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RESEARCH ARTICLE

AI-Integrated Traffic Information System: A Synergistic Approach of Physics Informed Neural Network and GPT-4 for Traffic Estimation and Real-Time Assistance

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ABSTRACT Traffic management systems have primarily relied on live traffic sensors for real-time traffic guidance. However, this dependence often results in uneven service delivery due to the limited scope of sensor coverage or potential sensor failures. This research introduces a novel approach to overcome this limitation by synergistically integrating a Physics-Informed Neural Network-based Traffic State Estimator (PINN-TSE) with a powerful Natural Language Processing model, GPT-4. The purpose of this integration is to provide a seamless and personalized user experience, while ensuring accurate traffic density prediction even in areas with limited data availability. The innovative PINN-TSE model was developed and tested, demonstrating a promising level of precision with a Mean Absolute Error of less than four vehicles per mile in traffic density estimation. This performance underlines the model's ability to provide dependable traffic information, even in regions where conventional traffic sensors may be sparsely distributed or data communication is likely to be interrupted. Furthermore, the incorporation of GPT-4 enhances user interactions by understanding and responding to inquiries in a manner akin to human conversation. This not only provides precise traffic updates but also interprets user intentions for a tailored experience. The results of this research showcase an AI-integrated traffic guidance system that outperforms traditional methods in terms of traffic estimation, personalization, and reliability. While the study primarily focuses on a single road segment, the methodology shows promising potential for expansion to network-level traffic guidance, offering even greater accuracy and usability. This paves the way for a smarter and more efficient approach to traffic management in the future.

INDEX TERMS AI-integrated traffic information system, physics informed neural network (PINN), traffic state estimation (TSE), traffic data processing, GPT-4, prompt engineering, natural language processing (NLP), large language models (LLM), foundation models.

I. INTRODUCTION

The escalating need for effective traffic management systems has become a matter of global urgency. As reported by the US Department of Transportation, more than 370,000 people lost their lives in transportation-related incidents over the last decade in the United States, with road incidents accounting for over 350,000 fatalities [1]. Globally, the issue extends beyond just safety; it is also an environmental concern. The World Bank in 2023 reports that the transportation

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sector contributes to a significant 20% of global greenhouse gas emissions [2]. Moreover, the safety of road users remains a pressing issue, with over 1.35 million lives claimed annually by road crashes, leading to serious injuries for an additional 50 million individuals [2]. In light of these statistics, the importance of accurate, real-time traffic predictions cannot be overstated. Current systems, despite their reliance on advanced monitoring technologies like surveillance cameras and GPS trackers, face considerable challenges in reliable traffic reading due to sensor failures and coverage scarcity [3]. Thus, the pursuit of a more robust and resilient traffic guidance system that can accurately predict traffic density even in the absence of real-time data is of paramount importance.

This is where the potential of neural networks comes into play. These complex algorithms designed to mimic the human brain can learn from historical traffic data, distinguishing patterns that might be unnoticeable to human observers [4]. By learning from past traffic scenarios, the methods could provide insightful predictions, specifically when real-time traffic sensors are not operational. However, standard neural networks often lack the ability to incorporate physical laws [5]. Moreover, this models struggle to learn complex traffic dynamics unless they are provided with extensive amount of training data [6].

On the other hand, the integration of language models with domain-specific machine learning models have witnessed a surge in the utilization across diverse domains. However, its potential remains largely uncharted territory, particularly in the context of traffic information dissemination [7], [8], [9].

To address these challenges, our research aims to develop a physics-informed neural network (PINN) model for traffic prediction. This approach uses historic traffic data to predict traffic density based on factors such as the position on a highway and the time of day. To enhance the user experience, we integrate this model with a Generative Pretrained Transformer 4 (GPT-4) API. GPT-4 serves as an interface between the user and the neural network model, interpreting the user's traffic inquiries and providing real-time responses based on the model's predictions. Thus, this novel approach combines the strengths of artificial intelligence and physics-based modeling, offering a potential solution to the current limitations of traffic management systems.

The integration of PINN and a GPT-4 interface into traffic guidance systems has broad implications. In addition to improving traffic prediction accuracy, this approach could also enhance the user experience of real-time navigation systems and applications. Currently, these apps heavily rely on live GPS feeds to provide guidance, which can be compromised during sensor failures or unexpected road conditions [3]. Our proposed solution could offer a reliable backup system when such sensors fail for providing traffic information, significantly improving the systems' reliability.

This paper is organized as follows: Section II provides an overview of the previous works in similar research avenues. Section III details the methodology used in developing our model. Section IV presents the results, while Section V offers a comprehensive discussion of these results. Lastly, Section VI concludes the paper, highlighting the limitations of our study and providing recommendations for future research in this exciting field.

II. RELATED WORK

Traffic guidance systems are fundamental to modern transportation networks, serving as the backbone for managing and regulating traffic flow [10]. They include a wide range of methods, from static traffic signage to complex real-time traffic guidance systems, enhancing the road user experience and ensuring the smooth traffic flow. Real-time navigation apps like Google Maps and Waze are examples of such systems, leveraging GPS data to provide real-time traffic updates and optimized routing [3].

A significant source of data for these real-time navigation apps are the extensive traffic sensor networks such as the GPS feeds from mobile devices. These sensors have become increasingly prevalent with the ubiquity of smartphones and in-vehicle GPS systems. The data from these sensors helps make traffic predictions more dynamic and accurate. By tracking the speed and location of a large number of vehicles, these systems can estimate current traffic conditions and even predict future congestion or delays [3].

However, these methods have several limitations. Mainly, they are heavily dependent on the availability and accuracy of sensors' data, requiring extensive sensor networks and constant data feeds. This dependency can pose challenges when there are data insufficiencies, such as in areas with low traffic sensor coverage or low smartphone penetration rates [11]. Furthermore, these systems can also falter in the case of sensor failures, potentially resulting in ineffective traffic management and exacerbating congestion. These limitations highlight the need for more robust and resilient traffic prediction methodologies capable of operating seamlessly within existing systems, even in case of inconsistent and intermittent traffic sensor data [12].

Neural networks have emerged as a powerful tool in traffic management, offering the ability to process and analyze vast amounts of data, pattern recognition from historical data and improved prediction accuracy [13], [14]. Neural networks, mirroring the human brain's structure, allow computers to learn from data, making them ideal for prediction and pattern recognition tasks [4], [15]. Yasdi, for instance, delves into the use of Recurrent Jordan networks, a specific type of neural network system, for forecasting short-term traffic flow based on time-series data [16]. This approach is echoed by More et.al, who apply Jordan sequential networks to predict future traffic volumes [17]. These networks, trained with real-time data, aim to optimize traffic flow and manage congestion. Building on this concept, Loumotis et.al proposed a novel system that blends the use of Artificial Neural Networks (ANNs) to predict road traffic [18]. This system employs ANNs to estimate vehicle speed, thereby offering a congestion indicator.

The exploration of neural networks in traffic prediction is further expanded by Abbas et.al. They investigate short-term traffic prediction using Long Short-Term Memory (LSTM) neural networks [19]. With the objective of enhancing Intelligent Transport Systems' proactive response abilities, their research introduces and juxtaposes three LSTM-based models, offering a comprehensive view of road traffic density prediction. This shows the increasing versatility and efficacy of neural networks in traffic prediction.

However, traditional neural network models have limitations. While they can learn complex patterns from data, they often struggle with scenarios that involve complex physical dynamics or when data is insufficient to learn the physical pattern. This has led to the development of more sophisticated models, such as PINNs [6].

PINNs integrate physical laws into model training, enhancing prediction accuracy and reliability [20]. Compared to traditional neural networks, PINNs offer advantages in scenarios with complex physical dynamics or insufficient data, as they leverage inherent physical principles to supplement data-driven learning [21]. The versatility of PINNs is evident in their applications across various scientific and computational domains. They have been employed as valuable tools in solving complex problems, from traffic state estimation, fluid dynamics and image reconstruction to material science and beyond [21], [22], [23], [24], [25], [26], [27].

In the context of traffic prediction, the integration of physical laws into PINNs can be particularly beneficial. For example, traffic flow follows certain physical laws such as the conservation of cars (analogous to the conservation of mass in fluid dynamics), which can be incorporated into the PINN model. This allows the model to make reasonable predictions even in the limited or absence of extensive traffic sensors, offering a potential solution to one of the main challenges faced by traditional traffic prediction methods. Accordingly, PINNs excel at "filling in the gaps" when data is incomplete, ensuring reliable traffic information [20]. Thus, this hybrid approach can potentially allow PINNs to overcome the limitations of traditional models, making them more robust in scenarios where data is sparse or noisy.

Another main limitation with current traffic management systems is data accessibility and interpretation especially by non-technical users. Recently, Large Language Models (LLM) such as GPT-4 have been employed to act as a bridge between the user and the domain specific information [7], [8], [9], [28]. The integration of GPT-4 chat interfaces with domain specific data and models enhances user interaction and accessibility. Large language models such as GPT-4 acts as a bridge between the user and the domain specific information. This integration enhances the accessibility and usability of the domain knowledge, making it more approachable for everyday users [8], [9], [28]. On the other hand, it improves the user experience by providing personalized results based on the user's specific inquiries [29], [30], [31].

In summary, despite the considerable progress made in the field of traffic prediction, several research gaps persist. One notable gap is the lack of comprehensive models for predicting traffic density under varied conditions, crucial for traffic guidance systems [32], [33]. Many rely on traffic sensor data, posing significant limitations in scenarios where such sensors are unavailable or unreliable [34]. The current study aims to fill these gaps by developing a PINN model that predicts traffic density based on position and time data. By integrating this model with a user-friendly pre-trained GPT-4 interface, the study aims to provide a more accessible and reliable traffic prediction tool. This novel approach not only addresses the limitations of existing models but also expands AI's potential in traffic prediction and management.

III. METHODOLOGY

Our traffic information system's methodology is organized into six primary components. The initial segment is dedicated to data preprocessing. In this phase, we address the methods applied to manage and refine the data for subsequent analysis. The next segment details the architecture of the PINN Traffic State Estimator (TSE) neural network. Here, we delve into the PINN-TSE model, examining both the data-driven aspect and the physical law aspect. Furthermore, we shed light on the synergy between these two facets of the model explaining the training process followed by the view of the entire system architecture. The next part of this section is centered around the integration of the GPT-4 interface. In this part, we discuss how GPT-4 is utilized to interpret user queries and the outputs generated by the PINN-TSE network. Lastly, we provide a holistic perspective on the approach we used in system testing and validation. Thus, this section elucidates each component of the system and illustrates how they interact to ensure the efficient operation of the traffic information system.

A. PRE-PROCESSING

The initial phase of our methodology is data preprocessing, an essential step that guarantees the validity and reliability of our traffic information system. This phase encompasses several primary procedures.

The first procedure is data cleaning, a method that ensures the data's quality and accuracy. This is accomplished by detecting and correcting any errors or inconsistencies in the data, such as missing or duplicate entries.

Once the data is cleaned, we delineate the spatial and temporal resolution of the data. This involves classifying the data into distinct spatial and temporal bins, facilitating a breakdown of the data into more manageable segments for detailed analysis.

Subsequently, we compute the average traffic density and speed within each spatial and temporal bin. This process offers a comprehensive overview of the traffic conditions within each bin, enabling a more focused analysis.

The concluding procedure in the data preprocessing phase involves employing regression analysis to discover the relationship between traffic speed and density, as well as between traffic density and traffic flux. Regression analysis is a powerful tool in this context, helping us to discern

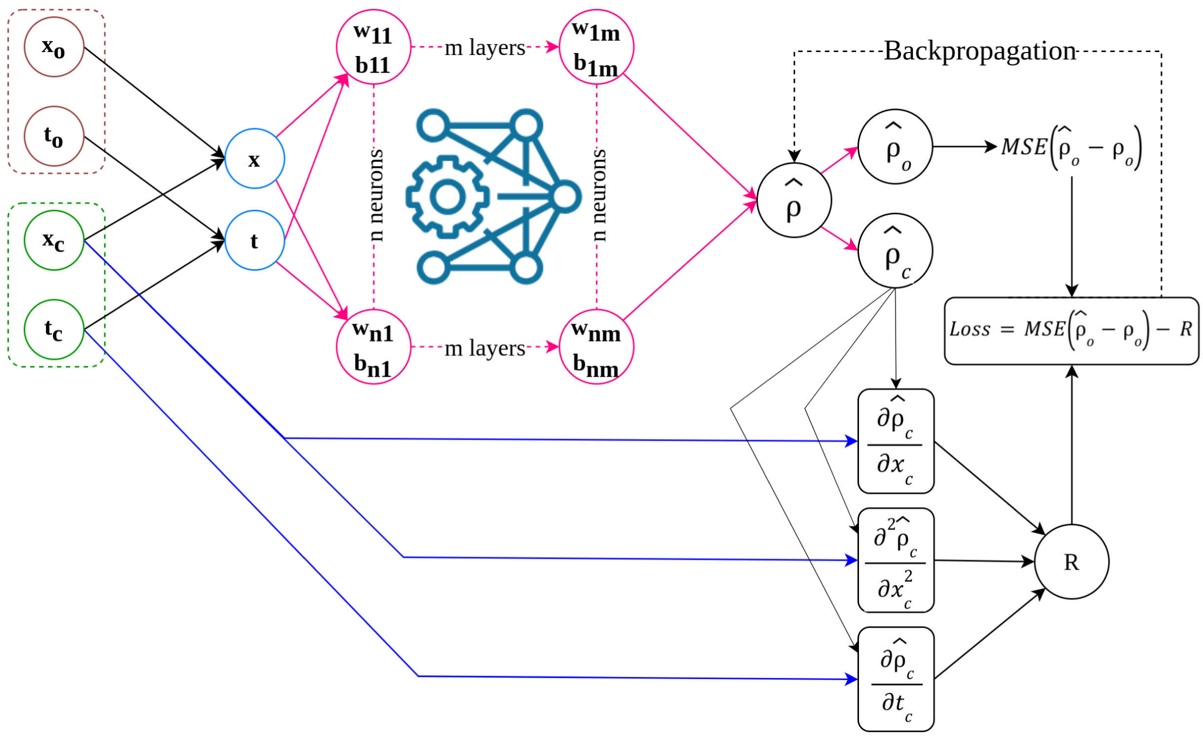

FIGURE 1. PINN-TSE architecture.

the underlying patterns and trends in our traffic data. This understanding, in turn, assists us in defining the maximum and optimum traffic density for the road section, along with the free flow speed. These are the main parameters required to characterize the test road section traffic dynamics and are used in defining the traffic state equation. This enhances the predictive capacity of our system, ensuring it can provide accurate and trustworthy traffic forecasts.

B. PHYSICS INFORMED NEURAL NETWORK TRAFFIC STATE ESTIMATOR (PINN-TSE)

The component of our traffic information system that estimates traffic patterns is constructed on a neural network model. This model is specifically engineered to leverage the processed data, learn traffic patterns, and check its estimations with the physical laws that govern traffic flow. A detailed explanation of each segment of the full architecture of the PINN-TSE model, represented in Figure 1, is provided in the subsequent sections.

1) DATA COMPUTATION ASPECT

In order to learn traffic patterns from the data, we employ a multi-layer perceptron (MLP). This type of neural network, known for its capacity to handle complex data patterns, incorporates an input layer, several hidden layers, and an output layer is used.

The input layer is designed to receive the processed independent variables input data, including position and time that determine the density and speed of the traffic. This data is then passed through the hidden layers, each consisting of a set number of neurons. These neurons apply various weights and biases to the data, and each layer's output becomes the input for the next layer. The final layer, the output layer, provides the predicted traffic density.

The MLP incorporates nonlinear activation functions to better capture the complex relationship between the different inputs. Each layer's number of neurons and the type of activation function used were determined through a series of experimental iterations to optimize the model's performance.

The architecture of the neural network is crucial for the accurate prediction of traffic density, which serves as the foundation of our traffic information system. By fine-tuning the structure and hyper-parameters of the network, we were able to create a model that can effectively learn from the historic traffic data and make accurate predictions.

2) PHYSICS COMPUTATION ASPECT

In addition to observed traffic pattern, our to traffic prediction leverages the power of physics-informed learning. By integrating physical laws into the neural network model, we ensure that our predictions adhere to real-world traffic behavior, enhancing the reliability and accuracy of our system.

The PINN uses the fundamental laws of traffic flow, mainly the conservation of vehicles, to guide its learning process. In traffic flow theory, the conservation of vehicles states that the number of vehicles in a given section of roadway is equal to the number of vehicles that entered minus the number of vehicles that exited. Incorporating this law allows the neural network to better understand the relationship between traffic density and speed, leading to more accurate predictions.

To implement this, the Lighthill-Whitham-Richards (LWR) model is used. The LWR model is a macroscopic traffic flow model used in transportation engineering to describe the evolution of traffic density on a roadway. While the LWR model assumes that all drivers behave identically and that traffic conditions are homogeneous across lanes, which may not always be the case. Despite its limitations, the simplicity of the LWR model has significantly influenced the field of traffic flow theory and continues to be a key reference point for researchers and practitioners alike.

The LWR model is mathematically represented by a first-order, nonlinear partial differential equation, a conservation law that describes how the density of traffic evolves over time and space. The equation reflects the principle that the rate of change of vehicle density within any segment of road depends on the difference between the flow rates entering and exiting the segment. The basic form of the LWR PDE is:

$$\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x}(\rho \cdot v(\rho)) = 0 \tag{1}$$

Here, $(\rho(x, t))$ represents the traffic density at position (x) and time (t), and $(v(\rho))$ is the velocity of traffic, which is a function of density.

To simplify the relationship, Greenshield's model that postulates a linear relationship between traffic density and speed, can be employed [35]. This relationship is expressed as:

$$v = v_{max}\left(1 - \frac{\rho}{\rho_{max}}\right) \tag{2}$$

where v represents the space mean speed, v_{max} is the maximum attainable speed, ρ is the traffic density, and ρ_{max} is the maximum traffic density.

By utilizing these relationships, we can substitute Greenshield's equation into the Lighthill-Whitham-Richards (LWR) conservation law (equation 1) to solve it for traffic density, as presented here:

$$\frac{\partial \rho(x,t)}{\partial t} + v_{max}\left(1 - \frac{2\rho(x,t)}{\rho_{max}}\right)\frac{\partial \rho(x,t)}{\partial x} = 0 \tag{3}$$

It's worth noting that this equation is a hyperbolic partial differential equation (PDE), which poses certain challenges in finding strong solutions. To address this, a second-order diffusion term with user defined small numbers, ϵ, can be introduced to the equation (equation 4), transforming the PDE into a parabolic form as in [27]. This modification helps ensure the existence of a strong solution and enhances our ability to study and model traffic flow dynamics accurately.

$$\frac{\partial \rho(x,t)}{\partial t} + v_{max}\left(1 - \frac{2\rho(x,t)}{\rho_{max}}\right)\frac{\partial \rho(x,t)}{\partial x} = \epsilon\frac{\partial^2 \rho(x,t)}{\partial x^2} \tag{4}$$

By rearranging the terms, we can introduce a regularization factor, denoted as R, which serves to enforce compliance with the underlying physics of traffic flow:

$$\frac{\partial \rho(x,t)}{\partial t} + v_{max}\left(1 - \frac{2\rho(x,t)}{\rho_{max}}\right)\frac{\partial \rho(x,t)}{\partial x} - \epsilon\frac{\partial^2 \rho(x,t)}{\partial x^2} = R \tag{5}$$

This regularization factor, R in equation 5, plays a crucial role in ensuring that the neural network adheres to the principles governing traffic flow. Using R, we formulated a loss function that combines the data driven standard mean squared error and R, a physics-informed term. This term penalizes predictions that violate the conservation law, guiding the network to generate results that align with real-world traffic patterns. The weights and biases in the neural network are then updated using a gradient descent algorithm, balancing the need for accurate data fitting and adherence to physical laws.

The integration of physics-informed learning into the neural network architecture is a key feature of our approach, bridging the gap between data-driven machine learning models and physics-based traffic prediction.

C. PINN-TSE TRAINING

As illustrated in Figure 1, the PINN-TSE training unfolds in two main steps:

1) DATA-DRIVEN TRAINING

During the first epoch, we utilize observed position and time data (x_o and t_o) as input to the neural network to compute the estimated-traffic density, represented as $\hat{\rho_o}$, while employing randomly initialized parameters. This estimated density is compared against the observed density (ρ_o). This comparison is quantified by computing the mean square error (MSE), constituting a vital component of the data-driven loss. Thus, the data driven loss function serves as a guide, steering the model towards minimizing the disparity between its predictions and the ground truth data sourced from the NGSIM dataset.

2) INTEGRATION OF PHYSICAL LAWS

In the second phase of our process, we utilize the collocation position (denoted as x_c) and time (denoted as t_c) points to derive the density at these arbitrary points, as shown in Figure 7.

These points are inputted into the neural network to compute an estimated density, represented as $\hat{\rho_o}$. Simultaneously, the differential network uses these data points and the corresponding density ($\hat{\rho_c}$) to solve the partial differential equation, yielding the regularization factor (R). Under ideal circumstances where the model fully complies with the physical laws, R should be zero. With each iterative step, the value of R quantifies the degree to which the neural network deviates with the fundamental conservation law, with the network's design aiming to reduce this factor at each iteration. This factor regulates the total loss, steering the model to respect the physical conservation law and ensuring the network adheres to the principles of traffic flow theory. By incorporating the regularization loss into the data-driven loss, we create a comprehensive loss framework that ensures the model learns from both the observed data and the physical conservation law. This integrated learning framework significantly enhances the accuracy and efficiency of our AI-integrated traffic guidance system in real-time traffic estimation and assistance.

D. USER INTERACTION AND STREAMLINED SYSTEM WORKFLOW

Our AI-empowered traffic guidance system is designed to provide a seamless journey from user input to insightful, contextually appropriate responses. This journey is facilitated through a well-structured series of steps, ensuring an accurate understanding of the user's query, precise traffic predictions, and delivery of easily understandable responses (Figure 2).

The journey begins with the interpretation of the user's traffic-related query. Using Spacy NLP and regular expression techniques, the system deciphers whether the query is time-specific or requires a more comprehensive response, based on the time and location input values provided.

Once the user's intent is understood, the system tailors input parameters for the PINN-TSE model according to the nature of the query. For specific queries, the model precisely extracts temporal and location values. For broader inquiries covering multiple inputs, the system assembles a coherent timeline, relative to when the traffic model was initiated, and pairs it with the corresponding spatial data.

Maintaining the system's integrity is paramount, hence, we've implemented a rigorous cleaning process. This process employs Spacy and regular expression techniques to eliminate any non-numerical values, rectify errors, and standardize the input format into time and location pairs.

With the refined input, the PINN-TSE model steps in, delivering real-time traffic density predictions. These predictions are informed by traffic flow conservation laws, capturing the dynamic nature of congestion and the complex mechanics of traffic shockwaves.

Subsequent to generating traffic density predictions, the system categorizes the traffic state. Here, traffic density is evaluated against predefined thresholds to provide a succinct description of the current traffic condition, preparing the system for the final user response generation step.

In the concluding phase, traffic density predictions and traffic state categorizations are handed off to the GPT-4 interface. This interface crafts precise, informative, and contextually rich responses, bridging the gap between the system's analytical prowess and the user's comprehension.

In essence, our AI-integrated traffic guidance system harmoniously blends the strengths of the GPT-4 interface and the PINN-TSE model. This blend ensures accurate traffic estimations and personalized user assistance, facilitated by a seamless workflow of user input interpretation, PINN-TSE integration, and response composition. This streamlined process guarantees a user-friendly experience.

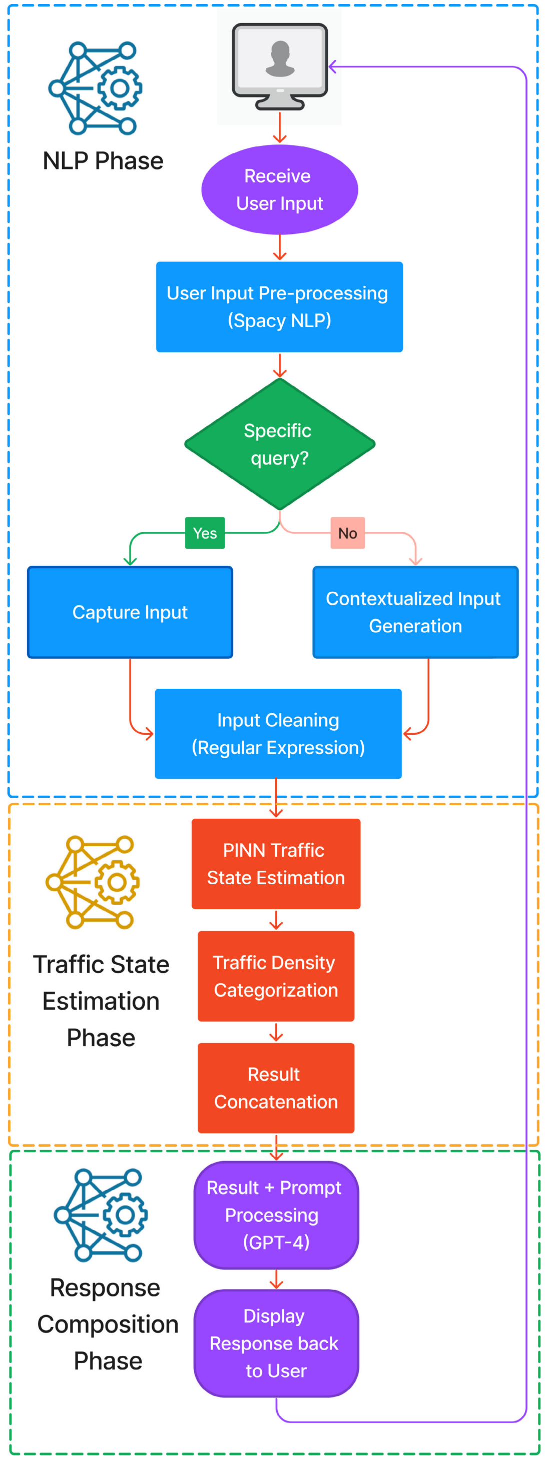

FIGURE 2. **AI-integrated traffic information system's architecture.**

E. GPT-4 INTERFACE DEVELOPMENT

The Language Learning Model (LLM), GPT-4, interface serves as the communicative bridge between the user and our AI-integrated traffic guidance system. It's responsible for interpreting user inquiries, linking them to the neural network's predictions, and generating understandable responses.

The interaction between the user and our AI-Integrated Traffic Guidance System starts with the user's query, which is stored in a payload. This payload provides the GPT-4 with the necessary information to understand and interpret the intent and context of the user query. It also reserves a slot for the output from the PINN-TSE model and the categorized information regarding traffic conditions, thus facilitating context-aware assistance.

To implement the GPT-4 interface, we use Azure's AI Studio API, with the model being a pre-trained GPT-4. To tailor the model to function as a traffic information system, we leverage the prompt engineering technique. The prompt, which is integral to the payload, guides the model on its function, purpose, and the compilation of the user query. It includes the role, persona, and background information, providing clarity and instructions specifying the role-playing requirement of it. The prompt used is: "I am an AI assistant designed to assist in predicting traffic conditions within a 2100ft long portion of I-80. My role involves receiving time and location information from users, along with calculated traffic density results, and then providing the result to users along with an explanation."

The NLP models prepare and infuse the input values into the PINN-TSE model, facilitating system response generation. After receiving the numeric traffic density predictions and traffic category insights from the PINN-TSE model, these results are integrated into the payload. Now enriched with user query, PINN-TSE's estimations, and traffic category details, this payload is directed towards an LLM instance. Utilizing the information from the enhanced payload, the LLM generates a response that merges physics-driven predictions with the sophistication of natural language understanding.

This integration results in a harmonious blend of intelligence. The linguistic proficiency of the LLM, intertwined with the precision of the PINN-TSE's estimations, creates a user experience that surpasses the capabilities of each individual component. The outcome is a streamlined user experience, where users are presented with clear, contextually relevant responses that decode the complex dynamics of traffic.

F. SYSTEM VALIDATION

Ensuring the reliability and accuracy of our AI-integrated traffic information system is of utmost importance. Therefore, we implemented a rigorous system validation process to assess its performance.

The validation process involves two key steps: PINN-TSE model performance test and overall system interaction experience test. In the PINN-TSE performance test, we partitioned the I-80 dataset into training and testing subsets. The neural network was trained on the training subset and then evaluated on the testing subset. This process was repeated several times, each time with a different partitioning of the data. Such model validation provides an unbiased estimate of model prediction performance and helps prevent overfitting.

To quantify the system's performance, we used several metrics including accuracy, precision, and recall. These metrics provided a comprehensive evaluation of the system's prediction capabilities, considering both the number of correct predictions and the proportion of relevant instances among the predicted ones.

Following cross-validation, we conducted the chat performance testing. In this step, we tested the system using live user interaction with GPT-4. This allowed us to assess the system's performance in understanding user query and its ability to compose tailored responses.

IV. IMPLEMENTATION AND RESULTS

A. TRAFFIC MODELING

The foundation of our traffic modeling lies in the implementation of the PINN-TSE traffic predictor. The essence of this system is the harmonious fusion of historic traffic data and the principles of physics to predict traffic density.

The model development leverages data from the Next Generation Simulation (NGSIM) program. Our focus was on the dataset from the I-80 eastbound freeway between Powell Street and Ashby Avenue in Emeryville, California. This dataset provides tenth-second vehicle trajectories for a 2,100-foot-long section of the freeway with five lanes, collected over three consecutive 15-minute periods on April 13, 2005.

The raw data was thoroughly cleaned and adjusted for spatial and temporal resolution to 20 feet and 1 second, respectively, during the preprocessing phase. This resolution adjustment was achieved after testing different combinations, and it resulted in a manageable data size and acceptable level of input data detail. We calculated traffic density by summing up the vehicle count across all five lanes and averaging the speed within the spatial and temporal bins (Figure 3 and 4). Then, we used regression analysis to establish the relationship between density and speed based on the average traffic density and vehicle speed data, as shown in Figure 5.

Using Greensheild's speed-density relationship, we computed the free-flow speed to be approximately 47 ft/sec and the maximum density to be around 37 vehicles per 20 feet of roadway. This calculation provided critical input for the PINN model. We then determined the traffic flow for each data point using the formula $q = \rho * v$ and established the traffic density-traffic flow relationship, as depicted in Figure 6.

The PINN model, defined using the PyTorch framework, was trained through a meticulous process involving testing of various hyper-parameters. The training process was monitored through the propagation of training and validation loss curves, which provided insights into the model's performance at each step. The principle of random search was used to explore a range of hyper-parameters, including learning rates, batch sizes, the number of hidden layers, and the number of neurons in each layer. The goal was to identify the

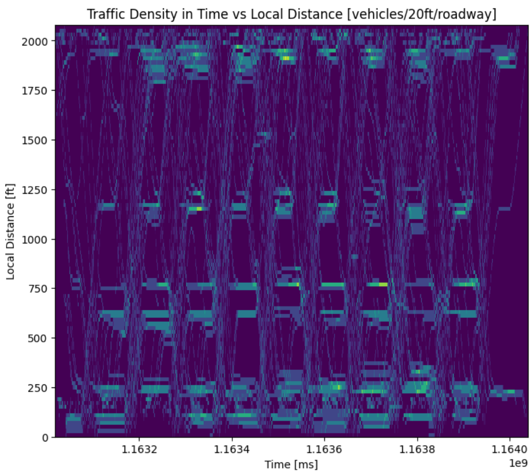

FIGURE 3. Traffic density map at 1 sec-20 ft resolution.

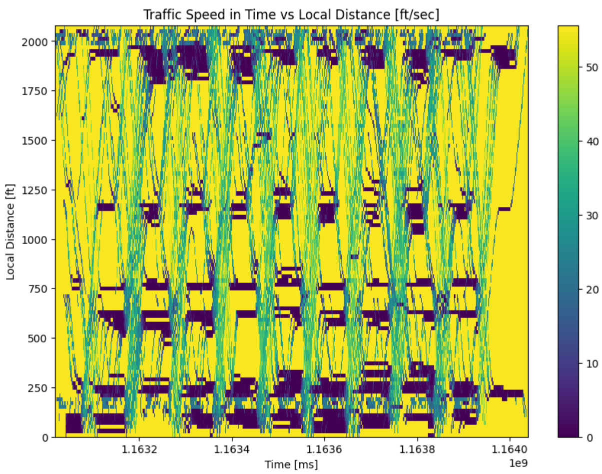

FIGURE 4. Average traffic density map at 1 sec-20 ft resolution.

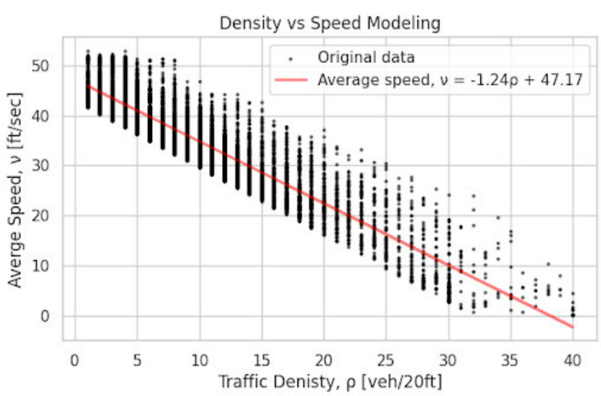

FIGURE 5. Density vs space mean speed plot.

optimal model configuration that offers a balance between computational efficiency and accuracy.

The I-80 dataset was partitioned into training and testing subsets to evaluate the performance of the traffic estimator. The model was trained on the training subset, and then evaluated on the testing subset to compute the data loss. Simultaneously, random collocation inputs, given in Figure 7, were utilized to derive the density at arbitrary points. These values are used to quantify the physics loss, given by R (equation 5), measuring the model's deviation from the underlying traffic flow principles. Both losses were used to optimize the network. This process was repeated multiple times, with different partitioning of the data each time, while noting the model's hyper-parameters.

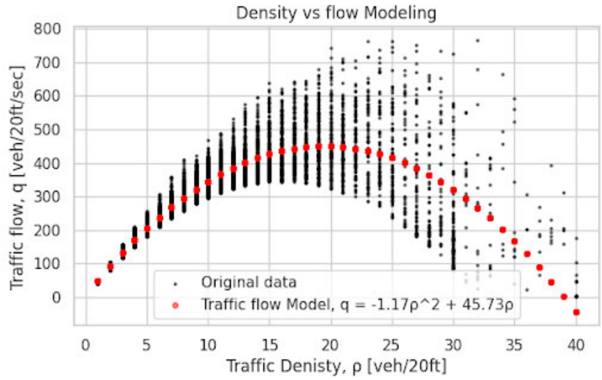

FIGURE 6. Density vs traffic flow plot.

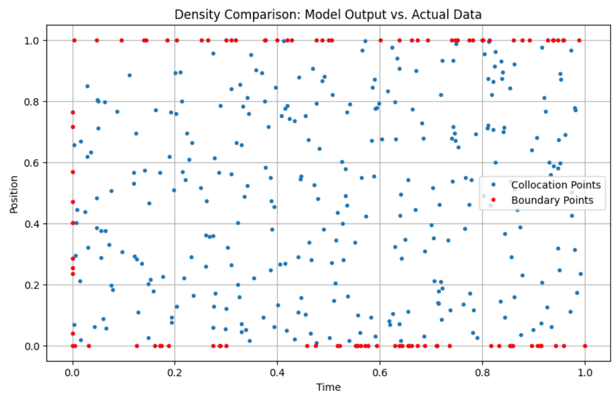

FIGURE 7. Boundary and collocation points (Red dots represent observed values(x_o, t_o) and blue dots represent collocation values (x_c, t_c).

The testing platform used was a desktop computer equipped with an Intel XEON @ 2.40GHz × 24 CPU, an NVIDIA Quadro M4000 GPU, and a 32GB RAM for data processing.

Accordingly, the implementation of the PINN-TSE involved extensive data preprocessing, meticulous training, and rigorous testing to ensure accuracy and compliance with traffic flow principles.

B. SYSTEM VALIDATION RESULT

The validation process involves two key steps: PINN-TSE model performance test and overall system interaction experience test.

1) PINN-TSE MODEL PERFORMANCE RESULT

Our assessment of the PINN-TSE model's effectiveness involved two key performance metrics. The Mean Absolute

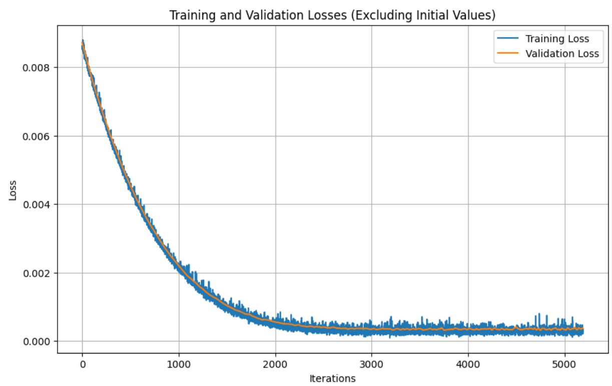

FIGURE 8. Training loss for epoch [26000, 31100].

Error (MAE) and Mean Squared Error (MSE) were used particularly in quantifying the average deviation of predicted traffic density from the observed values.

The Mean Absolute Error (MAE) obtained for the PINN-TSE model is 0.0188, representing the average absolute difference between the predicted traffic density and the actual observed data. A lower MAE indicates a higher degree of proximity between the model's predictions and the ground truth values, reflecting its accuracy and precision.

Furthermore, the Mean Squared Error (MSE) of 0.0007 quantifies the average squared difference between the model's predicted traffic density and the observed values. This metric offers valuable insights into the overall magnitude of errors present in the model's estimations.

The results obtained with these performance measures attest to the robustness and reliability of the PINN-TSE model in accurately predicting traffic density. The MAE value of 0.0188 for normalized traffic density corresponds to a deviation of approximately 4 vehicles per mile per lane. This demonstrates the model's ability to bridge data gaps along a 2100-feet road stretch, further reinforcing its effectiveness. Additionally, the low MSE value of 0.0007 highlights the model's consistent alignment with observed data, emphasizing its efficacy in capturing and interpreting complex traffic dynamics.

In addition, the training and validation loss curve for the PINN-TSE model steadily decreases over time, indicating effective learning from the training data (as illustrated in Figure 8). This graph visually depicts the model's convergence during the training process, with a final MSE loss of 0.00021, showcasing its ability to make accurate traffic density predictions.

In line with the model accuracy measure, the optimal model configuration of the PINN-TSE model that led to the reported MAE and MSE values, and best met our performance objectives, is outlined in Table 1. This table summarizes the hyper-parameters of the PINN-TSE model developed in this study.

In identifying these system configuration values through a random search, we prioritized minimizing both the model's

TABLE 1. Optimum hyperparameters of the experiment.

Hyperparameter	Value
Learning Rate	0.001
Activation Function	ReLU
L2-Regularization	0.01
Neurons per Hidden Layer	120
Hidden Layers	16
Batch Size	256

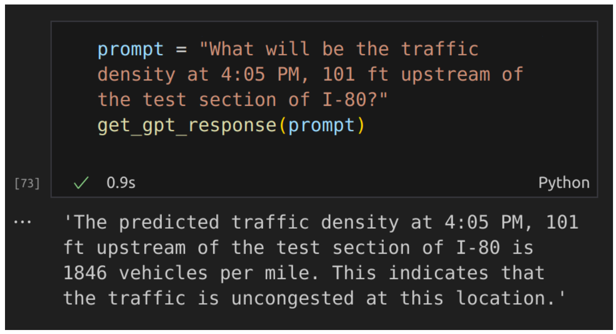

FIGURE 9. System response: specific time and location input.

complexity and the computational costs while monitoring models accuracy. As such, we employed a phased approach, initiating with simpler configurations and progressively advancing to more complex ones, all within the adaptable framework of PyTorch.

2) SYSTEM INTERACTION EXPERIENCE

Following PINN-TSE quantitative evaluations validation, the AI-Integrated Traffic Information System was assessed qualitatively through user interactions and the responses generated through text chat. These experiments aimed to assess the system's ability to provide customized, user-oriented responses, its comprehensiveness in conveying key insights derived from the PINN-TSE model, and its capacity to handle scenarios with incomplete queries.

In four distinct scenarios, we presented the model with varying prompts related to traffic density queries. The responses generated by the system were prompt-based and tailored to the user's query. These scenarios involved users posing traffic-related queries, and the system's responses demonstrated its ability to provide accurate and user-oriented information.

Scenario 1: Specific Time and Location:

In scenario 1, the system is queried about a specific time and location. The user asks, "What will be the traffic density at 4:05 PM, 101 ft upstream of the test section of I-80?" The system responds with a clear and precise answer, stating that the predicted traffic density at the given time and location is 1846 vehicles per mile, classifying the traffic as "uncongested.", as shown in Figure 9.

The system's response in this scenario demonstrates its capability to accurately interpret and respond to specific queries about traffic density at a given time and location.

```
prompt = "What is the traffic condition
at 4:10 PM, upstream of the road section?"
get_gpt_response(prompt)

✓ 0.9s                                        Python

'The traffic condition at 4:10 PM, upstream of
the road section, is uncongested. The number
of vehicles per mile gradually increases as
you move upstream, ranging from 1841 vehicles
per mile at 100 ft upstream to 1850 vehicles
per mile at 2000 ft upstream. However, these
numbers indicate a relatively low traffic
volume, suggesting that traffic is flowing
smoothly without any significant congestion.'
```

FIGURE 10. System response: No location input, generalization over distance (response 1).

```
prompt = "What is the traffic condition
at 4:10 PM?"
get_gpt_response(prompt)

[69]  ✓ 1.4s                                  Python

... 'Based on the predicted traffic conditions, at
4:10 PM, the traffic is uncongested at various
locations along the 2100ft portion of I-80.
The number of vehicles per mile gradually
increases as we move upstream, indicating a
smooth flow of traffic. The traffic volume
ranges from 1841 vehicles per mile at 100 ft
upstream to 1850 vehicles per mile at 2000 ft
upstream. Overall, it appears to be a
relatively smooth and free-flowing traffic
situation.'
```

FIGURE 11. System response: No location input, generalization over distance (response 2).

It also shows the system's ability to contextualize this information by classifying the traffic state, providing a more comprehensive response to the user's query. *Scenario 2: Specific Time, Generalized Location:*

In this scenario, the system is challenged with a prompt that specifies a time but leaves out details on the location. The user asks, "What is the traffic condition at 4:10 PM?" The absence of a specific location in the query is an opportunity to examine the system's capability to generalize over distance and provide a comprehensive understanding of the traffic progression over various locations.

Two separate instances of system execution, denoted as Response 1 and Response 2, are provided for the same prompt (Figure 10 and 11). This helps in evaluating the system's flexibility and its ability to convey similar traffic predictions in diverse ways. Response 1 indicates that the traffic condition at 4:10 PM, upstream of the road section, is uncongested. It provides additional details on the range of vehicles per mile as one moves upstream, thus presenting a dynamic picture of the traffic situation over distance.

```
prompt="What will be the traffic density
205 ft away from the I-80 test road
portion?"
get_gpt_response(prompt)

[76]  ✓ 0.9s                                  Python

... 'The predicted traffic density 205 ft away
from the I-80 test road portion is expected to
be around 1852 vehicles per mile at 4:00 PM.
The traffic is forecasted to remain
uncongested with similar densities of around
1847 vehicles per mile at 4:05 PM, 1842
vehicles per mile at 4:10 PM, and 1837
vehicles per mile at 4:15 PM.'
```

FIGURE 12. System response: No time input, generalization over time (response 1).

System response 2, on the other hand, offers a slightly different interpretation of the same traffic prediction. It provides a comprehensive overview of the traffic condition at various points along the I-80 section at the specified time. The detailed description of traffic volume at different points upstream emphasizes the traffic's smooth flow.

In both instances, the system successfully conveys the traffic's progression over an unspecified distance at a specific time. It demonstrates a commendable ability to generalize over distance and provide a comprehensive understanding of traffic conditions, despite the absence of a precise location in the prompt. Moreover, the system responses in this scenario showcase the system's flexibility in interpreting and elaborating on the same traffic prediction in different manners, underlining the traffic information system's potential to assist users in understanding traffic by composing responses with varying degrees of specificity and presenting the same traffic information in different ways.

Scenario 3: Specific Location, Generalized Time:

Scenario 3 tests the system's ability to handle inquiries about a specific location but with a generalized time. The prompt given is "What will be the traffic density 205 ft away from the I-80 test road portion?"

In response to this prompt, both response 1 and response 2 provide detailed traffic density predictions for the specified location, albeit with slightly varied interpretations (Figure 12 and 13).

Response 1 gives a comprehensive response by providing projected traffic density at various time points for the given location 12. It predicts a similar trend of uncongested traffic at 4:00 PM, 4:05 PM, 4:10 PM, and 4:15 PM, providing the user with a clear picture of the traffic pattern over time.

System response 2 also provides a detailed response, predicting traffic density at the specified location as uncongested 13. It, however, adds a warning that these predictions are based on historical data and that unforeseen events

```
prompt="What will be the traffic density
205 ft away from the I-80 test road
portion?"
get_gpt_response(prompt)
[78]  ✓ 1.4s                                Python

... 'Based on the predicted traffic conditions,
the traffic density 205 ft away from the I-80
test road portion is expected to be around
1852 vehicles per mile. The traffic is
classified as uncongested during this time
period. Please note that these predictions are
based on historical data and other factors
such as accidents or road closures can affect
the actual traffic conditions.'
```

FIGURE 13. System response: No time input, generalization over time (response 2).

```
prompt="What will be the general traffic density
the I-80 test road portion?"
get_gpt_response(prompt)
[102]  ✓ 0.8s                                Python

... 'Based on the predicted traffic conditions, the general
traffic density at the I-80 test road portion is
relatively low. The number of vehicles per mile ranges
from 1836 to 1860, and traffic is classified as
uncongested. This suggests that there should be smooth
traffic flow with minimal delays or congestion in the
area.'
```

FIGURE 14. System response: generalization over time and location (response 1).

like accidents or road closures can affect the actual traffic conditions.

It is shown that both system responses have effectively interpreted and responded to the inquiry about a specific location but with a generalized timeframe. This scenario showcases the system's capacity to generate traffic predictions for a specific location over a range of times, providing valuable insights to the user about the traffic pattern and potential fluctuations.

Scenario 4: Generalized Traffic Inquiry:

In Scenario 4, the system is presented with a generalized traffic inquiry: "What will be the general traffic density of the I-80 test road portion?" 14. This scenario is designed to evaluate the system's ability to generalize over both time and location, providing users with an overarching perspective of the traffic conditions.

System's response 1 offers a general outlook on the traffic density at the I-80 test road portion, indicating it as relatively low. It provides a range of vehicles per mile and classifies the traffic as uncongested, suggesting a smooth traffic flow with minimal delays or congestion. However, it fell short in specifying the time and location range over which the traffic density was generalized. This lack of specificity might leave users uncertain about the time and location range parameters of the provided traffic condition.

```
prompt="What will be the general traffic density
the I-80 test road portion?"
get_gpt_response(prompt)
[118]  ✓ 1.4s                                Python

... 'The general traffic density on the I-80 test road
portion is relatively low. At 4:00 PM, the traffic
density ranges from 1851 vehicles per mile at 100 ft
upstream to 1860 vehicles per mile at 2000 ft upstream.
As the time progresses, the traffic density slightly
decreases, with the density ranging from 1836 vehicles
per mile at 100 ft upstream to 1845 vehicles per mile
at 2000 ft upstream by 4:15 PM. Overall, the traffic is
uncongested during this time period.'
```

FIGURE 15. System response: generalization over time and location (response 2).

To address this issue, we modified and tested the prompt used for interacting with GPT-4 multiple times, with the aim of refining the system's ability to handle traffic predictions and compose responses. The revised and optimized prompt was as follows: "I am an AI assistant specialized in predicting traffic conditions along a 2100 ft segment of I-80. My primary function is to assist users in understanding and anticipating traffic scenarios. 1) I will share time and location information If the user prompt has a specific time or location; If either time or location is not provided, I will provide the general start, end or a specific time or location information at which the traffic is low or high. 2) Format of Response: The response will include traffic density results, an explanation of the prediction, and a summary."

Following these adjustments, System's response 2 demonstrated a significant improvement, Figure 15. It offered a more comprehensive traffic density prediction, detailing specific time points for the I-80 test road portion. This response effectively represented the evolution of traffic conditions over time and accurately classified the traffic as uncongested.

Examining all four scenarios, the traffic information system has shown remarkable proficiency in addressing a variety of traffic inquiries. In Scenario 1 to 3, the system adeptly handled specific traffic inquiries, providing precise traffic density predictions for distinct times and locations. However, in Scenario 4, while the system managed to provide a comprehensive response to a complex query, it exhibited minor limitations in providing time and location parameter information while providing traffic predictions. Accordingly, adjustments were made in Scenario 4, where the system was tasked with generalizing traffic density over time and location. Due to subsequent prompt modifications, significant improvements on lack of specificity in time and location parameters were fixed. Thus, response 2 provided detailed traffic density predictions, showcasing an understanding of traffic progression over time and correctly classifying traffic conditions. In conclusion, the system has proven its capability in providing both specific and generalized traffic predictions, demonstrating its potential as an effective tool for users seeking traffic information.

V. DISCUSSION

The research conducted on the traffic information system built upon PINN for traffic prediction and GPT-4 for user interaction highlighted several key findings. First and foremost, the PINN-TSE model exhibited a remarkable ability to fill data gaps in traffic information. The model achieved a Mean Absolute Error (MAE) of 0.0188, equivalent to a deviation of less than 4 vehicles per mile per lane. This finding serves as a strong indicator of the significant potential of PINN in modeling traffic pattern in the field of traffic management. The results underscores the model's capability to offer traffic estimates, particularly in regions where the availability of traffic detectors is limited, thereby paving the way for improved traffic management solutions.

The success of the PINN-TSE model in filling data gaps can be attributed to its incorporation of physics-based principles into neural network training. By leveraging the underlying physics of traffic flow, the model can make informed predictions even when data is missing. This aligns with previous studies in the field that have emphasized the potential of PINNs in various scientific domains [22].

Hence, our system's ability to bridge data gaps and estimate traffic conditions in areas between available data points is a significant breakthrough. This feature ensures the possibility that drivers receive comprehensive traffic information, not solely dependent on live data sources, which is often inconsistent. This aligns with the goals of intelligent transportation systems (ITS) aiming for robustness and adaptability [36].

Furthermore, the qualitative evaluation of our AI-integrated traffic guidance system revealed that the prompt design effectively laid the groundwork for the LLMs to comprehend user intentions and compose personalized responses that seamlessly integrated the PINN-TSE results. This synthesis of AI capabilities allows our system to not only provide accurate traffic predictions but also cater to the specific needs and queries of users, enhancing the overall user experience.

Our qualitative analysis also highlights the critical role played by the prompt design in user interactions. The ability of the Language Model to understand user intent and generate contextually relevant responses is reminiscent of recent advancements in NLP [37] and underscores the importance of natural language understanding in human-AI interactions.

Compared to previous studies, this research stands out for its innovative application of PINN-TSE for forecasting traffic trends, coupled with the utilization of GPT-4 to facilitate user engagement [20], [27], [38], [39], [40]. This research has successfully integrated GPT-4 and it has enhanced user interaction by serving as an intermediary, interpreting the model's output in response to user queries [].

The findings of this research have significant implications for the field of traffic information systems. The system's ability to predict traffic density and enhance user interaction suggests potential for its application in traffic management, route planning, and other related areas. Future research could focus on improving the system's capacity to handle additional and enhanced physical laws in estimating traffic and expanding its application to larger geographical areas.

VI. CONCLUSION

Our research demonstrates the effectiveness of the AI-integrated traffic information system, which combines the strengths of the PINN-TSE model and advanced natural language processing. It has the potential to revolutionize real-time traffic estimation and assistance, making it more accurate, user-centric, and robust.

The outcomes of this research will have the potential to revolutionize real-time traffic estimation and assistance, enhancing urban mobility and navigation. Additionally, the study contributes to the broader field of AI integration in urban infrastructure management, showcasing the benefits of combining different AI techniques to tackle complex real-world challenges.

However, it's important to acknowledge the limitations of our study. The experiment focused on a single 2,100 feet road segment, at US I-80. To expand the system's utility, future research could explore network-level implementations to guide drivers across a broader geographical area and various traffic conditions.

Furthermore, recommendations for future work include exploring the integration of real-time data sources, such as traffic cameras and sensor networks, to further enhance the accuracy of traffic predictions. Additionally, the system's scalability and deployment in diverse geographical and traffic scenarios should be investigated to ensure its applicability beyond the current scope.

In conclusion, our research not only presents an AI-integrated traffic information system but also offers a promising avenue for future developments in the field of intelligent transportation systems.

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