirements of commercial driving applications. In addition, the current model may fail to fully capture the complexity of driver behaviors and their various influencing factors [5]. However, this still demonstrates that customized optimization for specific scenarios can significantly enhance the model's ability to understand and generate contextual dialogue content in vehicle-mounted scenarios.

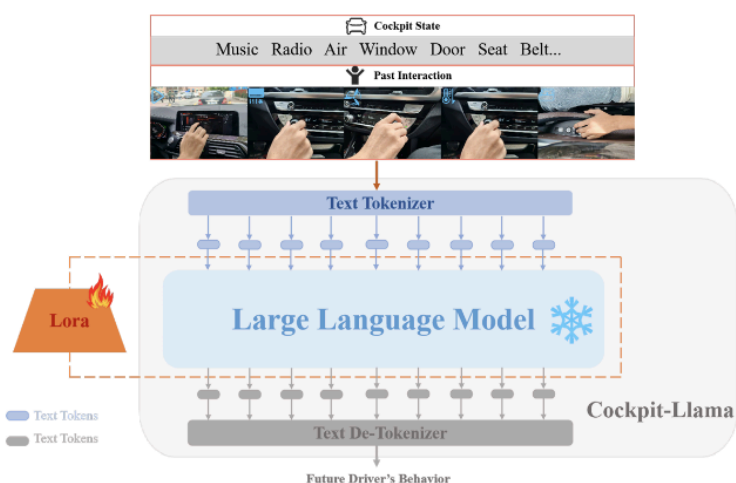


Figure 3. The overall architecture of Cockpit-Llama is divided into three parts: modal text data encoding, lightweight fine-tuning of LLM backbone using adapter, and driver behavior intent decoding [5]

Table 2. Baseline methods vs. Cockpit-Llama [5]

Method	Type	Bleu-4	Rouge-1	Rouge-2	Rouge-L
ChatGPT-4 [33]	LLM	37.08	28.21	39.32	27.03
ChatGLM-3 [41]	LLM	30.33	25.69	13.74	27.47
Cockpit-Llama	LLM	71.32	80.01	76.89	81.42

The stable operation of high-performance AI models in smart cockpits essentially relies on an innovative multimodal data processing system. Its capability implementation follows two parallel and collaborative technical paths. As mentioned in Section 2.1.1, the cockpit perception system has achieved a leapfrog evolution from single modality to multimodality. It integrates voice, gesture, eye movement, physiological signals, and internal and external vehicle environmental data into a unified perception network, establishing full-dimensional dynamic perception capabilities of the human-vehicle-environment system. In addition, the vehicle-cloud collaborative architecture provides computing power support for the processing and circulation of multimodal data. The cloud undertakes the training and iteration of large models, while the vehicle end is responsible for millisecond-level real-time inference and low-latency instruction execution. The division of labor and collaboration between the two ensures the fluency and safety of interaction. It enables smart cockpits to complete the paradigm shift from passive response to active cognition and achieve the intelligent leap of vehicles adapting to humans [4].

2.2. AI in BMS

The AI-driven intelligent battery management system (BMS) can dynamically optimize the battery charging and discharging strategy based on accurate battery state data. The AI-Based Control scheme achieves a mean annual capacity degradation rate of 2.8% with a standard deviation of 0.9, while the Conventional Control scheme has a mean degradation rate of 4.9% with a standard deviation of 1.2. This represents a 43% reduction in the annual capacity degradation rate of power batteries compared to the traditional solution, fundamentally lowering the full-life-cycle cost of EVs [6].

2.2.1. Application of AI in state estimation of EV's BMS

State of Charge (SOC), which refers to the ratio between the current remaining capacity of the battery and its fully charged capacity, is one of the most core parameters of the BMS for EVs. Drivers can judge the vehicle's driving range based on the displayed SOC value. In the core link of SOC estimation, the traditional technology in 2020 mainly relies on the statistics of the battery charging and discharging power, or the voltage of the battery after a long period of standing for a long time to judge the remaining power [7]. The new AI-driven BMS integrates multi-source data including voltage, current, temperature, historical driving data, environmental conditions, charging station load, traffic flow and more. Leveraging these data, the new BMS realizes adaptive learning, online updating, transfer learning and meta-learning, and can quickly adapt to different battery types and driving styles, which greatly enhances the model's generalization ability and real-time adaptability [8]. According to Figure 4, the AI-driven BMS in 2025 controls the error of SOC estimation within 1%, of which the LSTM model has an error of only 0.87% in a conventional vehicle environment at 40°C, as shown in Figure 5 [9].

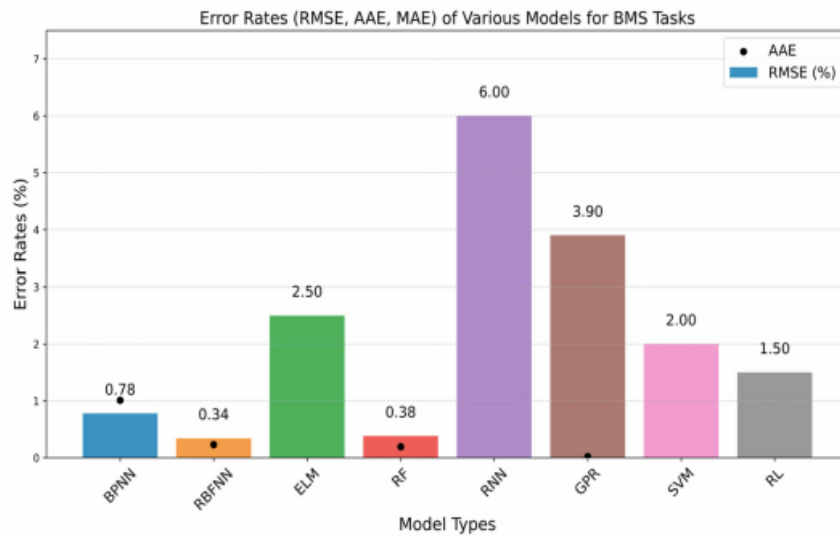


Figure 4. Error rate comparison of ML models for BMS in this research ADDIN ZOTERO_ITEM CSL_CITATION [9]

AI technology also realizes the accurate prediction of the remaining useful life (RUL) of the battery. The traditional method relies on a fixed empirical curve and the prediction bias is large. However, the AI-based BMS adopts the LSTM-GCN hybrid model to conduct RUL prediction by combining time series and spatial dependency relationships. For RUL prediction accuracy, the absolute prediction error of 12 battery packs ranges from 18 to 27 cycles, with an error percentage of 2.3–2.7% [8]. It can provide users with accurate battery replacement reminders and greatly reduce the uncertainty of using the car.

On this basis, in the state of health (SOH) prediction dimension, the BMS of the new AI introduces the Battery Health Score (BHS), an indicator that integrates thermal stability, SOC, RUL, stress and other factors. In contrast, traditional technology can only rely on empirical formulas and the number of battery charge–discharge cycles to judge the degree of aging. As reported in previous studies, the prediction accuracy of conventional methods is only 85.6%, according to Table 3 [6], with a mean absolute error ranging from approximately 3% to 5% [8]; The AI prediction method based on machine learning models can combine the operation data of the whole life cycle of the battery for comprehensive analysis, improve the prediction accuracy to 97.2%, and reduce the average absolute error to 1.4%-1.9%, which can accurately identify the aging state of the battery and avoid the risk of battery failure in advance [9].

Table 3. Comparison of battery SOH prediction accuracy [6]

Prediction Method	Mean Accuracy (%)	Std. Deviation	Error Margin (%)
Conventional Model	85.6	6.4	±7.8
AI-Based Model	97.2	2.1	±2.9

2.2.2. Comparison of AI applications in EV battery balancing and thermal management systems

In the core link of battery equalization control, traditional schemes generally adopt the passive equalization method, which features a simple circuit structure mainly composed of discharge

resistors and switches. When the voltage of a single battery cell is excessively high, the controller closes the switch connected in parallel with it. Current discharges through the resistor and generates heat, thereby consuming the excess energy. This method has the advantages of low cost and fewer components, yet it suffers from low efficiency and requires thermal management due to heat generation [10]. AI-driven battery management systems are usually equipped with an active equalization scheme, which balances battery cells through energy transfer rather than energy dissipation. Its typical structure includes inductors/transformers, capacitors, and DC-DC converters. Unlike passive equalization, active equalization recovers and reuses energy, thus featuring higher efficiency and being suitable for high-power and large-capacity battery packs such as those used in EVs [10].

In the dimension of battery thermal safety management (BTMS) and thermal runaway warning, the traditional system will only trigger the cooling fan to turn on, stop charging, or even trigger a fault alarm when the battery temperature exceeds a fixed threshold set in advance [11]. However, the real-time analysis of the temperature rise rate of the battery and the temperature change gradient at different locations through the AI model can identify the risk of thermal runaway in advance before the battery temperature reaches the danger threshold, according to Table 4, achieving early warning of up to 3.9 seconds [6].

Table 4 compares the performance of the new AI-driven Battery Management System (IoT-BMS) with the traditional BMS in four key thermal management indicators. The data shows that the temperature detection accuracy of IoT-BMS is as high as 98.4%, while that of the traditional BMS is only 91.7%. Meanwhile, K. Athiappan et al. also conducted a study on 12 latest EVs, and their respective thermal anomaly detection accuracy ranges from 95.5% to 97.6%, indicating that the model does achieve an improvement in accuracy. Secondly, the average response time measures the duration from the occurrence of temperature anomalies to the system's response. The average response time of IoT-BMS is 148 milliseconds, which is much lower than the 292 milliseconds of the traditional BMS. In addition, the resolution of IoT-BMS reaches 2.4 cm², compared with only 7.8 cm² for the traditional BMS, which means the intelligent system can identify hot spot locations with higher precision [8].

Table 4. Thermal runaway early warning performance of IoT-BMS [8]

Parameter	Proposed IoT-BMS	Traditional BMS	Notes
Temperature detection accuracy (%)	98.4	91.7	Cell thermal sensing
Avg. response time (ms)	148	292	IoT latency benchmarking
Hotspot spatial-resolution (cm ²)	2.4	7.8	Based on heatmap grid
Thermal-runaway early-warning time (s)	3.9	0 (reactive only)	Predictive vs reactive

2.3. Challenges and perspectives

2.3.1. Challenges

Although artificial intelligence technology provides core support for the interactive experience upgrade and driving safety of intelligent cockpits, its application in real vehicle scenarios still faces significant technical challenges, and the core bottlenecks are concentrated in the decline of recognition accuracy in complex environments and the technical limitations of multimodal integration. In an ideal laboratory environment, the accuracy of AI in recognizing the driver's emotions can reach 89.51%, but in real driving scenarios, this accuracy is only 41.67% [12]. In

addition, at Level 3 and lower levels of autonomous driving, drivers must be ready to take over vehicle control at any time. While AI-powered smart cockpits deliver a wealth of information and entertainment services, they inevitably distract drivers and degrade their situational awareness. This creates a high-risk moment at the instant of handover [3]. Designing appropriate modes and content for interaction with in-vehicle occupants and external road participants constitutes a key research topic and challenge for achieving high safety in smart cockpits.

In the field of EV BMS, the current advanced AI-driven BMS solutions, such as deep learning models, boast high prediction accuracy yet lack transparency in their decision-making processes, which limits their credibility and deployment in safety-critical scenarios. Traditional machine learning models have a relatively higher error rate but offer better interpretability, while high-precision models exhibit more pronounced black-box characteristics. According to user surveys conducted by G. Divya et al., only 22% of engineers fully trust unexplained AI prediction results [13]. At the same time, AI models require a large amount of high-quality training data covering multiple operating conditions. They exhibit weak generalization capability across different battery chemical systems and diverse driving environments, thereby the cost of data acquisition remaining high. Current AI-BMS training demands more than 10,000 time-synchronized samples, with data acquisition costs accounting for 30-40% of the total BMS research and development expenses [9].

2.3.2. Perspectives

On the input channel of AI-based intelligent cockpits, Japanese automakers have developed a multi-sensory collaborative emotion regulation system based on Electroencephalography (EEG). This system is designed to monitor the driver's emotional state in real time through non-invasive EEG. Once specific EEG patterns of negative emotions such as anger or anxiety are detected, the system automatically triggers the coordinated adjustment of ambient lighting and music. Unlike a single passive intervention, the system leverages the synergistic effect of multi-sensory stimulation to achieve a regulatory effect that goes beyond linear superposition. As shown in Figure 5 [14], it can effectively adjust the driver's emotional state through the combination of rhythmic music and a green light environment in the car, making driving safer and making the car experience better.

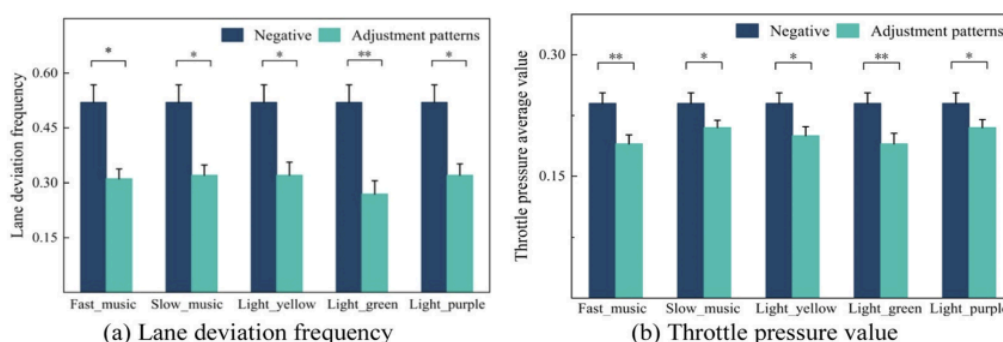


Figure 5. Results of driving behavior metrics under different conditions [14]

In the field of BMS, to address the black-box problem of model generation, engineers have proposed a lightweight XAI model for edge devices. The model is less than 1 MB in size and aims to generate feature importance graphs for each SOH or RUL prediction within 10 ms. For example, temperature contributes 27% and cycle count contributes 45%. Under such circumstances, XAI interpretation is incorporated into the certification process of the functional safety standard ISO 26262, which will greatly enhance the standardization of AI-based intelligent cockpits [13]. In

addition, it is difficult to train a highly reliable thermal runaway model with data from a single vehicle, and the cost of such a model is also relatively high. The Federated Learning framework enables multiple EVs to jointly train a global thermal runaway early warning model without sharing raw data. Each vehicle maintains a local digital twin to predict the probability of thermal runaway in real time and only uploads model gradient updates. According to the concept of H. Togun et al., this model can extend the early warning time to 60 seconds while ensuring a high level of privacy protection [15].

3. Conclusion

This paper systematically sorts out the application innovations and technical trends of AI in EV intelligent cockpits and BMS. In the field of intelligent cockpits, AI has driven the cockpit to evolve from passive response to active cognition, enabling long-distance pointing control, natural voice interaction, multimodal physiological monitoring, and full-domain perception inside and outside the vehicle, which greatly improves the fluency of human-vehicle interaction and driving safety. In the field of battery management, AI realizes high-precision estimation of battery SOC, SOH and RUL, optimizes the active equalization strategy, provides early warning of thermal runaway risks 3.9 seconds in advance, and reduces the annual capacity attenuation rate of power batteries by 43%, effectively extending battery life and lowering the whole-life cycle usage cost. Research shows that AI technology has become a core support for breaking through the performance bottlenecks of electric vehicles, yet it still faces multiple challenges in real vehicle scenario implementation: the accuracy of cockpit perception and emotion recognition drops significantly in complex driving environments, and there are technical barriers in multimodal data fusion; high-precision AI models in battery management suffer from the black-box problem, and insufficient interpretability leads to low engineering trust. Meanwhile, model training relies on massive high-quality data with high collection costs. In addition, at the L3 and lower autonomous driving levels, balancing intelligent cockpit interaction and driver takeover safety remains a key challenge. This study has multiple limitations. Most importantly, since most existing literature is mainly based on general data of lithium iron phosphate and ternary lithium batteries, this paper does not explore the AI adaptation differences between different battery systems and vehicle platforms. For instance, it fails to analyze the impact of differences in electrochemical characteristics of new battery systems such as sodium-ion batteries and solid-state batteries on AI state estimation and thermal runaway early warning models. Follow-up empirical research can promote the transformation of AI technology into large-scale vehicle-grade applications. In the future, the integration of artificial intelligence and electric vehicles will develop toward lightweight design, interpretability and collaboration. AI will continuously promote the in-depth coordination of electrification and intellectualization of electric vehicles, comprehensively enhance vehicle safety, reliability and user experience, and provide sustained impetus for the high-quality development of the new energy vehicle industry.

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