# Integrating Cyber-Physical-Social Intelligence for Safer and Smarter Transportation Systems: A Comprehensive Literature Review

**MD SADMAN ISLAM[1], AHMED IMTIAZ ZAMEE[2], and MOHAMMAD JALAYER[3]**
[1]Rowan University, Glassboro, NJ 08028 USA
[2]Rowan University, Glassboro, NJ 08028 USA
[3]Rowan University, Glassboro, NJ 08028 USA

Corresponding author: Md Sadman Islam (e-mail: islamm26@rowan.edu).

**ABSTRACT** The number of fatalities due to human error or mistakes has increased all around the world, including the United States, over the past decades. According to NHTSA, over 42,000 deaths have been recorded all over the United States in 2022, and 90% of which was due to human error or mistakes. Although there was a significant advancement in transportation technologies, the number of crashes has not decreased over the years. The need for integrating new emerging technologies with the physical and social layers is necessary to consider, as human feedback and interaction over the technologies can reduce crashes and improve mobility. Studies show that Cyber-Physical-Social-Intelligent (CPSI) technologies like Vehicle-to-Everything (V2X) communication can reduce traffic fatalities by up to 80%, while human-centered design in automation can significantly improve compliance and lower risky behaviors. Despite their growing importance, there is a lack of proper review to integrate these machine-based autonomous technologies with human feedback input, along with the implementation challenges. This paper provides a comprehensive literature review of CPSI applications in transportation sectors, exploring theoretical models, the potential scopes, and the immense possibilities of integration of Cyber-Physical-System (CPS)-based technologies in the current transportation system in a simple, easy, and fluent way. Real-world applications of these technologies have also been discussed for the smart city framework, wrong-way driving detection, human-machine interaction, and other aspects, along with their potential benefits. Despite these advancements, several technical and institutional challenges, like data security, data management, computational capability, and financial restraints, can impede the widespread deployment of Cyber-Physical-Social System (CPSS). By addressing these challenges, this review presents the key gaps in the implementation challenges of CPSI and proposes a roadmap for future development. This review will create scope for future researchers to study this growing field as well as support policymakers, engineers, and researchers in planning and designing transportation systems that are not only intelligent but also adaptive, human-centered, inclusive, and safer for all users, contributing to long-term sustainable goals like vision zero initiatives.

**INDEX TERMS** Cyber-Physical-Social Intelligence, Transportation Safety, Human-Centered Systems, Intelligent Infrastructure, Connected Vehicles

## I. INTRODUCTION

THE CPSI refers to the ability of interconnected systems to sense, interpret, and respond to data and events across cyber, physical, and social domains in an intelligent and adaptive manner [1]. These platforms integrate computing, control, networking, and analytics with real-world environments and users. They can change many things, such as medical gadgets and energy systems [2]. As the world moves forward and machine learning and computer vision are employed in more fields, more firms are adopting CPSI to develop systems that are smart, flexible, and people-centered. Some of these firms are in healthcare, manufacturing, energy, education, and city planning. By merging data from physical sensors, cyber infrastructure, and human behavior, CPSI makes it feasible to make judgments in real time, offer personalized services, and make these areas more efficient. [3], [4]. Similarly, CPS refers to an integrated system where computer algorithms interact with physical processes with the help of communication networks, hardware, sensors, or actuators, regardless of any intervention of social components. Building upon this concept, CPSS incorporates the social dimension by integrating human behaviors, social interactions, and user-generated data into the decision-making process.

CPSI can make travel safer by combining technology, roads, and how people behave, just like in other sectors. Different technologies are being used by scientists; the metaverse is one of them, which can make life easier by replicating the real world in simulation. It can also make decisions ahead of time to make everyone know, such as road damage and other disparities [5], [6], [7]. Another thing that can help make it more efficient is Autonomous Intersection Management (AIM). It means replacing the traditional traffic lights with smart, adaptive, and self-sufficient intersection control. [9]. It allows the Connected Autonomous Vehicle (CAV) to communicate with the infrastructure using virtual communications. Smart Intersection is another initiative taken by the USDOT in Ohio, which facilitates Vehicle to Infrastructure (V2I) to communicate with the traffic signals using the cloud-based data management system, integrating the driver behavior data. All three are parts of the physical, cyber, and social components, clearly demonstrating the combined effort of the system in CPSI. [2]. Another similar example is the Surtrac adaptive signal system in Pittsburgh, which also integrates real-time data to change and adapt the traffic signal using an Artificial Intelligence (AI)-enabled platform, resembling the usefulness of the CPSI system.[3].

Despite showing promising significance in the transportation sector, the CPSI has gaps. One of them is the lack of compatibility and standardization between different system infrastructures. Incompatible protocols and standardization by different manufacturers are one of these issues. For example, the Federal Highway Administration (FHWA) has indicated the problem of compatibility of these protocols with the integration of V2I infrastructures, along with various standards for companies. [12], [13]. As cloud-based data storage and the AI-driven structure are always connected online, there is another growing concern of cybersecurity and data breaches. For instance, the attack on a 2015 Jeep Cherokee showed how vulnerable data and security structure can lead to catastrophic consequences, even with loss of control of steering and braking of the vehicle. Additionally, the amount and the size of the data being stored and transferred cause problems of data management and storage. [6], [7]. On top of that, the cost of managing these huge data centers is another parallel impediment in the way, as many small municipalities and towns cannot afford to fund these programs due to funding restrictions. Making the updating of the historical infrastructure to accommodate real-time data transmission might be prohibitively expensive, especially in rural or impoverished locations [8]. Jurisdictional conflicts and barriers also need to be taken into consideration for overcoming these barriers.

To successfully bridge the gap between CPSI and the transportation sector, a thorough literature analysis is needed. Recent literature encompasses the CPS technologies in an enormous field, but the combined effort, especially with the transportation sector, is still around the corner for gaining importance. A well-structured review can identify these overlapping areas and discuss the gaps and barriers in terms of interdepartmental complexity, cybersecurity, and data management options.

This paper presents a thorough review of CPSI in transportation safety, as well as discusses the technical framework and barriers to closing the gaps in the transportation sector. It includes numerous examples like the Smart City project and others, to present more suitable and practical findings to bridge the gaps in the transportation sector using CPS system integration, focusing on solving the barriers like cybersecurity, data breaches, compatibility, and protecting data privacy. The paper also provides a very comprehensive knowledge of the overall use and integration of CPSI within the transportation sectors in a novel way to facilitate a newer research scope for researchers.

## II. METHODOLOGY

To ensure a comprehensive review of CPS, CPSS, and CPSI in transportation safety, a structured literature selection process was followed, as illustrated in Figure 1. Initially, 250 papers, reports, and articles were collected from major academic databases, including Scopus, Google Scholar, and ScienceDirect, along with other relevant sources. During the identification stage, 46 duplicate records found across multiple databases were removed. In the next stage, 31 records were excluded because their keywords or abstracts did not match the scope of the study. Following this, 173 papers were screened through full-text review. During the screening process, 47 studies were excluded because they did not directly address transportation safety, relevant technologies, or cyber-physical system impacts. Finally, 126 papers and reports were included for the final review, forming the basis for the analysis presented in this study.

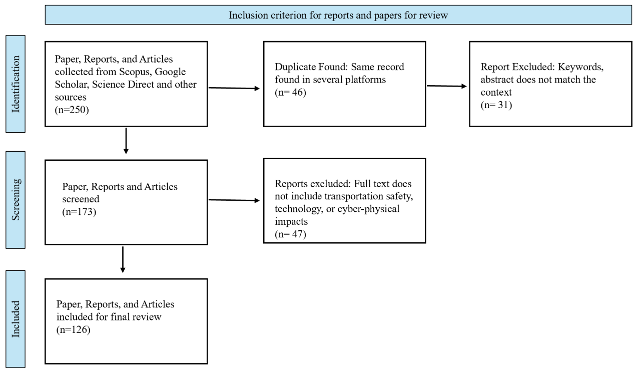


FIGURE 1: Literature identification, screening, and inclusion process used to select research papers and reports for the review.

## III. OVERVIEW OF CPSI

CPSI is a part of the traditional CPS system, which not only integrates the cyber and physical components as a computational framework but also includes the social layer in the form of human behavior and preferences in the decision-making process. In transportation, CPSI provides significant importance in making decisions and emerging as a future emerging sector in traffic control, wrong-way detection, autonomous vehicles, CAV communications, and others. This section provides a comprehensive review of CPSI frameworks that are actively shaping the future of transportation. Figure 2 demonstrates the layers and components of the CPSI system for the transportation sector.

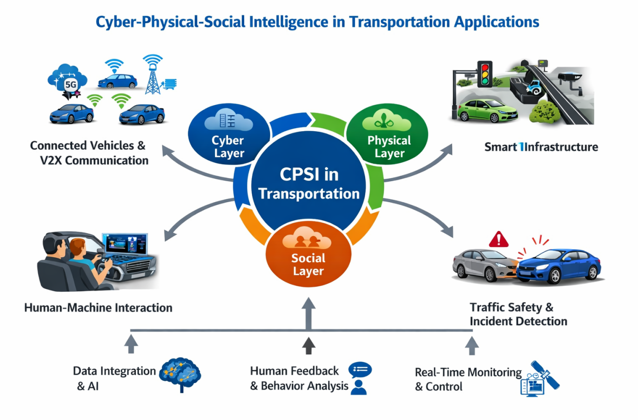


FIGURE 2: Conceptual overview of the CPSI framework integrating cyber, physical, and social layers.

### A. THEORETICAL FOUNDATION AND ARCHITECTURE

**A.1 Human-in-the-Loop (HITL) Systems**

Human-in-the-Loop (HITL) systems are a foundational CPSS framework where human input in terms of behavioral patterns and feedback is integrated with the cyber-physical layers in making the decisions. HITL is being largely used in adaptive cruise control and driver monitoring, which takes into consideration human attention, feedback, and behavior in controlling the vehicle maneuvers. These systems actually connect the eye tracker as a physical layer with the machine learning algorithm as a cyber integration, and make decisions along with the driver's decision pattern and behavior to integrate the social layer to make safety and personalization better in real time [9].

HITL is critical where full automation is not feasible, and it is possible to gain public trust and adoption of the automatic vehicle and other automated technologies. [10].

Key advantages of the HITL are to ensure and enhance safety. When AI systems encounter cases such as unusual traffic patterns, extreme weather, or unpredictable pedestrian behavior, human intervention can prevent potential crashes and ensure passenger protection [11], [12], [13].

Another benefit for the HITL is not only making the transportation safe using automation, but also making it learn using human feedback in the overall process to apply it in the future [14]. This iterative loop is fundamental for building trustworthy autonomous systems, which helps to gain human trust and create human accountability. In logistics and freight operations, HITL is helpful in managing route disruptions in terms of sudden incidents or delays, optimizing delivery paths for the freight movement, and responding to real-time challenges that require numerous decision-making processes. [15].

Examples of HITL in recent development are many, such as in autonomous vehicles, where human drivers can take control during high-risk situations, during heavy traffic, or in low-visibility conditions [15]. Moreover, in freight transportation with the larger vehicles, the HITL is being used in overall decision making using the driver's decision preference during secondary crash or delay to improve the travel time and overall mobility [16]. In addition to that, traffic management systems use human decisions to monitor traffic flow and make modifications to traffic signals and routing strategies based on real-time data and localized insights [17].

HITL can be classified into several operational modes: HITL, where humans directly participate with or override the system; Human-on-the-Loop (HOTL), where humans supervise and correct any anomalies during post-operation; and Human-out-of-the-Loop (HOOTL), which refers to fully autonomous systems with no human participation.

HITL systems are a pragmatic and important step toward fully integrating AI into transportation by involving the human in the decision-making process, which makes transportation safer, more reliable, and more acceptable to the public by balancing automation with human control. This will eventually lead to smarter, more ethical, and more resilient transportation solutions [18]. Figure 3 demonstrates the flows and advantages of the HITL system in transportation.

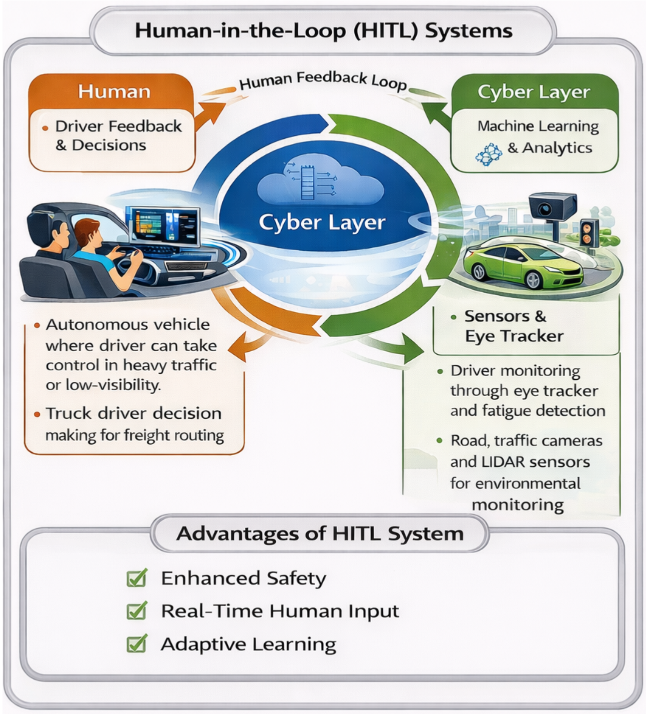


FIGURE 3: The flows and advantages of the HITL system in transportation.

### A.2 Digital Twin Frameworks

Digital Twins are prototypes for the real-world infrastructure that can continuously change and update themselves using the data available. In transportation, they model intersections, highways, or entire networks to simulate and optimize traffic flow as well as analyze any emergency conditions to reroute the traffic. Integration with the social level data, such as pedestrian flows, commuter preferences, or behavioral patterns input, Digital Twins can improve the traffic flow generation and control signals [19]. Digital twins are quickly becoming popular in the transportation sector with the real-time adaptive traffic control and infrastructure development, as well as future potential use in Autonomous Vehicle (AV) navigation and controls. One of the most prominent uses of digital twins is in real-time traffic management to monitor traffic flow, detect bottlenecks, and dynamically adjust traffic signal timings, receiving data from live feeds, working in parallel with other emerging technologies for optimizing traffic flow [20]. In infrastructure monitoring and maintenance, it provides the real-time condition of the infrastructure, such as bridges, tunnels, and roadways, in a predictive way for their maintenance and decay, which allows agencies to anticipate failures and schedule timely interventions, improving safety and reducing costs [19], [21].

Another growing use of digital twin is the various testing and validation of the AVs. Digital twin can replicate various scenarios for the real-world condition, which helps to test these Avs [22]. Companies like Waymo and NVIDIA use high-fidelity digital twins to test autonomous driving systems in virtual environments that replicate complex urban and highway scenarios. These environments simulate sensor input (LiDAR, radar, camera) and vehicle control responses, allowing for safe training and testing of autonomous systems under variable weather, lighting, and traffic conditions without risk to the public. These simulations actually help to make decisions faster in a cost-effective, safe, and efficient way compared to traditional ways. Not only these, in public transportation optimization, it also helps to make route optimization and delay reduction, which ensures that transit systems provide more reliable and efficient services [23].

For the testing of AVs, companies like Transport for London (TfL) integrate digital twins to analyze traditional ridership patterns, bus movement, and passenger occupancy loads. Using these data, TfL dynamically adjusts service frequencies and route patterns, which help the agencies to change the bus fleet during the peak flow time or in case of demand surges [24]. Additionally, in the sector of urban planning, which is also an integral part of the transport system, digital twins help to incorporate different new infrastructure development and zoning in the planning processes to predict the future demand or mobility changes [25]. Cities like Helsinki and Singapore utilize digital twin models to test urban development scenarios, integrating geospatial datasets, building information models, and utility layouts to support long-term planning by simulating the impact of new transit corridors, pedestrian zones, and population growth on transportation demand and infrastructure capacity in the future [26]. Moreover, in freight movement, digital twin helps to improve the logistics and supply chain, which also affects the transportation mobility and travel time improvement in a broader way [27].

Digital twins are projected to become significantly more advanced in the future. They will help with more complex simulations of how traffic behaves and how infrastructure works in different situations, which will help with better planning and policymaking. For example, large-scale citywide traffic simulations using tools like PTV VISSIM or AIMSUN will integrate real-time demand, driver behavior models, and policy interventions (e.g., congestion pricing) to forecast system-level impacts before implementation [25], [28]. Their contribution to autonomous systems will increase with more use of testing and validation in a cost-efficient way. It will also open the door to building integrated transportation networks, connecting various modes such as public transit, personal vehicles, drones, and other automated systems into a single umbrella of an ecosystem [29]. The future of asset management and monitoring is going to be greatly impacted by it, as the use of digital twins can help to predict the condition ahead of time, towards efficient monitoring and maintenance for infrastructures [30]. Platforms like IBM Maximo do condition-based maintenance on pavement, track, and tunnel systems, and use digital twins in their systems for effective monitoring, using past performance data, consumption rates, and exposure to the environment [31].

Despite the potential growth of these systems with digital twins, there are gaps in implementing them due to data variation and data sizes. Sources like GPS, Supervisory

Control and Data Acquisition (SCADA), ITS sensors, and vehicle On-Board Diagnostics (OBD) systems create a huge amount of data in real-time conditions, often in incompatible formats, making them highly difficult to integrate under a unified database [32]. Large-scale digital twin models also need high computational power and scalable cloud or edge computing infrastructure, which are often costly and require highly trained individuals to operate. Additionally, the lack of interoperability correct standards for frameworks, APIs, and data management limits cross-platform integration and system scalability [33], [34]. Finally, the chance of a data breach can affect the privacy and requires robust regulations such as the General Data Protection Regulation (GDPR) [33]. Figure 4 provides the use of digital twins in the transportation sector under various conditions.

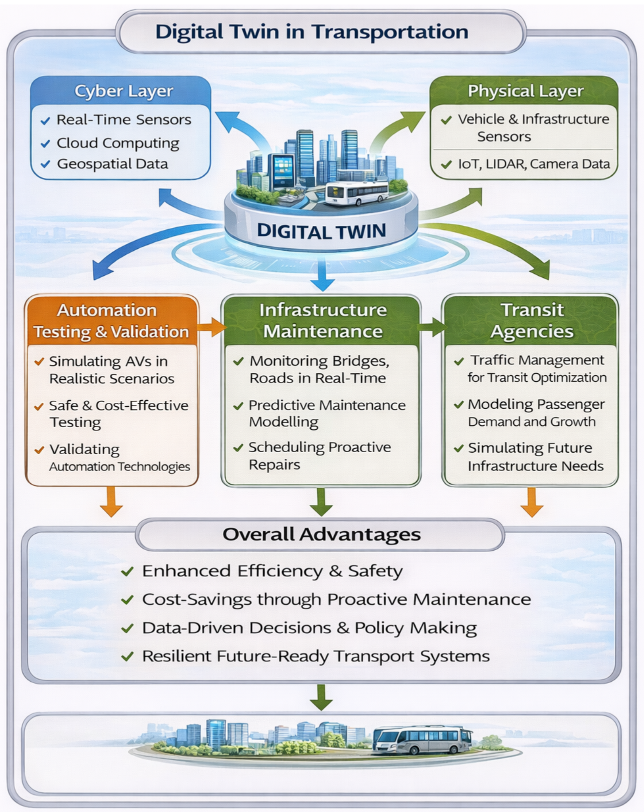


FIGURE 4: The use of digital twins in the transportation sector under various conditions.

### A.3 Smart Mobility Frameworks

Smart Mobility Framework is a system that incorporates infrastructure, cyber, and social data in a single environment. Applications such as dynamic routing, demand-responsive transit, and collision avoidance are highly used in the smart mobility framework data management plans, such as Singapore's Smart Mobility 2030 plan and Helsinki's Mobility-as-a-Service (MaaS) initiatives, which incorporate every human behavior input, a scalable data sharing platform across all infrastructure and jurisdictional levels to ensure a smooth and efficient transportation system [35].

Integration of digital technologies, such as sensors, IoT (Internet of Things) devices, GPS, and communication networks such as Dedicated Short-Range Communications (DSRC) and 5G, are the main components for the smart mobility framework [36]. Data provided by these sensors and technologies stored in a centralized database helps the agencies to keep an eye on the evaluation and improvement of the traffic patterns. Data analytics and AI play a crucial role by identifying trends, demand, and deciding in real-time, such as adjusting signal timings or rerouting transit vehicles during disruptions [37].

A multimodal approach is another component of the smart mobility framework to facilitate people in choosing their mode of transportation instead of using a personal vehicle. This approach encourages a shift from car-centric transportation toward a more integrated system that consists of public transit, walking, cycling, ride-sharing, and emerging mobility options like e-scooters or autonomous shuttles [38]. MaaS platforms also support the goal of a multimodal approach by unifying different modes into one digital interface where users can plan, book, and pay for their journeys, improving convenience and accessibility [39].

Whenever we are talking about the smart mobility framework, sustainability is always an integral part of it. By promoting energy-efficient travel options like Electric vehicles (EVs), these systems help to reduce emissions. Some frameworks also incorporate autonomous vehicles and connected infrastructure to increase fuel efficiency and reduce human error-related crashes [40]. For example, the use of self-driving shuttles can improve travel safety and reduce human error while moving between neighborhoods to the main arterial or expressway stations. Smart applications can also include a user-centric environment that can notify users of delays, suggest faster alternatives, or integrate accessibility features for individuals with disabilities [41]. Adaptive traffic signals and ITS-managed traffic flows are the technical components for smart mobility in terms of physical infrastructure to ensure better movements inside the city. These systems can reduce delay and improve travel time, especially when paired with predictive analysis models and an AI-driven decision-making platform, which works as a cyber layer. Electric and autonomous vehicles are also integral; when supported by connected infrastructure and built into city planning systems, they help create transportation networks that are cleaner, safer, and better prepared for the future.[42].

The benefits of Smart Mobility reach not only simply moving people from one place to another, but also spreading travel demand across different modes and times of day, which helps ease traffic congestion and keep cities flowing more smoothly. Reducing conflict points and lowering the risk of crashes can be achieved by using real-time updates and monitoring, which can save money and shorten travel time. Moreover, it also supports environmental goals by reducing emissions and encouraging the transition to cleaner, low-carbon transportation options. [36], [43].

Cities across the U.S. are already considering and adopting these frameworks. For example, Alexandria, Virginia, has utilized integrated data systems to enhance traffic flow, transit scheduling, and parking efficiency, which not only reduced travel time but also improve mobility. In California, Caltrans Smart Mobility Framework offers a structured approach to implementing sustainable transportation practices statewide, including support for non-motorized travel and land-use integration. Several metropolitan areas are piloting or scaling MaaS platforms, offering a glimpse into the future of seamlessly connected mobility. Figure 5 shows the conceptual framework of the Smart Mobility system, integrating data, technology, and multimodal transportation services

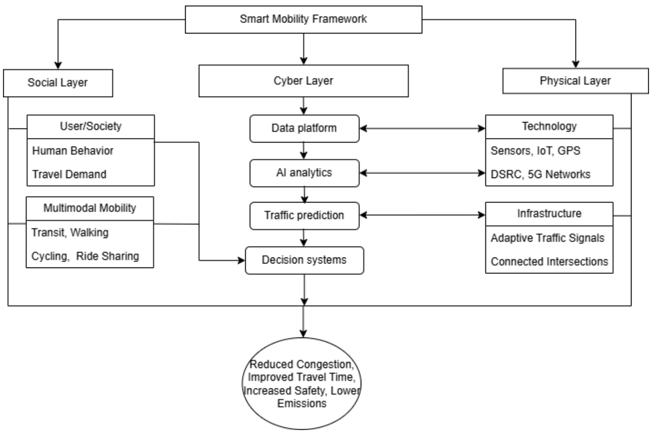


FIGURE 5: Conceptual framework of the Smart Mobility system integrating data, technology, and multimodal transportation services.

### B. EMERGING CPSS APPLICATIONS IN TRANSPORTATION

**B.1 Social-Aware Traffic Systems**

Social-aware traffic system uses crowd-sourced data in terms of social media, mobile phone, or other features to make decisions and update in real-time. These systems significantly update the traffic signal timing using crowdsourced data, mobile phone input, which enhances situational awareness and improves system responsiveness.

Social-Aware Traffic Systems (SATS) are a new emerging area of transportation safety that includes human data in terms of social signal to ensure traffic safety. It can analyze the contextual information, such as a persons travel purpose, the presence of companions (e.g., children or elderly), or nearby environments (e.g., parks, schools, or events), and provide real-time prediction for travel behavior and patterns [44]. These predictions are analyzed based on the data collected from roadside sensors about CVs and pedestrian travel patterns, where the ridership data comes from the on-board transit sensors. Moreover, social media-based event data as well as weather data also integrate with these regular data to analyze a more robust prediction of the human travel patterns. SATS can be put into action through the Social-Aware Driver Assistance System (SADAS). It takes information from sensors and GPS to figure out the roadway scenarios. For example, if you are driving near a school or park, it can guess the more walking traffic or pedestrian activity near the area and make the driver slow down. In one test done in a busy shopping area, the traffic lights changed based on how many people were walking and what types of vehicles there were. This made traffic flow better and also made things safer [45]. Similar frameworks, like the Socially-Aware Evaluation Framework (SAEF), consider broader social impacts and traffic patterns to guide SATS in decision-making. They use more significant analysis to aware drivers about specific land use patterns, as well as keep aware of the community goals of pedestrian, equity, and sustainability. Additionally, Social Network Analysis (SNA) adds another layer to Social-Aware Traffic Systems by predicting the results that will impact most. It works by mapping how people, places, and transportation options are connected. With this insight, planners can spot the most critical points in the network. For example, busy school zones, popular event areas, or major transfer hubs, and apply social-aware strategies there. This means resources are directed where they can truly make travel safer, smoother, and more efficient for the community [46]. SATS introduces a lot of benefits, including efficient traffic flow, enhanced road safety, better public transit planning, and increased rider comfort by predicting how people move and interact. However, like other technologies, there are implementation challenges, such as privacy of the data and cybersecurity concerns, as the collection of social data may raise surveillance concerns. On the other hand, technological implementation barriers such as network availability, validation of collected data, and accuracy of the data also need to be monitored [47].

**B.2 Human-Centered Autonomous Driving**

Human-centered autonomous driving is integrating the peoples choice and social behaviors into the control over the decision-making logic, which helps to build trust in the acceptance of these autonomous technologies. A key part of this is HMI, which is how people and cars communicate. Simple tools like clear dashboards, voice commands, touch screens, or even gestures let passengers understand what the car is doing and act if needed. By keeping things easy to use, autonomous vehicles become safer and more welcoming in everyday life.[48].

In addition to that, shared autonomy is another concept, where the control of the vehicle is shared flexibly between the system and the human. This permits a smooth transition to taking over control in times of emergencies, considering the human behavior, attention level, and reaction time [49]. On the other hand, building trust and acceptance is also important as AVs need to clarify their intention to the driver in an easy way, depicting the reason for their actions, like applying brakes or changing lanes. In this kind of scenario, explainable AI decisions in terms of providing real-time user notification can enhance user confidence and reduce anxiety associated with it [50]. As safety is the main concern for the human-centered design, the AVs need to adapt to the unpredictable human behavior, especially for pedestrians, to gain trust among the drivers, demanding that AVs go through extensive testing and regulation criteria to enhance safety against these kinds of challenges [48]. As an example, Toyota Research Institutes Human-Interactive Driving, which enhances driver skills and safety through assistive technologies; Human-Centered AV Design, which promotes collaboration between humans and AI; and user-centered design in shared autonomous vehicle systems, which focuses on uncovering new mobility needs through empathetic, creative problem-solving [51], [52].

AV's focus is to create more human-centered algorithms to adapt to human needs and enrich their experiences, not only to improve usability and safety but also to foster broader acceptance of autonomous vehicles as an inclusive and human-friendly mobility solution.

**B.3 Wrong Way Driving Detection**

Wrong-way driving (WWD) detection systems are a leading example of CPSS applications in transportation, combining physical infrastructure, advanced computational intelligence, and human interaction to detect and mitigate this highly dangerous roadway behavior. These systems are built to detect vehicles going the wrong way, often on highways or exit ramps, and quickly respond to prevent dangerous head-on collisions by notifying the drivers and the other vehicles, as well as the corresponding authorities. The detection system consists of various technologies based on the need and roadway geometric design, weather conditions, or other features. Generally, LiDAR, radar, camera-based systems, or even pavement lighting or marking are used to detect wrong-way vehicles entering through the ramp of a freeway. These systems provide real-time data when an event is detected to notify the TMC or enforcement authorities to take immediate action against the wrong-way drivers [53]. The cyber layer, which analyzes the data collected by the physical infrastructures using the AI algorithm and computer vision technologies, uses historical data to distinguish between false positives and actual WWD events. The system is trained to accurately classify the severity, allowing for real-time detection and predictive analytics [53]. The next layer, which is the social layer, works with the human drivers when an actual WWD event is detected. Flashing LED activation to notify the driver that he is going in the wrong direction is the preliminary action; if not, the systems can notify the TMC to make other drivers through dynamic message signs or lane closure using enforcement authorities. Advanced systems may also integrate the behavioral inputs from the drivers to predict the intent and take necessary remedies, like redesigning high-risk ramps or enhancing signage placement [54].

These integrated CPSS systems offer several key benefits, such as enabling real-time response, allowing authorities and drivers to act before a wrong-way event escalates into a crash. The use of visible and dynamic driver alerts helps correct behavior immediately. On a broader level, these systems can help the agencies to take necessary actions in a short period of time to avoid fatalities and ensure safety [55]. Recent developments like the U.S. DOTs SMART Grant program, which funds projects across the country to pilot advanced wrong-way detection technologies, are a pathway to embrace these emerging technologies.

**B.4 Connected Autonomous Vehicle (CAV) Systems and Frameworks**

Another technology in CPSS in transportation is CAV, which integrates autonomous driving technologies with real-time V2X communication. It also includes V2V and vehicle-to-everything (V2I), which enable cooperative perception and enhanced traffic control [56]. CAVs operate across three integrated layers: the physical layer (vehicle sensors such as LiDAR, radar, cameras, and infrastructure devices), the cyber layer (AI algorithms, edge/cloud computing, and communication networks), and the social layer (human behavior, takeover intentions, and interactions with road users) [57]. These strategies enable cooperative adaptive cruise control, which supports traffic efficiency and fuel savings [58]. It also helps to reduce distracted driving-related crashes, which is one of the biggest concern now a days [59].

Although CAVs have a long-term impact to make transportation safer, large-scale deployment still faces challenges for interoperability, latency, cybersecurity risk, cost of infrastructure and maintenance, and HMI in mixed environments [57].

**B.5 Artificial Intelligence and Machine Learning in CPSI-Based Transportation Systems**

AI and Machine Learning (ML) are also an integral part of the whole CPSI systems for the safety of transportation engineering. These help to transform multiple data sources into actionable intelligence in predicting, optimizing, and autonomous decision making. AI operates within all three layers of the CPSI system: processing data from different detection technologies like Lidar, Camera, or infrared systems in terms of the Physical layer, optimizing traffic control, routing, and vehicle coordination through deep learning and reinforcement learning as a part of the cyber layer and analyzing the behavioral patter, pedestrian movement and mobility preference serves as a social layer [60], [57]. Reinforcement learning-based signal control systems dynamically adjust phases based on traffic demand, reducing delay and congestion compared to fixed-time control [61]. Deep learning models also improve short-term traffic flow forecasting, enabling proactive congestion mitigation [62].

Convolutional Neural Networks (CNNs) and transformer architectures enable accurate detection, which helps the CAVs to detect the road users and infrastructures [57]. ML and AI can also help to reduce ran of the road, distraction related crash and crashes related to school buses by analyzing and predicting the historical crash data and featuring the impactful variables [59], [63], [64]. Despite the advancement, there are challenges for these technologies. High computational demand, data bias, limited model explainability, cybersecurity, and vulnerabilities are the barriers to successful integration of these technologies, which can be addressed by introducing HITL or Explainable AI (XAI) to help gain trust and accountability [65].

### C. CHALLENGES AND FUTURE RESEARCH

While CPSS frameworks hold great promise, several technical and social challenges may affect their widespread adoption and effectiveness:

Interoperability and Standardization: One major technical barrier is that agencies lack standardized regulation and protocol, and different architectures between the agencies, as well as different heterogeneous data types from sources like GPS, social media, on-board units, and roadside units, create complications for integration under a single data management tool. Without these unified frameworks, the successful CPSS integration will not be possible [66].

Data Privacy and Security: The combination of cyber, physical, and social data presents significant privacy problems, especially the social data, which includes sensitive behavioral and geographical information, may raise severe privacy issues without proper storage and management. In addition, ensuring secure data transfer, anonymization, and access control while maintaining data value is a difficult challenge as well, because transportation CPSS systems may be subject to assaults such as spoofing, data theft, or denial of service, which might risk public safety [67]. Computational Complexity and Real-Time Constraints: CPSS applications require real-time updates and modifications based on the data inputs, which need high-end computational capability, cloud computing, and edge computing. So, achieving a balance between these system responsiveness, computational cost, and model accuracy is a critical challenge for the successful operation of a CPSS [68].

Trust, Ethics, and Human Acceptance: Public trust in CPSS systems in terms of automation, surveillance, and driving control is not yet established. Moreover, ethical concerns arise due to logical bias, decision-making anomalies, and the potential loss of human control during emergencies. Addressing these concerns requires XAI, human-centered design to let people understand the logic behind the actions of AVs, as well as an inclusive policymaking to promote societal acceptance and build trust. [69].

Scalability and Infrastructure Constraints: Implementing CPSS on a city or regional scale requires upgrading the current existing technologies at the physical and cyber layer levels, creating a challenge for the need for a scalable and flexible system. Scalability is further challenged by significant investment and deployment schedules. More research is needed on modular, low-cost deployment strategies and scalable systems [70].

Table 1 represents the CPSS technologies with their description and implementation challenges.

TABLE 1: Summary of CPSS Technologies in Transportation: Descriptions, System Type, Implementation Challenges, and References

| **Technology** | **Type** | **Description** | **Challenges** | **Ref.** |
|---|---|---|---|---|
| Human-in-the-Loop (HITL) | Existing | Integrates human input into decision-making loops using sensors, ML, and social data. | Reliable timing, ethics, public trust. | [17] [26] |
| Digital Twin Frameworks | Emerging | Virtual replicas of systems simulating traffic, infrastructure, and emergency response. | Integration, high cost, cybersecurity. | [27] [42] |
| Smart Mobility | Existing | IoT, AI, and user feedback for dynamic routing and multimodal transport. | Integration, accessibility, digital divide. | [43] [51] |
| Social-Aware Traffic Systems (SATS) | Emerging | Crowdsourced and contextual data for real-time traffic and safety. | Privacy, infra needs, ethics. | [52] [55] |
| Human-Centered AVs | Emerging | Humanmachine interaction, shared control, explainable AI. | Seamless transitions, trust, ethics. | [56] [60] |
| Wrong-Way Driving Detection | Emerging | Sensors + analytics for real-time detection and alerts. | False positives, TMC coordination. | [61] [63] |

## IV. CYBER LAYER IN TRANSPORTATION SAFETY

The cyber layer is the computational and decision-making core of CPSS in transportation. It transforms raw data from physical sensors and social inputs into actionable intelligence through advanced technologies such as AI, ML, Big Data analytics, IoT, and V2X communications. This layer enables real-time monitoring, control, prediction, and coordination within transportation networks, supporting a wide range of functions from automated traffic management and autonomous driving to infrastructure monitoring and crash prevention. By serving as the digital brain of transportation systems, the cyber layer plays a critical role in operational efficiency, safety, and responsiveness. Figure 6 summarizes the use of the cyber layer for the transportation system.

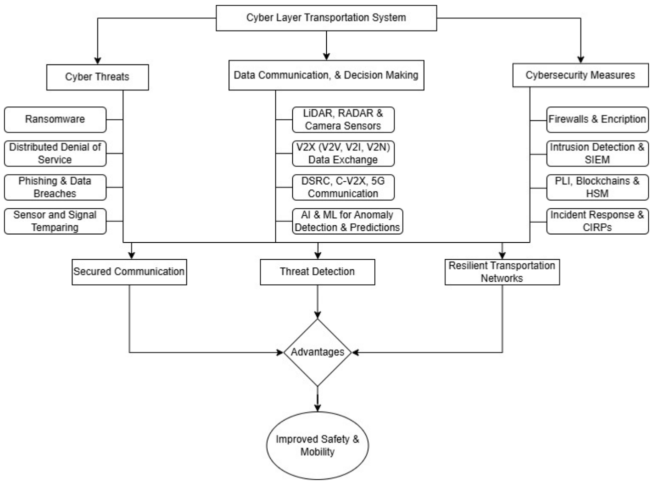


FIGURE 6: The use of the cyber layer for the transportation system.

### A. CYBER THREATS AND SAFETY

The cyber layer is very significant in the transportation sector for integrating CPS technologies. The importance of this layer is based on the dependence on technologies like ITS, CAVs, and smart infrastructure that rely on real-time data exchange using the sensors, controllers, and centralized platforms [71]. Cyber threats such as ransomware, phishing, Distributed Denial of Service (DDoS) attacks, and data breaches can severely affect the safety of and operation of these systems. Possible cyber-attacks, like traffic signal hacks and disabling vehicle braking systems, can result in significant public threats, security issues, economic disruptions, or even fatalities. Thats why strong cybersecurity measures are crucial to maintaining and gaining public trust and support for the adoption of emerging innovations like MaaS and autonomous transportation [71], [72].

Several strategies have been developed to mitigate the cyber threat in transportation systems. Unauthorized access can be prevented using the public key infrastructure (PKI) and secure V2X technologies [73]. One other prominent threat is network intrusion, which can leak important and sensitive data to the public, and can also be protected through Intrusion Detection and Prevention Systems (IDS/IPS) if it is used with advanced AI/ML [74]. Additionally, edge computing and secure over-the-air (OTA) updates improve system resilience by reducing centralized vulnerabilities and ensuring timely security patches [75]. All these technologies are readily available and easy to integrate with proper training and knowledge. Apart from these, emerging technologies like blockchain-based frameworks and standardized cybersecurity guidelines (e.g., National Institute of Standards and Technology (NIST) and ISO/SAE 21434) further enhance data integrity, system reliability, and protection against the connected transportation environment [76].

### B. DATA, COMMUNICATION, AND DECISION-MAKING

**B.1 Data and Communication**

The cyber layer integrates large-scale data from diverse sources, including onboard vehicle sensors such as LiDAR, radar, and cameras, roadside infrastructure such as loop detectors and DSRC units, and user devices, interoperability including smartphones and smart cards. These heterogeneous data streams enable continuous monitoring of traffic conditions, vehicle movements, and infrastructure status. Advanced communication technologies such as V2V, V2I, and Vehicle-to-Network (V2N), collectively known as V2X, facilitate real-time data exchange between transportation components [77].

With the deployment of Cellular-V2X (C-V2X), 5G networks, and edge computing, transportation systems can achieve low-latency, high-reliability communication necessary for safety-critical applications. For example, V2V communication enables vehicles to share speed, trajectory, and braking information to prevent collisions, while V2I communication allows infrastructure systems to transmit signal timing, road conditions, and emergency alerts. These technologies support real-time situational awareness and coordinated transportation operations [69].

**B.2 Decision-Making and System Intelligence**

Beyond data collection and communication, the cyber layer provides intelligent decision-making capabilities through AI and machine learning techniques. These tools analyze real-time and historical transportation data to detect anomalies, predict traffic conditions, and support automated control strategies. Decision-making frameworks such as reinforcement learning, decision trees, and rule-based systems are widely used in Traffic Management Centers (TMCs), autonomous vehicle control systems, fleet management platforms, and emergency response coordination [78]. These intelligent systems enable adaptive traffic signal control, predictive crash risk identification, dynamic routing, and automated vehicle navigation. By transforming raw transportation data into actionable intelligence, the cyber layer enhances system responsiveness, operational efficiency, and overall transportation safety.

### C. CYBER SAFETY FRAMEWORK

As transportation systems become increasingly interconnected, a robust cybersecurity framework is essential. Firewalls, network segmentation, and Security Operation Centers (SOCs) defend the control system and signal networks at the infrastructure level against any intrusion, maintaining redundancy for safety. In CAVs, with the help of encrypted communication and regular software updates, the security against data breaches is preserved. PKI and blockchain, as emerging methods, are also used to ensure that updates sent in wireless media are protected against any intrusion. Encryption frameworks like AES-256 encryption (a method used to keep data safe by turning it unreadable code), multi-factor authentication, Hardware Security Modules (HSMs), and data anonymization for public datasets are essential to safeguard the shared information. In addition, networks are continuously monitored using IDS/IPS and Security Information and Event Management (SIEM) tools to flag any anomalies and detect real-time threats [79]. Cyber Incident Response Plans (CIRPs) guide immediate countermeasures during real-time failover and backup restoration to limit downtime during breaches where compliance with global cybersecurity standards, including the NIST Cybersecurity Framework, ISO/SAE 21434, UNECE WP.29, and IEC 62443, ensures harmonized protections for road vehicles, industrial systems, and software updates across international transport ecosystems [72], [80].

## V. PHYSICAL LAYER IN TRANSPORTATION SAFETY

The physical layer of CPSS provides the infrastructure support to gather data, control vehicles, operate systems, and make real-time decisions. Its system architecture consists of field components like roads, traffic lights, cars, and roadside units like sensors, actuators, and communication devices like traffic lights and beacons. As transportation becomes more intelligent, the physical layer plays a critical role in ensuring smooth collection, transmission, and analysis of the data. Figure 7 summarizes the use of the physical layer for the transportation system.

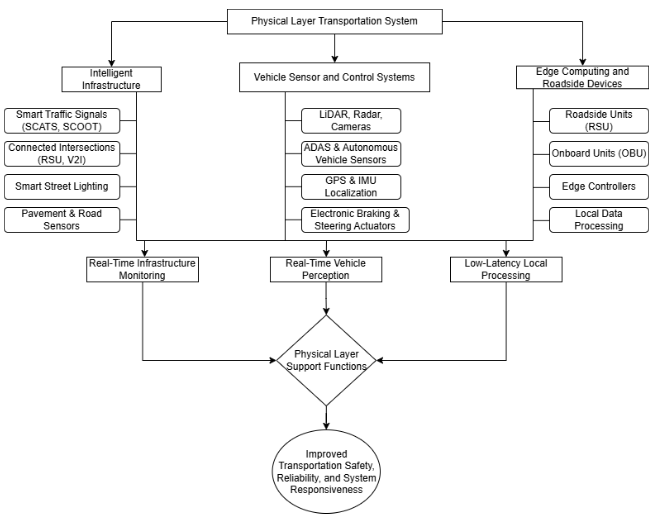


FIGURE 7: The use of the physical layer for the transportation system.

### A. INTELLIGENT INFRASTRUCTURE: SMART SIGNALS AND CONNECTED INTERSECTIONS

Intelligent infrastructure represents a pivotal evolution in transportation systems by integrating digital technologies, sensor networks, and communication protocols into traditional roadways and intersections. These technologies are designed to communicate with other vehicles and infrastructure in real time. For example, cities like Los Angeles and Pittsburgh have implemented adaptive traffic control systems that respond to changing traffic volumes using real-time data directly from the autoscope mounted on the signal poles, significantly reducing congestion and travel delays [81]. Other similar technologies, like the SCATS and the SCOOT, which also adapt their signal phases with real-time updates, are frequently used in cities worldwide. SCATS has been installed in over 180 locations, including Toronto and Hong Kong, which optimizes signal timings using real-time traffic data from loop detectors [82], where the SCOOT system, installed in London, automatically modifies signal cycles depending on traffic flow data [83]. Both systems use multiple smart technologies, including cameras, radar, and inductive loops, to detect congestion, the presence of pedestrians, and queue lengths to change the signal timing accordingly. On the other hand, the cost of installation, maintenance, and the high skillset of the workers are vital for operating these systems. Connected intersections are another domain surging in the smart transportation sector rapidly. Largely used in transit signal priorities using OBU data shared by the vehicles with the RSU to communicate. For example, the U.S. Department of Transportations Connected Vehicle Pilot in Tampa, Florida, demonstrated how V2I systems could alert drivers about red-light violations and pedestrian crossings, which improves intersection safety. Additionally, advanced sensor integration, such as LiDAR, radar, or video analysis, helps the detection process of pedestrian activity as well as vehicle movement with less modification in current systems. Cities like Las Vegas and Columbus, Ohio, Salt Lake City, Boston, New York, etc, have already adopted these systems. [84].
Alongside smart intersections, smart street lighting, and pavement sensing are other intelligent infrastructures being used in cities. In San Diego, smart LED streetlights with integrated motion sensors adjust their brightness based on pedestrian or vehicle activity, which leads to significant savings in energy, as well as needing less maintenance [85]. Similarly, pavement sensors embedded in road surfaces can also measure vehicle speed, weight, and temperature to monitor road wear and forecast maintenance needs. For example, the Road Surface Monitoring System used in Stockholm uses these embedded sensors and wireless communication to alert operators about freezing risks and pothole formation [86].

### B. ADVANCED DRIVER ASSISTANCE SYSTEMS (ADAS) AND AUTONOMOUS VEHICLES

ADAS and AVs are growing, emerging technologies within the physical layer of the transportation sector. These technologies rely on sophisticated software and hardware platforms to support safety and automation in driving. ADAS features such as adaptive cruise control, lane-keeping assistance, and emergency braking are already built into many existing vehicles. According to the NHTSA, ADAS features can prevent up to 40% of all vehicle crashes if implemented widely [87].
Both ADAS and AV technologies rely on a comprehensive sensor to provide 360-degree situational awareness and strong environmental perception. LiDAR and radar are new technologies largely being used in the AVS and ADAS for detecting the vehicle and surroundings, even in rain or foggy weather conditions, where cameras are required for activities

including lane detection, traffic sign recognition, and object categorization. In addition, Inertial Measurement Units (IMUs) and GPS systems are employed in high-accuracy vehicle localization and travel time estimation [88]. ADAS systems often include dual electronic and hydraulic braking, power backup, and steering control that helps if the driver loses control of the vehicle, where mechanical components are replaced with electronic actuators, allowing for more precise vehicle responses during emergencies. These systems are governed by standards such as ISO 26262, with Automotive Safety Integrity Level D (ASIL-D) certification.

Collaborative perception is another new development in AVs, which involves the sharing of sensor data and traffic context between nearby vehicles and infrastructure using V2X communication protocols. For example, Mobileyes RSS model in Michigan has demonstrated how cooperative perception can allow AVs to communicate and detect objects beyond the line of sight, such as detecting a pedestrian blocked by a truck using information shared from other vehicles or roadside units [89]. This improvement is essential for high-level (level 4 and 5) autonomy, especially for dense urban land use patterns.

### C. INTEGRATION OF EDGE COMPUTING AND DISTRIBUTION SYSTEM

Adding edge computing and distributed systems to transportation is changing rapidly. Instead of relying only on a central server, decisions can now be made faster and closer way where the data comes from intersections or inside vehicles, via wireless communications. Where traditional systems struggle, edge computing fixes this by processing the data without any cloud support, which is important for AV navigation and signal phase adaptations.

Edge devices include OBUs, RSUs, and system controllers, which can run analysis locally. For instance, an RSU at a smart intersection might analyze video and LiDAR data to detect a pedestrian who is about to cross and can turn the crossing signal on without any additional support from external sources [90]. Similarly, in-vehicle edge processors can complete different tasks such as lane detection, obstacle avoidance, and trajectory planning in real time. These systems can help to reduce computing time and ensure more robust impacts and safety. Distributing systems in forms of centralization of all data in a single database manager can also help to smooth the whole process. For example, the European Horizon 2020 project "5G-CARMEN" uses a distributed architecture that uses both edge computing and cloud servers to operate computation in several countries for AVs [91].

In addition, as edge devices do not need a higher volume of data transfer, they can also lower the energy consumption and ensure faster upgradation with the current existing systems. This is especially crucial for large-scale deployments in both urban and rural areas, where upgradation might be costly if flexible and scalable systems were not used.

## VI. SOCIAL LAYER: HUMAN FACTORS AND USER BEHAVIOR IN TRANSPORTATION SAFETY

The social layer of CPSS focuses on the human interaction with the transportation system. In safety-critical applications such as AVs, it is essential to not just work on the automation level but also take into consideration user interactions. Thats why this layer serves as an important link between the cyber (computational) and physical (infrastructure/vehicle) layers.

### A. HUMAN-MACHINE INTERACTION

As automation is being integrally connected with the transportation sector, it is important to build a human-friendly environment. During the operational phase, the design must address the behavior understanding and situational awareness of humans. Studies found that the most perfect human-centered interface is the semi-autonomous level (level 2 and level 3) [92]. Therefore, an effective HMI not only supports usability but also becomes a safety-critical feature.

Explainability, made possible through XAI, is becoming a key part of building trust in HMI. People are more likely to trust automated cars when they understand why the vehicle is deciding. For example, if the car explains, Slowing down because a pedestrian was detected 50 meters ahead, either through voice or a simple visual alert, it can help passengers feel more confident and less anxious [93]. Research has shown that explanation modalities, whether presented through Head-Up Displays (HUDs), audio output, or adaptive visual warnings, improve user interaction with system behavior [94]. Another key component is trust generation, which is the process of matching user trust to the actual reliability of an automated system. Estimating user trust levels and dynamically modifying interaction modes are two growing applications of real-time physiological and behavioral monitoring (e.g., eye tracking, heart rate variability, posture analysis) [95]. For instance, to recover focus during a crucial driving activity, a system may intensify its warnings or provide an indication via haptic steering wheels. This HITL technique is heavily dependent on HMIs, which run on different AI models.

In addition, during the partial automation, a multimodal human-machine interface is important. To improve responsiveness and lessen the cognitive load, modern AVs use different interaction approaches using haptic feedback, audio, or visual notification with the driver. Multimodal systems reduce reaction time and error rates, particularly during emergency situations or when transitioning control from the vehicle to the human. In Level 2 and Level 3 AVs, these issues are addressed by a countdown timer or cognitive help. These features are important to avoid any anomalies or latencies during the control overtake, which is a key reason for crashes [96].

### B. BEHAVIORAL DATA ANALYTICS

Behavioral data analytics is important to evaluate an individuals interactions in real-world conditions for system adaptability. Systems like in-vehicle monitoring systems (IVMS), mobile data, or social crowdsourced data are being used by agencies to discover and evaluate the behavioral patterns of drivers in terms of route selection or response during dynamic traffic conditions. For example, IVMS data on eye movement and brake usage helps assess driver attentiveness [97]. Agent-Based Model, on the other hand, can detect how these interactions can affect during the large-scale deployment, such as evacuations. Reinforcement learning techniques are also being used to adjust signal timings based on real-time data [98].

Variable Message Signs (VMS) can be used to help individuals with any specific safety concerns, such as school zones or work zones [99]. Incentive-based systems used in Singapore to promote environmentally efficient routing also help to promote good driving practices, considering the vulnerable road users.

### C. HUMAN FACTORS: COMFORT, TRUST, AND USER ACCEPTANCE

Human aspects, including comfort, trust, and user acceptance, are very important for the successful use of CPSS-enabled transportation. Users may feel uncomfortable if they do not understand the process or integration of the whole system, even if it is highly reliable. Research shows that passenger comfort is influenced by vehicle motion characteristics, including acceleration smoothness, braking behavior, and lane-keeping stability, which directly affect user perception of safety and system acceptance [100]. Gradual acceleration or anticipatory braking strategies in the form of adaptive driving techniques can help to gain trust by reducing anxiety. On the other hand, trust is developed based on the systems reliability, transparency, and consistency. XAI and transparent system feedback mechanisms allow users to understand system decisions, improving confidence in automated operations [101]. Studies have demonstrated that providing real-time system status updates, warnings, and clear explanations significantly increases user trust and reduces hesitation during automated driving scenarios [102]. Moreover, technologies like HITL can provide humans the ability to take control if required and generate a comfortable user control mechanism, which is also another main factor for the successful integration of these technologies and their large-scale deployments.

## VII. APPLICATIONS

Transportation is going to undergo a change in the near future, and the application of CPSS plays a vital role in it. [103].

The integration of CPSI-based systems into transportation sectors helps to create better dynamic and adaptive solutions towards safer and more reliable transportation options. By combining data from physical infrastructure (e.g., sensors, traffic signals), cyber technologies (e.g., machine learning, cloud platforms), and social systems (e.g., driver/passenger behaviors, crowdsourced information), CPSI facilitates real-time decision-making and proactive safety interventions. Big data, IoT, and machine learning are integrated into CPSS, which facilitates more efficient options to compute bigger datasets with various attributes within a short period of time, using edge computing and cloud-based analysis [104].

### A. INTELLIGENT TRAFFIC CONTROL SYSTEMS

The shortcomings of the traditional traffic lights have motivated researchers to invent adaptive intelligent traffic control systems, which can dynamically adjust signal timings to enhance traffic flow by analyzing the real-time traffic data. Compared to traditional systems, smart traffic light control is more advanced as it has the capability of smart decision-making algorithms, which have largely improved the travel times. These systems can also integrate other important features such as pedestrian detection and signal control, emergency vehicle perception, transit priority, and integration with broader smart city infrastructures, making them more scalable and flexible to upgradation [105].

### B. CRASH RISK PREDICTION AND PREVENTION

An important application of CPS in transportation is the Vehicular Cyber-Physical System (VCPS), which offers smart solutions to complex traffic challenges by combining real-time data sensing, computation, and updates to enhance vehicle control, traffic mobility, and safety. For example, existing adaptive cruise control, lane departure warning systems, and early collision avoidance technologies, which operate in a fully autonomous way, lack human-centered design, creating a gap between these technologies and the human driver using them. Bridging this gap is essential to improve the effectiveness of CPSS to ensure proper safety [106]. A study presents the development of a VCPS using CARSIM simulation, which collected and analyzed data on vehicle motion and location, driver behavior, and road geometry within half-second intervals. By integrating a collision risk assessment method with a Kalman Filter (KF) algorithm, the system can predict the movement of both the subject vehicle and nearby obstacles with real-time evaluation of crash risk. It can also provide a prediction of vehicle trajectory, speed, and distance traveled, using data acquired from virtual sensors dynamically. This shows how CPS can enhance vehicle safety by anticipating potential crashes and enabling timely preventive measures in short-term deployment capabilities [107].

### C. CONNECTED AND AUTONOMOUS VEHICLES

CAVs represent a holistic embodiment of CPSI. These systems rely on cyber-physical components like V2V and V2I communication, while also considering social behavior, such as lane-changing patterns and interaction with pedestrians. In projects like Waymo and Tesla Autopilot, deep learning algorithms integrate sensor data (LiDAR, cameras) with contextual indicators like driver intention and road user behavior to make real-time decisions. Another critical aspect of autonomous vehicle systems is the integration of multiple sensing and processing modules to ensure reliable perception and control. Autonomous platforms typically combine data from cameras, laser scanners, radar, GPS, and inertial measurement units to generate a comprehensive understanding of the surrounding environment. These sensors provide overlapping and redundant information that allows the system to detect obstacles, identify lane markings, track other vehicles, and estimate terrain conditions. The collected data are processed through onboard computing systems and fused into a unified representation of the environment, enabling the vehicle to plan trajectories and control steering, acceleration, and braking in real time. Such multisensory fusion and modular system architecture are essential for achieving robust autonomous driving performance under diverse traffic, weather, and road conditions [108]. Another example is driver re-engagement in Level 3 semi-autonomous cars tested by Honda and Audi, which shows that when drivers are asked to take back control, it takes them an average of 7 to 10 seconds to respond. This delay, despite being short, can cause serious and fatal outcomes during an emergency situation [109]. HMI systems discussed before, such as oral notification, seatbelt tensioners, and haptic steering wheel notification, can help to reduce the distraction and faster takeover, which is being installed in many cars by the manufacturers. Another study from urban land use, like Boston, shows that AVs equipped with external human-machine interfaces (eHMIs), such as LED strips displaying projected crosswalk signals in the intersections, helped pedestrians to understand the intent efficiently and conveniently. Similar studies found that when AVs communicate with the VRUs regarding road crossings, the pedestrians were 22% more likely to cross the street safely compared to no communications or signals. Another example from emergency response in California showed how CPSS integration improved wildfire evacuation outcomes by evaluating real-time behavioral data from GPS and social media-based crowdsourced data. The authorities dynamically adapted signal control and evacuation routes during the evacuations. The result shows that the clearance time improved by 25% compared to the previous no modification options [110].

### D. DISASTER RESPONSE AND EMERGENCY EVACUATION

Based on a study, CPSI offers a transformative application for disaster response and emergency evacuation by enabling networks to adapt to rapidly changing conditions. A real-world demonstration in the Philippines field experiment using a Wireless Mesh Network (WMN) of Access Points (APs) to track changes in user location, demand, and resource availability. The system adjusted itself automatically, for example, by switching the main Gateway AP, to reduce data delays and improve speed where demand was highest, like how evacuees naturally gather at shelters. This allows CPSI to maintain critical communication services using existing, potentially infrastructure-independent resources (like WMNs or UAVs) even in the middle of damaged infrastructure or fluctuating user movement patterns. It ensures efficient resource use without requiring immediate additional hardware deployment. By reliably providing connectivity for safety confirmation, coordination, and situational awareness during chaotic evacuations and response operations, CPSI significantly enhances resilience and lifesaving capabilities [111].

### E. SMART LOGISTICS AND TRANSPORTATION SERVICES

CPSI is applied to optimize urban logistics and transportation through a framework that helps optimize supply and demand while keeping the data safe. The system uses a Transparent Data Exchange Platform (TDEP) to store and safely aggregate real-time mobility demand data from users without compromising individual privacy. This data is then processed by Mobility-Oriented Large Models (MOLMs) to predict the resource that will be needed and then optimize the allocations, such as matching self-employed truck drivers with freight jobs (e.g., Didi Freight). At the same time, MOOS can also manage the deployment of resources by switching between three modes: Autonomous, Parallel, and Expert, to adapt to different situations, such as sudden traffic congestion or emergencies. This helps the mobility for freight transportation to become more efficient and sustainable [112]. Moreover, the 4th Industrial Revolution is about combining existing technologies with cyber-physical systems. Smart Logistics could contribute to the revolution by providing services in 10 areas of application, including distribution and logistics models for operators, capacity sharing, infrastructure development, use of advanced information technologies, promotion of environmentally friendly means of transport, access control, regulations on enabling activities, enforcement, routing optimization, and training. Smart logistics integrated with CPS can effectively respond to the dynamic needs of both economic systems and society[113].

### F. WRONG-WAY DRIVING DETECTION

WWD detection and prevention are largely dependent on CPS-based technologies, which are also a booming sector in transportation safety. It contains physical sensors like thermal detection, radar, and LiDAR-based technologies (e.g., Arizonas thermal systems triggering signal changes) to detect incidents, which are then processed by TMCs, where algorithms validate incidents, activate alerts (e.g., flashing LED signs, DMS warning right-way drivers), and notify law enforcement. On the social level, the crash narrative, enforcement implementation, and public awareness, such as DMS messages prompting driver corrections, are distributed to reduce the chance of a potential collision. Missouris systematic approach combines low-cost signage with ITS at prioritized ramps to notify the driver and others, while Connecticuts red-flasher system uses video analytics to alert drivers and authorities immediately after an incident is recorded [114].

## VIII. CHALLENGES

There are numerous challenges associated with CPS development and deployment. The process of modelling, analyzing, and verifying should be accurately maintained to avoid flawed or hazardous systems. The safety and security of CPS systems rely on structuring a robust engineering sector that is mathematically precise, cost-effective in analytical methods for practical implementation [115].

In transportation systems, CPSI can revolutionize safety, mobility, and sustainability by introducing components to build smarter and more efficient transportation networks. However, the technical, organizational, and ethical challenges are required to be addressed in the case of CPSI to reach its full potential.

In CPSI systems, there are various threats, vulnerabilities, attacks, and failures. The threats can be divided into cyber and physical threats, which include wireless exploitation, jamming, unauthorized access, GPS exploitation, disclosure of Information, physical damage, loss, repair, service disruption, or denial, etc. Whereas the vulnerabilities can be divided into network, platform, and management, such as spying, heterogeneity, bad practice, etc. The attacks consist of cyber and physical attacks, which can be described as wire cuts, fake identity, physical breach, phishing, malware, password cracking, virus, spyware, ransomware, etc. The failures that CPSI systems suffer from are content failure, timing failure, sensor failure, etc [116]. The main challenges faced by CPSI systems involving transportation systems are described below:

### A. HETEROGENEOUS DATA INTEGRATION

One of the prominent challenges in CPSI-enabled transportation systems is the integration of data from different sources. Physical sources like sensors generally produce highly structured real-time information data, whereas social media platforms and human feedback provide unstructured but context-based datasets. To enable effective decision-making, cyber systems must harmonize these heterogeneous data sets, which involves complexity in alignment of incompatible data sources, filtering out null or void data, and maintaining both temporal and spatial consistency across datasets [117]. Additionally, a CPS generally consists of various subsystems that include different devices, components, and equipment, mostly from different vendors. This contributes to the challenge faced by CPS in managing intractability while achieving real-time execution of diverse tasks[118].

### B. INTEROPERABILITY AND SYSTEM COMPLEXITY

Interoperability refers to the capability of different systems, units, or organizations to exchange services with one another and effectively utilize those shared services so that they can function and operate together efficiently [119]. In order to seamlessly connect multiple devices, a the CPSI-basedstandardized communication protocol is needed [120]. Transportation systems involve multiple components such as vehicles, infrastructure, mobile devices, and control centers. These components often use different standards and communication protocols. Ensuring interoperability among these components is difficult, especially when existing traditional legacy systems are involved, as social crowdsources data, and the HITL system is incompatible with the current dataset. In case of data storage complexity, cloud computing can be a solution as it offers a significant amount of processing and storage capabilities [121].

### C. REAL-TIME PROCESSING AND DECISION MAKING

To respond rapidly and provide real-time updates, the CPSI system needs to analyze high volumes of data. This requires edge computational power with low latency and accuracy. The edge computing system needs higher bandwidth, which might create a problem for implementation in rural areas [122]. Changes in framework or design frequency can help ensure real-time operations [118].

### D. SECURITY AND PRIVACY

CPSS is always vulnerable to cyber threats or data breaches as it relates to the online cloud-based platforms. These systems often collect sensitive data, such as location, travel patterns, and personal information, which is important to protect individual safety. Cyberattacks that penetrate these databases using sensor manipulation can pose a great threat to individual and national security. That is why a comprehensive cyber safety protocol backed by strong architecture and policy is needed for a sustainable CPSS system. [123]. Using specialized programming languages and safe connectivity techniques can ensure safety against attacks [118].

### E. MODELING HUMAN BEHAVIOR AND SOCIAL DYNAMICS

Incorporating social intelligence requires understanding and modeling human behavior, which is uncertain, diverse, and context sensitive. Driver behavior, pedestrian intent, and public reaction can influence system performance, which is a challenge for designing predictive models that accurately reflect real-world human actions across different environments and demographics [124].

### F. ETHICAL AND LEGAL ISSUES

CPSI systems raise significant ethical and legal challenges as well. For instance, if a CPSI-based AV falls into a crash, who should be considered responsible, how should data be collected and used while protecting individual privacy, is a growing concern. As well as the level of surveillance acceptability towards maintaining safety, it is also necessary to specify which require regulatory involvement, and inclusive stakeholder engagement. [125].

## IX. FUTURE DIRECTIONS

### A. AVS AND ADAPTIVE CONTROL SYSTEMS

Future research should focus on prioritizing the integration of human-centered mechanisms with the existing AVs and adaptive control systems. Comprehensive personal and employee training is also needed to protect these systems against cyberattacks or data safety threats. Future studies should include different system architectures to counter the gaps in traditional systems. Another important study is needed in the behavioral sector of these systems, such as how these systems perform with human interaction. Moreover, guidebooks and training documents can be the scope of study for future researchers.

### B. ADVANCED SECURITY ARCHITECTURES

From a technical perspective, advanced security architectures such as AI-powered hybrid IDS/IPS and adaptive honeypots are needed to detect and counteract complex socio-technical threats in real time. In parallel, forensic-by-design approaches are supported by blockchain-based chain-of-custody protocols that can strengthen accountability and preserve evidentiary integrity. Ethical hacking research could contribute to these studies in a broad manner by stopping or minimizing cyberattacks. Developing a generation of cyber attack prevention teams could be part of CPSI based research wing of several transportation agencies. Additionally, the state and federal transportation agencies should contribute to the research on the prevention of cyber-attacks and the enforcement of associated laws.

### C. POLICIES AND REGULATIONS

Organizational incompatibility and interdepartmental policies need to be discussed and come with sophisticated unified regulations that will support the integration of these technologies smoothly into the current transportation systems, which is necessary for future integration [126]. Most transportation agencies could develop a specific guidebook with the policies and regulations to follow for different CPSI-related projects. Statewide research could be a starting point to understand the best practices. With the best practices analysis, several performance metrics could be developed to track the implementation and enforcement of these policies and regulations. Overall, the success of CPSI integration research in transportation projects heavily relies on the contribution of state and federal agencies.

## X. CONCLUSION

This paper presented a comprehensive review of CPSI-based systems in the context of modern transportation and emphasized their role in enhancing safety, mobility, and system intelligence. By discussing the human-centered interaction modules with existing autonomous technologies such as HITL and providing examples of practical solutions like digital twins, Smart Mobility Framework, Social-Aware Traffic System, Connected Autonomous Vehicles, and the study illustrates how integrating cyber, physical, and social layers can create more adaptive, resilient, and user-focused transportation networks. Unlike many existing surveys that primarily focus on individual technological components such as autonomous vehicles or intelligent transportation infrastructure, this review uniquely synthesizes these developments through a holistic CPSI perspective, highlighting the interactions among technological systems, human behavior, and infrastructure.

Through this review, the potential scopes and immense possibilities of integration of CPS-based technologies in the current transportation system have been presented in a simple, easy, and fluent way. This integrative perspective provides a unified understanding of how cyber analytics, physical infrastructure, and human behavioral data collectively contribute to safer and more intelligent transportation systems. These technologies support proactive safety features by integrating social behavioral data with computer-based analysis to provide a more user-friendly experience.

However, despite these advancements, several technical and institutional challenges hinder the widespread deployment of CPSS, such as the integration of heterogeneous data sources, system interoperability, real-time processing demands, and the growing risks of cybersecurity and data privacy breaches. Additionally, predicting and modeling the correct human behavior remains a challenge for these systems. Moreover, ethical and legal concerns for surveillance boundaries and data sharing are also growing issues that need to be specified before implementing a sustainable CPSS system. Lastly, the fragmented organizational structure and inconsistent policy framework also create a threat to the rapid adaptation of these technologies.

Addressing these challenges requires a multi-approach strategy and collaboration between different government agencies to create a unified and easily adoptable policy. Developing standardized communication protocols, centralized data sharing platforms, and regulations for cybersecurity is essential. Future research should focus on real-time validation algorithms for low-latency and cost-effective systems, along with efficient system architectures and ethical frameworks for balanced innovation and social responsibility. By focusing on and solving these challenges, the CPSI-based transportation sector can ensure safety, mobility, and faster communication facilities.

## APPENDIX

The authors affirm that the entirety of this manuscript, including its research design, analysis, interpretations, and conclusions, was developed solely by the authors. Artificial intelligence (AI) tools were employed exclusively for technical editing tasks, such as grammar refinement, spelling correction, and language clarity. The intellectual content and scholarly contributions remain entirely the responsibility of the authors.

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MD SADMAN ISLAM Md Sadman Islam, born in Dinajpur, Bangladesh (1998), earned his B.Sc. in Civil Engineering (Transportation) from BUET in 2022 and is pursuing a Ph.D. at Rowan University, USA, focusing on transportation safety. He has worked as a Project Executive at Dom Inno Real Estate Development, a Lecturer at Bangladesh Army University of Science and Technology, and is now a Graduate Research and Teaching Fellow at Rowan. His research covers school bus safety, pavement markings, transit accessibility, and wrong-way driving detection, with publications on heavy vehicle crashes and machine learning. He has presented at TRB and received awards, including the ITSNJ 2024 and Rowan CEE 2025 Outstanding Graduate Student Awards. He is active in ITE, ITSNJ, and ASCE, and serves as President of Rowan ITE and Vice President of Rowan Bangladesh Student Association.

AHMED IMTIAZ ZAMEE was born in Kazla Village, Rajshahi, Bangladesh in 1999. He received the B.Sc. degree in civil engineering from the Bangladesh University of Engineering and Technology (BUET), Dhaka, Bangladesh, in 2022. He is currently pursuing a Ph.D. degree in civil engineering at Rowan University, Glassboro, NJ, USA, with a focus on public transportation. He worked as an Assistant Engineer in the Tendering and Planning Department of Sinamm Engineering Limited, Dhaka, Bangladesh. He is currently working as a research fellow at Rowan University. His work includes several state-funded research projects such as wrong-way driving detection technologies, school bus safety, and identifying travel needs. His research interests include public transportation, Intelligent Transportation Systems (ITS), spatial analysis of data, and smart mobility solutions. Mr. Zamee is a Student Member of the Institute of Transportation Engineers (ITE), the Intelligent Transportation Society of New Jersey (ITSNJ), and the American Society of Civil Engineers (ASCE).

MOHAMMAD JALAYER was born in Iran. He received the B.Sc. degree in civil engineering from the University of Mashhad, Iran, in 2007, the M.Sc. degree in transportation engineering and planning from Sharif University of Technology, Tehran, Iran, in 2010, and the Ph.D. degree in civil engineering with a focus on transportation engineering from Auburn University, Auburn, AL, USA, in 2016. His major field of study is transportation safety and intelligent transportation systems. He has worked in both academia and industry, including positions as Project Manager and System Analyst in Iran, Research Associate at Rutgers University, and Research/Teaching Assistant at Southern Illinois University and Auburn University. Since 2018, he has served as a faculty member in the Department of Civil and Environmental Engineering at Rowan University, where he is currently an Associate Professor. His professional work includes principal investigator roles in more than 30 research projects funded by agencies such as NJDOT, NJ TRANSIT, USDOT, and NHTSA. His research has resulted in numerous journal articles, conference papers, and technical reports, primarily focusing on highway safety, crash modeling, ITS, connected and autonomous vehicles, and traffic operations. Dr. Jalayer is a member of several professional organizations, including ASCE, ITE, TRB, ATSSA, and ATSIP. He serves on national review panels for NCHRP and TCRP projects and holds editorial board positions for journals such as the Journal of Transport Safety, Journal of Safety Studies, and Journal of Sustainable Development of Transport and Logistics. He has received multiple awards, including the 2016 National HSIS Research Paper Award, the ASCE Young Civil Engineer of the Year (2017), and Rowan Universitys Innovations in Teaching Award (2019).