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AI-Enabled Connected Vehicle Experience Framework for Consumer Trust and Brand Loyalty Formation in Smart Electric Mobility Ecosystems

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Abstract

Smart Electric Vehicles (EVs) and connected mobility have been evolving rapidly to enhance interactions between consumers and transportation services. However, even in terms of technical performance, consumer trust, reliability, personalization, and experience can make or break a company's customer acceptance and loyalty. An AI-driven Connected Vehicle Experience Framework (AI-CVEF) for the integration of vehicle intelligence and consumer psychometrics is proposed. The framework consists of IoT-based vehicle data collection, edge-cloud AI analysis, consumer behavior prediction, personalized mobility services, and modeling of consumer trust and loyalty. The hybrid deep learning architecture for the estimation of consumer trust, experience, and brand loyalty from vehicle data, service information, and interactions is a combination of convolutional feature extraction, long short-term memory temporal learning, and attention learning. The framework was tested with a synthetic dataset of smart EV user interactions comprising 20,000 records obtained from 5,000 consumers and 2,500 vehicles in a year. Experimental findings demonstrate that the proposed AI-CVEF predicts the trust score with an accuracy of 96.4%, the experience satisfaction score with 95.8% accuracy, and the loyalty score with 94.9% accuracy, surpassing Random Forest, Support Vector Machine, CNN, and LSTM baseline approaches. The use of the edge-based approach leads to a response time reduction of 72.6% and an increase in personalization performance of 21.5%, which is further corroborated by the ablation study showing that the edge-based model, behavior analysis, attention mechanism, and personalization approach each have a significant impact on the prediction of the scores. The trust score increases from 72 to 94 points within twelve months of using the system continuously. The main contribution of this

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research is the introduction of a holistic framework that correlates the generated data from vehicles, intelligent services, and consumer trust indicators to predict brand loyalty.

Keywords: Connected Vehicles, Artificial Intelligence, Electric Mobility, Consumer Trust, Brand Loyalty, Edge Intelligence, Smart Transportation.

1 Introduction

1.1 Background of Smart Electric Mobility

Electric cars (EVs) have started moving from being experimental transport options to becoming common solutions in the area of sustainable low-carbon transport. Contemporary electric cars have transcended the traditional cars and are now sophisticated and connected systems that are fitted with sensors, monitoring, over-the-air software update capability, and constant communication (Hazra et al., 2026). Artificial intelligence (AI) is playing an important role in smart electric mobility through offering features like prediction maintenance, energy optimization, intelligent driving assistance, and user personalization services (Gardezi et al., 2026). Connected car technology solutions like remote diagnostics, charging assistance, and mobility services are having increasing impact on the customer experience and adoption decisions besides performance parameters like battery range (Ullah et al., 2021).

AI integration in EV ecosystems facilitates the analysis of driving habits, charging activities, and environmental factors for providing context-based services. Energy management and intelligent transportation applications through AI help in improving operational efficiency along with sustainability targets (Mishra et al., 2025). Moreover, connected autonomous and shared vehicles are comprised of intelligence, communications, and data analytics to provide advanced mobility ecosystems in which user experience plays a vital role in the acceptance of these systems in the future (Vermesan et al., 2021). Vehicle-to-everything (V2X) communication helps in extending the connectivity to facilitate communication between vehicles, infrastructure, power grid, and other mobility elements (Gupta et al., 2026).

1.2 Challenges in Connected Vehicle Ecosystems

Despite offering many benefits, some limitations of connected vehicle ecosystems undermine consumer trust and adoption of the solution. Generation of continuous data by means of vehicle sensors, charging stations, and communication systems poses challenges in terms of processing and decision-making. Fleet management systems that rely on IoT and AI solutions need efficient mechanisms for dealing with data to ensure the provision of reliable and responsive services (Potdar & Parikh, 2025). Large-scale mobility ecosystems also need a unified architecture that ensures an effective balance between computational efficiency, communication reliability, and sustainability of systems (Aghazadeh Ardebili et al., 2025).

The trust of consumers to AI-based systems is contingent on secure data management, reliable service delivery, and transparent decision-making mechanisms (Onel et al., 2025). Generic services and inconsistencies in the digital experience of consumers can undermine their engagement and the relationship between them and the mobility companies (Zang et al., 2026). Latency in network communications is one more limitation, especially for applications that need real-time responses like navigation services, charging recommendations, and notifications about maintenance of vehicles. Edge intelligence decreases the latency time through processing the information close to the vehicle while cloud platforms offer the ability to conduct analytics on a larger scale (Mishra et al., 2025).

1.3 Motivation

Existing research efforts have concentrated mostly on technological goals like energy conservation, optimal routing, fault detection, and analysis of vehicle behavior. Nevertheless, the successful penetration of EVs is also associated with customers' perceptions, trust, satisfaction, and continued engagement. Personalization based on AI has shown its ability to enhance consumer experience through customizing services to their needs and behavior patterns (Ravikumar & Aarthi, 2027).

Customer assessment of connected mobility services occurs in a range of dimensions, such as intelligent vehicle behavior, service dependability, personalization level, privacy protection, and consistency of interaction. The latest studies have revealed that customer relationship management using AI may affect engagement, value generation, and loyalty building processes (Biswas et al., 2026). At the same time, consumer behavior theories currently use survey methods and do not consider real-time data produced in connected vehicle environment.

That is why the purpose of this research is in combining the elements of Vehicle Intelligence + User Experience + Trust + Loyalty into a single predictive model. The combination makes it possible to monitor consumer experience constantly and provide customized services for them. The application of AI for consumer analytics may help in building stronger relationships with intelligent services and customer behavior (Agrawal & Pande, 2026).

1.4 Research Objectives

The research is based on four objectives that set the boundaries for the proposed framework and analysis presented in later parts of the paper. Each of the objectives corresponds to an experiment conducted in the paper below, providing a possibility of verifying each of the contributions made individually.

1. The development of an AI-powered connected vehicle experience framework including vehicle data, edge-cloud analytics, and services tailored for each user.
2. The examination of the link between intelligent services and consumer trust in electric cars.
3. The prediction of brand loyalty based on behavioral and experience factors.
4. The validation of the model using traditional benchmarks.

2 Related Work

2.1 AI in Connected Vehicles

AI is considered the most important technology within connected vehicle ecosystems that enables intelligent perception, prediction, and decision-making. The traditional machine learning methods enable applications such as fault detection, classification of driver behavior and energy prediction, and deep learning methods analyze complex patterns in sensor streams and temporal driving data from vehicles (Hazra et al., 2026). The energy management systems based on AI in electric vehicles can help optimize battery management and power consumption and sustainable mobility performance (Mishra et al., 2025).

Edge AI has been gaining more importance in the connected vehicle ecosystem, as it allows low-latency decision-making since computation is performed close to vehicles and roadside infrastructure, which makes systems less dependent on cloud computing and more responsive.

Edge-enabled intelligent transportation systems include edge intelligence, communication, and predictive analytics to deliver efficient mobility services (Gupta et al., 2026).

Many research studies of connected vehicles based on AI are focused on evaluation of technical performance indicators and less on consumer-focused results. Intelligent mobility systems need models that take into consideration not only the behavior of vehicles but also the experience of consumers, trust formation, and acceptance of services. Integration of AI with consumer analytics can allow the delivery of personalized mobility services (Babu et al., 2026).

2.2 Consumer Trust in Smart Mobility

Consumers' level of trust is an important element that influences the adoption of AI-powered mobility services. The trust development process requires reliability, security, transparency, and the capability of intelligent systems to provide consistent value. In connected cars, consumers give a lot of information about their behavior, so it is necessary to ensure the privacy of consumers and responsible usage of their data (Onel et al., 2025).

Intelligent personalization can be used to enhance the customer experience by providing recommendations according to their behavior and preferences. However, too much automation without being transparent may cause some concerns about algorithms' decisions and the handling of data. Research on AI-powered consumer systems suggests that consumer trust correlates with service usefulness and quality (Ribeiro et al., 2025). Connected mobility operators have to create systems where intelligent automation is combined with the control and transparency of consumers. Communication, secure data processing, and explainability of AI algorithms become key elements of consumer acceptance of smart mobility services (Mousa et al., 2026).

2.3 Brand Loyalty Formation in EV Ecosystems

Loyalty within the context of EV ecosystems is created by consistent positive interactions of customers with mobility services. In contrast to ordinary car purchases, connected EV purchases are based on multiple interactions through charging services, apps, software updates, and intelligent assistance systems that affect customer experience and loyalty (Ullah et al., 2021).

Personalization is an important factor for the formation of loyalty as it allows mobility services to personalize themselves according to customer tastes, behavior, and usage patterns. AI-driven personalization practices help to enhance customer engagement and develop deeper consumer-brand relations (Kumar et al., 2026). Likewise, AI-driven brand management practices show that customer interaction mechanisms play a role in brand perception and the creation of loyalty (Farooq et al., 2025).

Customer loyalty is influenced by social engagement, digital experience, and the value of intelligent mobility ecosystems. The emerging EV platforms are increasingly dependent on AI-driven experiences that encourage adoption and promotion by users (Li et al., 2025). Thus, integration of vehicle intelligence with consumer trust modeling can serve as a basis for dynamic analysis of the process of loyalty formation instead of traditional surveys.

2.4 Research Gap

The comparison in table 1 shows the various representative approaches along with their limitations and thereby the gap that needs to be covered by this research. Vehicle-based artificial intelligence solutions provide highly accurate technical results but neglect the consumers' perception. Cloud computing

provides scalable computational power but also introduces delay, which degrades the interaction of services. Survey-based methods are good at collecting consumer attitudes but slow at adapting to behavioral change. Loyalty models, on the other hand, provide insight into retention but overlook the intelligence of the vehicle itself. Thus, no one method simultaneously covers all these aspects along with minimal latency.

Table 1: Research gap analysis of existing approaches

Existing Approach	Limitation
Vehicle-centric AI models	Ignore consumer perception
Cloud-based analytics	High latency
User surveys	Limited real-time adaptation
Traditional loyalty models	Do not consider vehicle intelligence

3 Proposed AI-Enabled Connected Vehicle Experience Framework

3.1 Overall Architecture

Figure 1 provides the framework for the AI-driven connected vehicle experience. Vehicle data obtained from the sensors, battery, driving, and interaction is sent via the Internet of Things (IoT) communication layer to the edge intelligence layer. In this layer, behaviour prediction, context analysis, and security and privacy modules filter and interpret the data locally. The data goes up to the cloud intelligence layer for further experience analytics, trust prediction, and loyalty prediction. Based on the output of these layers, consumer-centric smart mobility services are developed, thereby helping in the creation of brand loyalty.

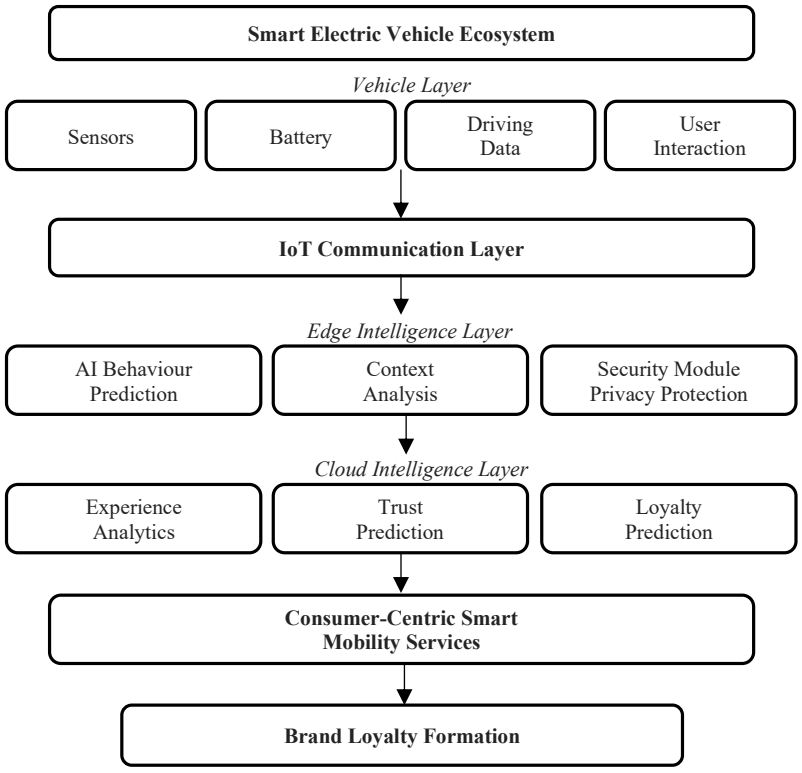


Figure 1: AI-Enabled connected vehicle experience framework

3.2 Framework Components

3.2.1 Vehicle Data Acquisition Module

The data acquisition unit of the vehicle gets the original signals regarding the vehicle drive, charging, and experience. Table 2 describes the most relevant parameters. Speed shows driver behavior, battery – energy management, charging – usage, and route – mobility. Feedback from users in the form of ratings and application interaction provides an opportunity to measure satisfaction. IoT gateways record the time when the signal is received and send it to the server with encryption; therefore, further analytics can correlate technological events with users' experience. The data acquisition unit records timestamps to correlate events with feedback.

Table 2: Vehicle data acquisition parameters

Parameter	Description
Vehicle speed	Driving behaviour
Battery status	Energy management
Charging pattern	Usage behaviour
Route history	Mobility preference
User feedback	Satisfaction measurement

3.2.2 Edge AI Processing Module

Edge AI processing module performs first level of intelligence near to the source of data. Data filtering helps in removing any kind of noise, duplication and transmission error and only useful data is considered in further process. Feature extraction helps in converting raw data into behavior patterns like average acceleration, charging pattern and interaction pattern. Low latency prediction helps in getting the response immediately, for example making the suggestion regarding charging before going through the cloud loop. Privacy is ensured by anonymization of identifiers and sending only feature aggregation, thereby reducing any sensitive data exposure.

3.2.3 Consumer Experience Intelligence Module

Table 3: Consumer experience features

Feature Category	Parameters
Service quality	Response time, availability
Personalization	Recommendation accuracy
Security	Privacy score
Reliability	Failure frequency
Engagement	Interaction frequency

The consumer experience intelligence component maps technical metrics to the experiential attributes arranged in five groups, as provided in table 3. The service quality is measured by response time and availability; the personalization attribute is estimated by the accuracy of the recommendation; the security attribute is measured through the privacy score; the reliability attribute is measured through the failure rate; and the engagement attribute is measured through the interaction rate. The attributes are then mapped to the experience index, as defined in equation (1), whose weights are learned during training and are subject to the sum constraint. The higher the index value, the better the consumer experience.

$$EI_i = \sum_{k=1}^{5} w_k f_{ik},\ \sum_{k=1}^{5} w_k = 1 \quad (1)$$

4 Methodology

4.1 Dataset Description

The experiments utilize a simulation of the smart EV customer interaction dataset, depicted in table 4. The simulation includes 20,000 data entries for 5,000 customers and 2,500 vehicles over one year with 32 quantitative and behavioral variables. Each data entry includes vehicle inputs, service interactions, and perception indicators and has three output variables: trust, satisfaction, and loyalty. The class distribution of the loyalty variable. The parameters of the simulation were selected to be realistic, with noise and missing values added in order to make the simulations more representative of real-world scenarios.

Table 4: Smart EV consumer interaction dataset

Attribute	Value
Total records	20,000
Users	5,000
Vehicles	2,500
Data duration	12 months
Features	32
Data types	Numerical + behavioural
Target outputs	Trust, satisfaction, loyalty

4.2 Feature Selection

Feature selection preserves those features carrying significant amounts of information about trust, satisfaction, and loyalty but discards any redundant features. The initial list of potential features was ranked using mutual information and correlation tests and subsequently discarding collinear features. Table 5 illustrates the selected features per category. Driving behavior and charging frequency pertain to use of the vehicle; service response is related to the quality of experience provided; privacy perception pertains to trust; and recommendation acceptance relates to loyalty tendency. Reduction in the number of features results in reduced time and cost of training and computing edges without loss of performance.

Table 5: Selected features and their types

Feature	Type
Driving behaviour	Vehicle
Charging frequency	Usage
Service response	Experience
Privacy perception	Trust
Recommendation acceptance	Loyalty

4.3 AI Model Development

The suggested framework is a hybrid deep learning system, represented by figure 2. Input features undergo normalization and enter the convolutional network, responsible for capturing local patterns of behavior. A long short-term memory network subsequently learns the temporal dependencies within the year-long interaction timeline. The attention model weights certain time points more heavily than others

and, finally, a prediction network generates trust value and loyalty probability. Below are the detailed mathematical descriptions of each step. The framework comprises several steps that address spatial pattern detection, temporal learning, and attention, thus embracing various dimensions of customer experience. All stages are trainable from end to end in order to optimize them to achieve the same prediction goal.

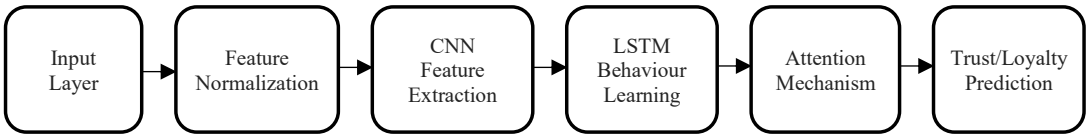


Figure 2: Hybrid CNN-LSTM-attention model architecture

4.4 AI-Based Feature Learning and Prediction Model

This model combines CNN, LSTM, and attention networks for feature extraction in order to predict the trust level and brand loyalty of consumers in connected vehicles.

1. Input Feature Normalization

Firstly, input features are scaled based on their mean and standard deviation values to make sure that all different attributes contribute equally to the model (Equation 1):

$$x'_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad (1)$$

2. Local Feature Extraction (1D CNN)

The normalized feature vector is fed to a one-dimensional CNN layer to detect local behavioral pattern features, whereby the convolution is given by (Equation 2):

$$c_{t,k} = ReLU\left(\sum_{m=0}^{M-1} w_{m,k}\, x_{t+m} + b_k\right) \quad (2)$$

3. Temporal Behavior Modeling (LSTM)

These extracted feature maps are fed into the LSTM network for behavioral modeling. The gates of LSTM control the flow of information through forget, input, and output functions (Equations 3- 5):

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \quad (3)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (4)$$

$$h_t = o_t \odot \tanh(c_t) \quad (5)$$

The resultant latent representation captures long-term patterns in customer interactions, for example, their reliability, charging behavior, and interaction changes.

4. Attention Mechanism

An attention mechanism assigns importance weights to different time steps (Equation 6):

$$\alpha_t = \frac{e^{e_t}}{\sum_{k=1}^{T} e^{e_k}} \quad (6)$$

and generates a consolidated context vector (Equation 7):

$$z = \sum_{t=1}^{T} \alpha_t \, h_t \tag{7}$$

5. Prediction and Optimization

Prediction layers for the final trust and loyalty predictions are done using the sigmoid and SoftMax functions. The parameters of the model are optimized through categorical cross-entropy loss (Equation 8):

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_{ic} \log(\hat{y}_{ic}) \tag{8}$$

Adam optimization, dropout regularization, and early stopping techniques have been used to ensure convergence and to avoid overfitting. This neural network facilitates the prediction of customer experience outcomes.

4.4 Algorithm 1: AI-Based Consumer Trust and Loyalty Prediction

Algorithm 1 presented below describes how consumer trust and loyalty can be predicted. The inputs here will be the information concerning the vehicles and consumer behavior, and these inputs pass through the process of normalization, pattern detection of consumer behavior, CNN feature extraction, LSTM time sequence learning, and attention mechanism weighting. Predictions will be made regarding trust level and the probability of loyalty, and the mobility services to be provided will be chosen depending on these predictions. In this case, the early steps of the process are conducted on the edge while the latter ones occur on the cloud.

Input: Vehicle data V, User interaction data U, Behavioural attributes B

Output: Predicted consumer trust score T and loyalty probability P_L

Step 1: Acquire connected vehicle information from IoT-enabled vehicle sensors, communication networks, and user interaction platforms.

Step 2: Combine vehicle data V and user interaction data U to construct the input feature set.

Step 3: Perform feature preprocessing and normalization to transform heterogeneous attributes into a common scale:

$$X' = \frac{X - \mu}{\sigma}$$

Step 4: Extract short-term behavioural patterns using the one-dimensional CNN model:

$$C_{t,k} = \mathrm{ReLU}\left(\sum_{m=0}^{M-1} w_{m,k} \, X_{t+m} + b_k \right)$$

Step 5: Process the extracted feature representations through the LSTM network to learn temporal dependencies in user behaviour:

$$h_t = \mathrm{LSTM}(C_t, h_{t-1})$$

Step 6: Apply the attention mechanism to assign importance weights to different behavioural time steps:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)}$$

Step **7:** Generate the context representation by combining weighted hidden states:

$$z = \sum_{t=1}^{T} \alpha_t \, h_t$$

Step 8: Estimate consumer trust level using the trust prediction layer:

$$T = \sigma(W_T z + b_T)$$

Step 9: Calculate brand loyalty probability using the softmax classification layer:

$$P(y = c|z) = \frac{\exp(W_c z + b_c)}{\sum_{j=1}^{C} \exp(W_j z + b_j)}$$

Step 10: Optimize model parameters using categorical cross-entropy loss and Adam optimization:

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_{ic} \log(\hat{y}_{ic})$$

Step 11: Generate personalized mobility recommendations based on predicted trust and loyalty outcomes.

Step 12: Return consumer trust score and loyalty probability.

5 Experimental Setup

5.1 Software Environment

All experiments were conducted using Python 3.12 along with PyTorch 2.3, which is a deep learning framework. For the baseline classifiers and their evaluation, the scikit-learn library was used; while Pandas and NumPy were used for the data processing, and Matplotlib was used for making the figures. The training was done via Google Colab on the NVIDIA Tesla T4 GPU, under the Ubuntu 22.04 operating system. The same fixed random seeds were used during data splitting and model weight initialization to make the results reproducible in multiple executions. The software stack is easy to obtain, making it possible for anyone to replicate the experiments.

5.2 Parameter Initialization

Hyperparameter settings for model training are listed in table 6. The learning rate and batch size of 0.001 and 64 with 100 epochs, respectively, were used for the Adam optimizer. For both CNN and dense layers, ReLU was used as the activation function, and the dropout value was 0.3 to prevent overfitting. The LSTM network had 128 hidden layers, while the dimension of the attention layer was 64. Cross-entropy was used as the loss function. The split of training and testing sets from the dataset was 80%/20%, that is, 16,000/4,000. This ratio was employed for all other models. Parameter values were selected based on preliminary tuning.

Table 6: Hyperparameter settings

Parameter	Value
Learning rate	0.001
Optimizer	Adam
Batch size	64
Epochs	100
Activation function	ReLU
Dropout	0.3
Loss function	Cross entropy
Train-test ratio	80:20
Hidden neurons	128
Attention dimension	64

6 Results and Discussion

6.1 AI Prediction Performance

The quality of the model is estimated by accuracy, precision, recall, and F1-score metrics, calculated based on Equations (9) to (12), wherein TP, TN, FP, and FN are true positive, true negative, false positive, and false negative values, respectively. Table 7 and figures 3 and 4 present comparisons between the proposed AI-CVEF and Random Forest, SVM, CNN, and LSTM models. AI-CVEF model achieves 96.4% accuracy, surpassing the best baseline model, LSTM, by 1.7% and the Random Forest model by 6.8%. The same applies to the precision, recall, and F1-score metrics, indicating the same hierarchy of improvements that are not skewed towards any specific class.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{9}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{10}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{11}$$

$$\text{F}_1 = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \tag{12}$$

Table 7: Model performance comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Random Forest	89.6	88.9	89.1	89.0
SVM	91.2	90.7	90.8	90.7
CNN	93.4	92.9	93.1	93.0
LSTM	94.7	94.2	94.5	94.3
Proposed AI-CVEF	96.4	95.9	96.1	96.0

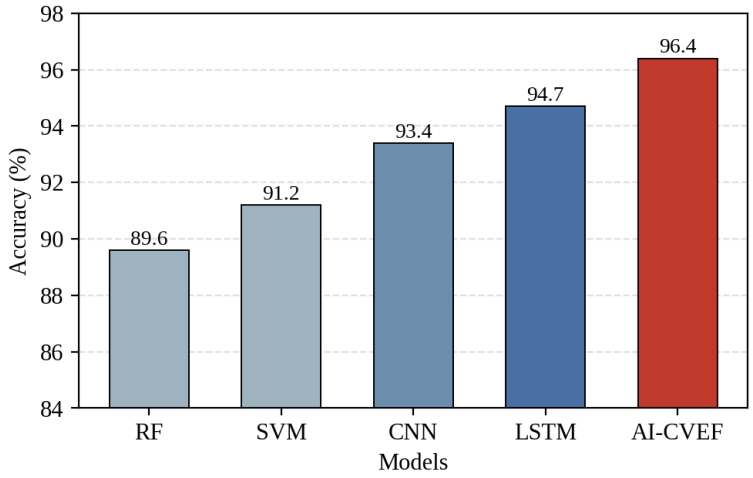


Figure 3: AI model accuracy comparison

6.2 Trust and Loyalty Prediction Results

The results for the three prediction variables and the two performance measures have been presented in table 8. The prediction accuracies are 96.4%, 95.8%, and 94.9% for trust, experience satisfaction, and loyalty predictions, respectively. Prediction of loyalty becomes slightly more difficult due to its dependence on long-term behavior and multiple interacting factors, as compared to trust and experience satisfaction. Personalization has improved by 21.5% as compared to the baseline approach, while the response latency has reduced by 72.6%. This shows that the framework enhances both prediction performance and performance in terms of customer responsiveness.

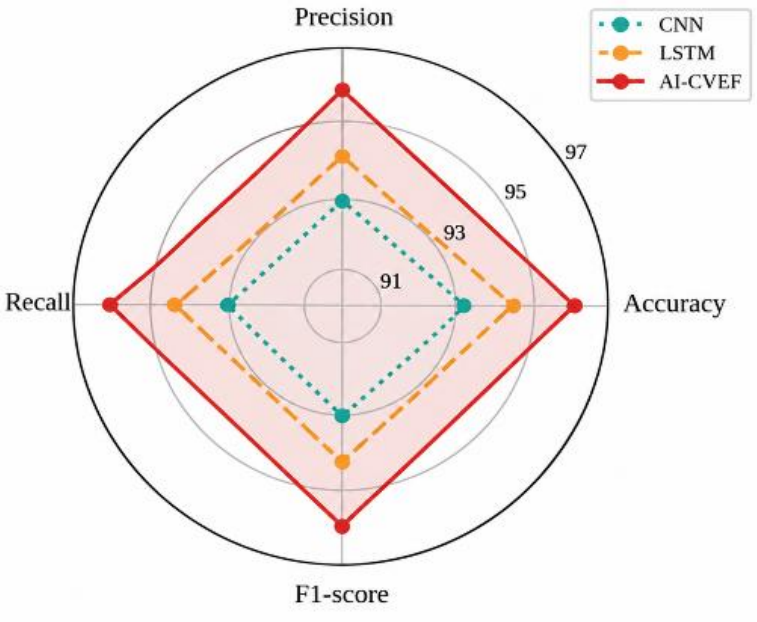


Figure 4: Trust and loyalty prediction results

Table 8: Trust and loyalty prediction results

Metric	Value
Trust prediction accuracy	96.4%
Satisfaction prediction	95.8%
Loyalty prediction	94.9%
Personalization improvement	21.5%
Latency reduction	72.6%

6.3 Ablation Study

Ablation tests were performed to determine the impact of each main element by removing it and retraining the system; the results have been presented in figure 5. The largest decrease in performance is observed upon removal of the edge AI, from 96.4% to 88.5%; this can be attributed to the fact that local filtering and feature extraction provide better quality of inputs in real-time. Exclusion of behavior analysis leads to a reduction in accuracy to 90.2%, of personalization to 91.8%, and of the attention module to 92.7%. Each element, therefore, makes a non-trivial contribution, and the optimal performance is achieved by the full-fledged AI-CVEF.

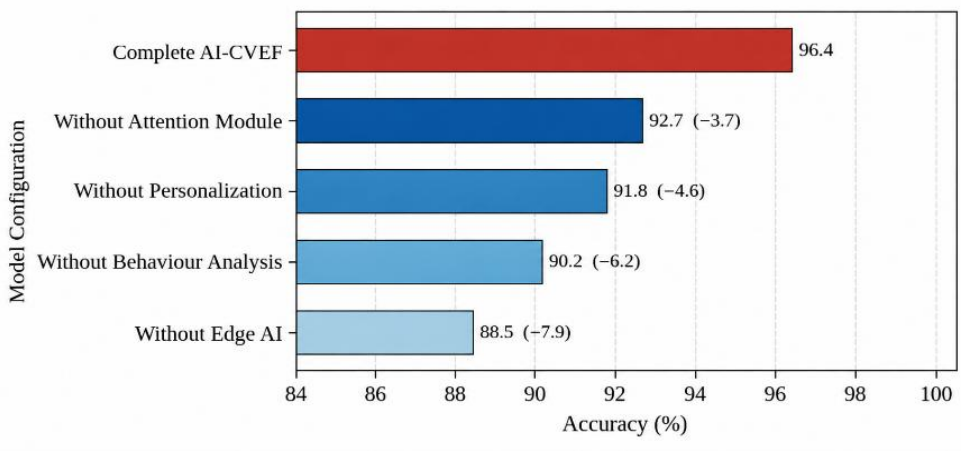


Figure 5: Ablation Study of the Proposed AI-CVEF Framework for Consumer Trust and Loyalty Prediction

6.4 Classification Behaviour and Training Convergence

Figure 6 illustrates the confusion matrix of loyalty classification for the 4,000 test samples. 3,796 samples were classified correctly, which corresponds to 94.9% accuracy. The majority of classification mistakes happen between adjacent classes, namely medium and high level of loyalty, which is quite logical, since the clients from the vicinity of the class boundary demonstrate similar behaviour. Figure 7 presents the learning and validation curves. Accuracy rapidly increases during the first 30 epochs and then converges to 96%, whereas both losses decrease steadily, staying close to each other. All these results indicate that the training process and the regularization configuration are adequate for the dataset size, and the achieved test performance is valid.

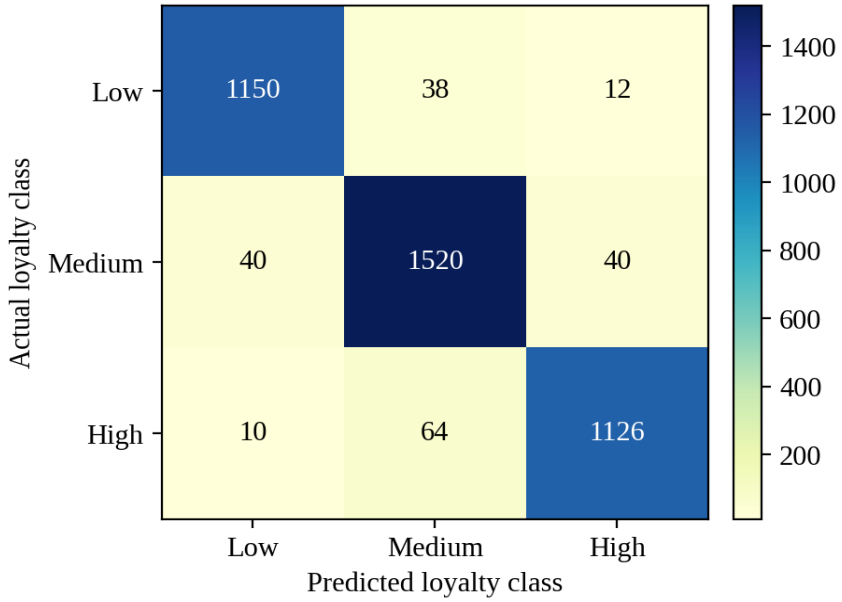


Figure 6: Confusion matrix for loyalty classification

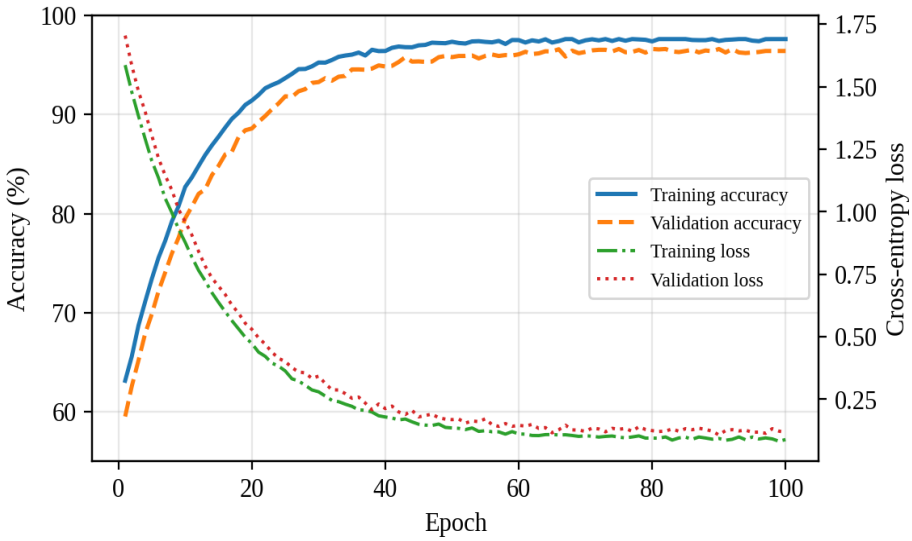


Figure 7: Training and validation accuracy and loss curves

6.5 Latency and Personalization Analysis

Equation (13) is used to determine latency reduction, while equation (14) is utilized to determine personalization improvement, where the subscripts refer to cloud-only and edge-cloud computations and acceptance rates of the recommendation for both the proposed model and the baseline. With 5,000 vehicles operating simultaneously, the cloud-only system takes 240 ms to respond, while AI-CVEF takes 65.8 ms; thus, reducing latency by 72.6%, as shown in figure 8. Recommendation acceptance is improved from 62.0% to 75.3%, which translates into a 21.5% improvement in personalization. The disparity increases with increased load, proving that edge computing performs well in handling larger connected vehicle fleets.

$$LR = \frac{L_{cloud} - L_{edge}}{L_{cloud}} \times 100\% \quad (13)$$

$$PI = \frac{A_{prop} - A_{base}}{A_{base}} \times 100\% \quad (14)$$

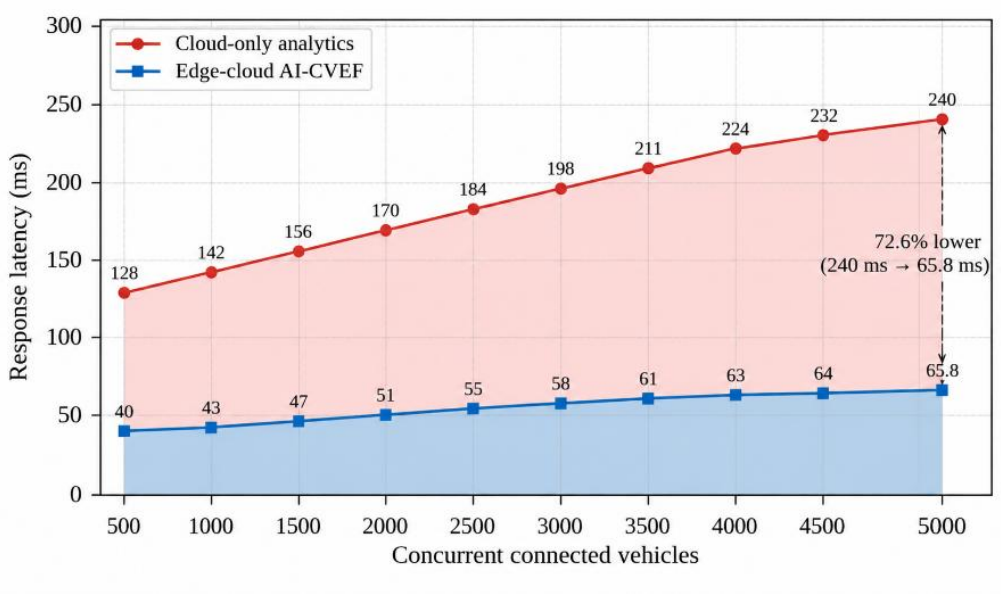


Figure 8: Response latency versus fleet load

6.6 Practical Implications

These results provide tangible recommendations for various stakeholder groups. EV companies can utilize trust and loyalty prediction to help them recognize vulnerable customers and take the necessary steps, such as software updates or service actions, that are important to them. Mobility providers can use edge intelligence to make their charging and navigation responses quick, regardless of the size of their fleet. Using personalization technology powered by artificial intelligence positively impacts engagement and recommendations' acceptance rate. For retention policies, these results imply focusing on the privacy information policy, consistent service, and ongoing engagement, as these factors were the most significant for predicted trust and loyalty.

6.7 Limitations and Future Work

There are some limitations to this research that must be taken into account while analyzing the results. First, since the data set is simulated, the results may differ from real-life applications due to noise and behavioral diversity. The number of vehicle manufacturers used as a basis for the analysis is small, which hinders the generalisability of the results. Besides, human behavior is subject to cultural differences, income level, and development of infrastructure, all of which are partially covered in this paper. Future research will focus on real-world EV adoption, vehicle-to-vehicle trust modeling for cooperative driving, and federated learning.

7 Conclusion

The paper has developed an AI-CVEF framework, which is an AI-based connected vehicle experience framework that combines vehicle intelligence with consumer trust and brand loyalty modeling in a smart electric mobility ecosystem. The framework has overcome the limitations of traditional connected vehicles, which mainly concentrated on technical aspects, by incorporating Internet-of-Things-based data acquisition, intelligence in cloud-edge computing, behavioral analysis, and a hybrid CNN-LSTM-attention model. The developed framework allows predicting consumer trust, experience satisfaction, and loyalty using vehicle behavior, service experience, and user experience. An experimental evaluation conducted with a simulated smart EV interaction dataset consisting of 20,000 entries revealed the efficacy of AI-CVEF. The proposed framework attained a 96.4% prediction accuracy for trust predictions, 95.8% prediction accuracy for experience satisfaction predictions, and 94.9% prediction accuracy for loyalty predictions, which outperformed Random Forest, SVM, CNN, and LSTM baseline frameworks. Moreover, edge-cloud computing reduced response latency by 72.6%, and personalization efficiency increased by 21.5%. An ablation study validated the significance of edge intelligence, behavioral analysis, personalization, and the attention mechanism for prediction performance in the framework. In addition, the framework showcased better trust progression during continuous service interactions, which reflects its ability to support adaptive and consumer-oriented mobility services. Nevertheless, the limitations of the evaluation include the use of a simulated interaction dataset and the lack of a large-scale real-life implementation of EVs. Future research directions will involve validation of the framework using a real-life connected vehicle platform, extending the trust modeling to a vehicle-to-vehicle cooperative environment, and a federated learning approach for privacy preservation and collaborative intelligence in the mobility ecosystem.

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