**Human-Centered Artificial Intelligence in Smart Transportation Systems: Balancing Automation, Safety, and Human Decision-Making**

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**Abstract:** Transportation has undergone a seismic shift due to advances in artificial intelligence, connectivity, and smart technologies. Yet, relying solely on technology to advance mobility is shortsighted. Human-centered artificial intelligence (AI) holds promise to mitigate risk and foster safe, sustainable, and inclusive smart mobility technologies in urban and rural environments. The research surrounding AI-enabled mobility services, including ride-hailing, traffic management, and vehicle delivery, increasingly centers on the benefits, strategies, and impacts of access. Human-centered AI explores user needs, preferences, and behaviors to help these services, thus reducing barriers that limit individual and collective movement. Recently, AI technologies have attracted significant interest due to their huge economic and societal potential. Containing Artificial Intelligence (AI) is important due to the serious consequences of permitting AI to run free. The need for retained human decision-making, leadership, choice, and direction of intelligent machines is paramount. Highly capable intelligent agents and machines may soon outstrip the intelligence of big swathes of human activity. The control of AI systems and the expectation that AI systems remain under the control of humans is a core theme of ethical AI; Humans should be able to understand how AI works and how it is making suggestions, recommendations, advice, and predictions; desirable recommendations and options from AI should be explicit.

**Keywords:** Human-Centered Artificial Intelligence in Smart Transportation Systems: Balancing Automation, Safety, and Human Decision-Making.

**INTRODUCTION**

The rapid advancement of artificial intelligence is transforming transportation to improve safety, sustainability, and user experience. While several domains such as aviation, railways, and automotive are deploying intelligent transportation systems for safety, traffic flow, parking assistance, and onboard entertainment and information, the full benefits of these systems cannot be realized without addressing societal and human-centered aspects. Moreover, academia has proposed various principles for human-centered AI but few comprehensive and universally accepted unifying frameworks have emerged. This paper seeks to address these gaps by investigating the following research questions:

• What are the characteristics, challenges, and user needs of human-centered AI in transportation systems?

• How can intelligent transportation systems assist stakeholders in making informed decisions while ensuring safety, compliance with regulations, and user acceptance?

To answer these questions, the study employs key theories such as human-in-the-loop, shared control, user trust, usability, cognitive workload, and decision-support. The exploration of the characteristics and challenges of human-centered AI in the transportation domain reveals that users at different levels of elaboration—macro, meso, and micro—require information on various aspects of transportation systems. Further, the paper presents a conceptual framework for enhancing human-centered AI in intelligent transportation systems. The human transportation system consists of three levels of stakeholders: macro (council), meso (agencies), and micro (operators). At each level, users have diverse needs and are subject to different regulations, constraints, and limits. Adhering to a human-centered design enhances safety, facilitates stakeholder consultation, and increases user acceptance.

A smart transportation system is a system of systems integrating various modes of transportation, including terrestre (e.g., road transport), aerial, marine, and rail transport. Safety has been defined within a system-theoretical framework as a state of a system characterized by the absence of hazards, which can be caused by hazards originating from the system (internal hazards) or from outside the system (external hazards) [2]. Generally speaking, Safety is associated with risk, which can be measured and managed. Automation is one of the enablers for transport safety improvement; hence, extensively studied decision-making and human-in-the-loop models center around decision support for automatic or semi-automatic systems, wherever possible avoiding interactions with the fully automatic functions of automation-level-4/5 systems (Dumas & Boucher, 2020). However, the existence of the automatic functions remains as an unavoidable risk originating from the system itself.

A decision with or about automatons subject to automation-level-3 and lower in a move towards hybrid-maning human–machine cooperation for safety has been examined. Attention toward trust in and transparency about the functioning of automatons with regard to road-safety-related variables has also been drawn (Dumas & Boucher, 2020) since the safety culture and degree of trust lie close to each other.

The necessity to encompass human–machine cooperation in risk- and safety-assessment modelling for transportation systems undergoing a transition from fully-human-driven towards fully-automated driving has been highlighted. Safety Aggregation for human–machine cooperation or decision-making of a hybrid–manipulation kind within the broader topic of safety for Smart Transportation Systems is another consideration (Dumas & Boucher, 2020); it has focused more on the nature, form (formalism), and direction of the broad classes of information, knowledge, and the different agglomerating functions than on Safety Aggregation itself.

**METHODS**

This study adopts objective analysis to identify emerging smart transportation technologies and examine their implications for human-centered AI. Research follows the principles of transparency and reproducibility. Findings derive from a comprehensive desktop survey undertaken between 2019 and 2023, during which numerous documents, including publications, reports, articles, and regulatory texts pertaining to smart transportation and human-centered AI, were collected. Sources were subject to rigorous filtering, and 170 documents were selected for detailed examination. The investigation concentrated on safety and human decision-making in the context of smart transportation under three lenses: (1) the architecture of urban, interurban, and freight transportation systems; (2) human–machine system design, focusing on automation, autonomy levels, and oversight roles; and (3) safety assurance, encompassing risk management and interaction between human-centered AI and safety [1].

The objective of an intelligent or smart transportation system is to maximize travel efficiency by relatively prioritizing individual user needs. Three kinds of data related to such a system may be collected: vehicle monitoring data, user journey data, and socio-economic data. Vehicle monitoring data are about each vehicle’s location, trajectory, speed, and mode. The user journey data reflect user start location, destination, preferred route, and willingness to share other data. Socio-economic data provide information on the socio-economic status of user groups. Various spatial data may also be integrated into the data collection to help the system identify relevant user groups and understand connections among the three data types to enhance users’ travel experience.

Smart transportation systems are increasingly adopting advanced technologies, an approach known as smart or intelligent transportation systems. Broadly defined, a smart transportation system is an integrated system of transportation management that uses a variety of sensing technologies guaranteed by communications and computing systems to gather information, and then performs analysis, fusion, decision-making, and action in order to guide vehicles and transport users. A smart transportation system may use a set of sensing devices (e.g., cameras, traffic signals, and environmental sensors) coordinated, and centrally processed through a cloud or edge solution. After fusion of all data, the collected information is mapped into the real road conditions and transported to the users through a communication network. The computing and communication systems are responsible for the real-time analysis and respond promptly.

Following the system-of-systems perspective which considers transportation systems that sufficiently provide a valued service to society, the construction of intelligent transportation systems may be defined as:

- the deployment of intelligent transportation systems that follow the system-of-systems approach. This viewpoint perceives transportation systems as a behavioural database and an intelligent social regulation process or network involved in all transportation organs. Yet, existing models consider mainly intra-urban transport and ignore freight movements necessary to sustain economic growth. Additionally, human decision-taking has to be embedded in every transport scenario being unfortunately neglected until now. Proper information and guidance, respecting human perception, cognition, and habits are required [3].

Transportation systems are becoming increasingly automated, which prompts the discussion of automation transparency. Automation can fixate on controlling devices or monitoring their operation, but an optimal human-automation relationship balances the two. Numerous frameworks for defining automation tiers exist, but a clearer distinction is needed between levels of functional automation and levels of operational autonomy. The latter can involve different roles for humans concerning decision-making, execution, and authority within a given responsibility area. Automation can be applied to multiple facets of transport systems, including vehicle control, traffic management, and driver assistance. Depending on the capability of the system or the organization’s conditions, one of four operational tiers can characterize the predominating relationship between human and system. Manual operation grants complete human authority and control over vehicles or traffic. Intermittent operation permits the transfer of responsibility between the human and the system while a single authority remains. Complementary operation assigns the vehicle or control system a secondary responsibility without conducting any monitoring or verifying the delivery of actions. Cooperative operation allows the human and the system to possess individual, separate responsibilities while sharing, monitoring, and ensuring a consistent level of performance across both [4].

The concept of risk includes the definitions of hazard, danger, and threat. A hazard is a source of potential damage, harm, and adverse effects; a danger is a condition that might induce such damage, harm, or adverse effects; a threat is a statement of a danger related to a vulnerability. Risk is the combination of the probability of an event and its consequences. In general, risk prioritisation must combine severity and likelihood [5]. Various stages in the transport pipeline must also be taken into account when performing hazard and risk analysis.

The analysis must be as comprehensive as possible, and safety analyses are normally iterative. Aboriginal communities with limited Internet connectivity can take advantage of an NDS in combination with fresh local input to model road hazards in real time [6]. Only disturbance parameters are required, and by remodelling observations transported from the NDS, naive baysian modelling can be used to infer yet additional road hazard parameters. Combination with existing road hazard databases and monitoring processes taking into account weather conditions and developing obstruction risks permit the generation of novel snow-clearing service requests. Road congestion monitoring in big data-driven scenarios has developed tools published in the academic literature. Urban traffic estimation and control, non-urban traffic prediction, vehicular traffic hotspots, rerouting detection, road segmentation, and traffic completion are possible, opening large research opportunities.

Cognitive processes play a prominent role in transport automation systems. A large body of literature has explored operator workload and stress, distraction and information overload, reliability and trust, and user experience, but there has been little emphasis on how automation impacts the decision-making processes of transport operators and users. Transport decision-making depends on cognition, perception, information, automation transparency, and understanding of the system. Handover decisions must optimise safety and efficiency while also considering the dynamics of the human-automation interaction.

Decision-making in transport traditionally follows an interactive sequence: managing the ongoing situation, initiating the action, planning the procedure, and executing the procedure. Transport decision making includes, but is not limited to, planning, route selection, and schedule adherence. Automation may assist the decision process by producing alternatives and assisting in the evaluation. Humans make best use of such automation when they understand the system capabilities and limitations, thus transfer and maintenance of situation awareness remains a key consideration.

The emergence of AI algorithms and decision-making systems raises interrelated ethical, legal, and social implications. For example, the development of privacy-preserving techniques is a crucial challenge in the digitalization and governance of global transportation systems. Since transportation systems significantly rely on data collection and data sharing, maintaining user privacy and ensuring proper data governance is imperative to plan and implement a digitization approach [7]. This concern particularly emerges in intelligent mobility involving shared and automated transport modes, influenced by algorithmic decision-making and machine learning. Multimodal datasets and data-intensive simulation tools, explore the attributes of data, privacy requirements, and the impact of privacy-enhancing technologies on user trust in on-demand services and transport network systems. They investigate whether, how, and in which direction the integration of decentralization and privacy-preserving mechanisms affects users’ trust in intelligent mobility. Studies show that users’ trust in intelligent mobility has gradually increased over time and that diverse mobility datatypes and privacy-preserving solutions have a positive effect on user trust [8].

**RESULTS**

Smart transportation systems (STS) operate on three interdependent layers: data generation, data-driven learning, and human-centered decision-making [9]. Data from the physical world enter the STS at the level of sensors that measure variables of interest (e.g., vehicle location) and from which context-specific digital information (e.g., geo-reference) is generated. Drawing on available data and models, the system performs on-line inference to generate relevant knowledge (e.g., traffic situation) and estimate the likelihood of future events (e.g., travel time delays). Decisions made related to traffic control or routing are transmitted to the physical world through actuators, such as variable-message signs, traffic lights or redirection of vehicles.

An estimated 94% of all crashes are the result of human error, whether due to inadequate situation awareness, decision-making, or misinterpretation of information provided [2]. Public trust in intelligent systems and AI-enabled transport solutions decreases when misleading or incorrect information is systematically provided, leading to a positive feedback loop of mistrust and system abuse. Even when not required, road users assess and adjust their driving style so that they remain compatible with the anticipated style of surrounding vehicles. To facilitate this adjustment — and thus the intended positive societal benefits of enhanced safety and efficiency — there is a growing trend to design automated vehicles (AVs) for trustworthiness.

In 2020, the Dutch government sought a tighter relationship between innovation and public values in the development of AI, in response to the 2019 Assessment Framework of the Dutch Council for Public Administration. A human-centered approach to AI enables policymakers to safeguard citizens’ interests while fostering innovation. Autonomous driving is shaped by the environmental–psychological aspect: it is crucial to give non-driving users situational awareness. If travel time is too long or driven activities do not meet users’ requirements, they may resort to alternative ways of transportation. Longitudinal studies of user trust in vehicle automation show that while accuracy and robustness in lane-keeping and traffic-jam assistance critically affect initial trust, the perceived safety and learning ability of automated driving are also important. Since a fully automated vehicle has not been realized yet, an intensive study of user trust towards higher automation levels is recommended. Large-scale experiments of fleet learning verify users’ varying willingness to share driving behavior with the hypothesis of behavioral adaptation [10].

In road transport applications of automated driving systems (ADS), the automation capability has been expressed by means of safety criticality metrics, using the desired application scenarios as boundary conditions for the acceptance of external ADS functionalities. Actually, safety assurance can consist of both supply-side (i.e. safety of the ADS) and demand-side (i.e. acceptance of the ADS functionalities by the user or human overseer) constraining parts. Safety metrics allow characterising and evaluating the driving function according to the define scenarios with a human actor involved.

Such a performance evaluation methodology and aspect, when dealing with road transport systems, can also be used for the assessment of the safety of automated container terminals, when moving towards the ambition of a totally autonomous container terminal. The activity often involves either a limited or a periodic human supervision of the entire activity, being safety assurance therefore a critical aspect [11].

Safety requirements set forth in standard IEC 61508 are applicable to manned vehicles used for transport and earthmoving, for instance, on the transloading machinery of an automated container terminal. Human-system interaction can have a considerable impact on the safety of earthmoving vehicle operations, making it crucial for the system safety standards defined in IEC 61508 to deal with the humans involved in the operation. Safety-critical elements, and their associated safety functions and safety performance requirements, are defined in the standard. The widest obstacle detection of earthmoving operations can be implemented with sensors that detect obstacles in the overall operable area of the machine, for an evaluation system with a level of safety configurable according to the safety performance required [12].

**DISCUSSION**

Autonomous vehicles (AVs) have the potential to reduce traffic accidents, lower emissions, and enhance travel efficiency; yet, passengers still face safety risks as AVs become more prevalent. Significant safety concerns accompany the growing implementation of automation in various transport systems. Safety assurance can therefore benefit from human-centered artificial intelligence (HCAI) frameworks that incorporate human decision-making needs and constraints. Human-centered AI engages with system-supportive handover and sharing strategies when human oversight is required; focuses on decision support throughout guidance, explanation, and recovery; and emphasizes human factors such as cognitive workload and trust [13]. HCAI addresses high stakes in human involvement by aligning transport automation design with driver needs and enabling more effective passenger protection. Hence, stakeholder interactions, transport domains, and design levels become critical for developing broadly applicable HCAI approaches—imperatives that HCAI in AVs tackles via a framework that spans modal, system, and automation frameworks [14].

Automation in road transport affects vehicles across all domains—including urban, interurban, and freight transport. Smart transportation systems, in dense, smart cities, help users blend private and public transport. The urban transport case study examines a 2017 project in the city of Lyon. Additional hardware in public transport vehicles and private Uber-style vehicles assists multi-modal routing. Transport companies can send passengers seamless, real-time information about vehicle arrival, departure, route, service interruption, or modification.

Interurban transport connects cities using various vehicle categories. The case study on the 2016 Tramway Congrès project integrates into the system of the Geneva Public Transport Company, linking interurban with the Trams and Bus network. Time, distance, route modifications, system disruptions, and driver availability are key considerations. Multimodal routing between public vehicles and the private Uber-style offer increases system efficiency.

Freight transport within cities is subject to strict regulations aimed at optimizing delivery yet reducing impact. Generalized-multi-agent simulations carried out through a cooperation between the Urban Transport and Mobility unit of the Geneva Office and the Urban Transport department of the Geneva canton demonstrate the efficiency of the intelligent system and effective optimization of delivery through shipment distribution. A key consideration is to maintain interurban transport performance when tackling the urban environment. Studies show that an interurban joint route can absorb up to 38 cars.

Lorry-pooling options such as a connected GPS allow the collaboration of shippers to join capacity constraints. Several lorry-sharing between the same origin and destination at the same period require only one vehicle to make the journey. An additional project investigates temporal handover between two trains during extreme-events scenarios. Time schedules, origin-destination, and vehicle configuration have an impact when seeking candidates.

A multi-level approach to governance tolerates varying implementation depth across jurisdictions while strengthening alignment with safety and ethical objectives [2]. A framework can facilitate the progressive alignment of intelligent-transit technologies with community values by promoting multimodal safety, mobility equity, data governance, public-transport enhancement, and design transparency. Clear norms and standards, together with mechanisms enabling broader engagement in both technology development and data stewardship, can help secure public trust. Ethics-understanding initiatives addressing autonomous-vehicle deployment also show promise for steering shared-automated-transit governance, as the subjects concern not only individual vehicle operation but also the potential transformation of urban mobility.

Governance discussions need to acknowledge that human-centered AI extends beyond smart transportation to other steps where advanced systems affect human decision-making on public safety, critical infrastructure, and social justice. Developing a multi-level framework to navigate rationale, relative automation grades, societal objectives, and technological trajectories would aid consideration and knowledge-sharing. Human-centered principles and standards can accompany specific geographies, technologies, and application domains through shared resources, rather than being independently established within the different domains or technologies alone.

Although advancements in artificial intelligence and smart transportation systems have expanded the automation frontier, fundamental difficulties remain. The decision-making process of automated vehicles becomes more complex in shared urban contexts with pedestrians and bicycles, even at the lower automation levels of L3 (conditional automation) and L4 (high automation) [15]. Other technical challenges involve achieving the broad autonomy needed for a fully automated mobility system, maintaining user trust in shared and collaborative modes, ensuring system safety, and guaranteeing that automated vehicles accept commonsense norms for human-centered operation [16]. Research priorities include understanding how to control or influence such systems and developing socio-awareness and other skills complementary to, to preserve rather than undermine, human agency in the transportation process. Alongside the conventional objectives of mobility system performance—such as safety, efficiency, equality, and convenience—developing automated systems aligned with human decision-making and system experience will continue to gain importance.

Automation often intersects with other technologies such as virtual assistants, digital twins, electric or flying vehicles, supply chain innovations, and block chain. These technologies enable promising applications for transportation systems at low automation levels, facilitating planning of activities before the trip, or learning user preferences over time.

**CONCLUSION**

Recent years have seen significant progress in smart transportation, including efforts to integrate Artificial Intelligence (AI) and Machine Learning (ML) into Intelligent Transportation Systems (ITS) and Transportation Systems Management and Operations (TSMO) around the world. This is evident in the developing applications guiding taxis and commercial vehicles toward the most favorable routes, and traffic pattern prediction systems at the city or national level. Such systems have the potential to greatly alleviate urban traffic congestion and road safety concerns. [13] They also offer a wider perspective when it comes to Human-Centered Artificial Intelligence (HCAI) research. A collaborative framework encompassing autonomous and cooperative vehicles employing a combination of input from the road (from EdgeCloud to vehicle for Locality) supplied by Geographic Information System (GIS) data, video feeds, aerial images, and Artificial Intelligence support can achieve significant mission success rates for urban traffic management. Mission states judged from the scene context, corresponding objectives, mission spaces and route planning, real-time operation, regulating speed and maintaining following distance while aggregating for green lights must also be included. The same trend applies when introducing decisions intelligently guiding Cooperative Intelligent Transportation Systems (C-ITS), Intelligent Traffic Signal Systems (ITSs), Vehicle Information and Communication Systems (VICS), Public Transportation Information Systems, Evolutionary Investment System (E-I-S), Advanced Traveler Information System (ATIS) etc.

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