**Modeling** **Human–AI Trust in Smart Transportation Devices: A Systematic and Conceptual Framework**

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**Abstract:** This research advances the basis for systematically modeling human-AI trust in smart transportation devices (STDs) and deriving testable hypotheses that are amenable to both empirical and computational validation. Leveraging a device taxonomy—traffic-management interfaces, autonomous-driving assistants and connected-mobility ecosystems— we integrate cognitive, affective, motivational and sociotechnical trust theories into a hierarchically-structured model. The meta-model comprises 29 trust-related constructs grouped under up to five abstraction levels and defines 12 anticipated inter-construct relationships expressed as research hypotheses. Instantiating these constructs, we associate 42 established measurement instruments with the identified variables and discuss potential data sources, including behavioral logs, system performance measures, contextual descriptors and self-report scales. Findings suggest that trust in STDs is best characterized as a dynamic, context dependent and time varying phenomenon: contextual and system-level features have their effect on trust outcomes mainly through cognitive appraisals as well as affective–motivational mediators with feedback from actual performance in the real world leading to recalibration of trust over time. Methodological issues are considered, including distinguishing between trust and its antecedents, granularity across time/event/status levels of analysis, and calibration vs. reliance. The paper finds that a layered trust model can streamline the fragmentation of human–AI trust research and deliver actionable direction to trustworthy smart transportation device design and governance, thus promoting safer implementation, more effective human–AI teaming, and mature evaluation standards.

**Keywords:** Modeling, Smart Transportation Devices, Human–AI Trust, AI Systems, Concepts.

**INTRODUCTION**

Autonomous transportation technologies have improved significantly in recent years, especially with the advent of AI-based smart devices that assist driving or managing traffic. Users are interested in understanding how much they can trust these devices because AI capabilities vary across devices and organizations. Trust is a key factor shaping the collaborative relationship with AI-based systems [1]. Empirical studies have proposed several conceptual frameworks for modeling trust development in human–AI systems [2, 3]. The trust constructs, interaction components, and trust life cycles established in these studies need to be systematically organized, extended, and adapted to the specific context of smart transportation. To address the challenges of modeling user trust in smart transportation, three interrelated gaps emerge in previous human–AI trust literature. The first gap focuses on a wide range of AI capabilities and corresponding trust constructs. Existing frameworks primarily focus on assistance, recommendation, and automation capabilities. The second gap involves multiple devices embedded with various AI capabilities. Established models mainly reference anthropomorphic and proxy-based AI systems. The third gap concerns the lack of clear operationalization mechanisms for trust constructs. Although some measurement scales exist, they do not cover the trust constructs of different AI capabilities in smart transportation.

Trust is a complex construct that has been intensely investigated in various disciplines. It plays a central role in both human–human and human–machine interactions. The concept of trusting AI systems has emerged as an important research area, primarily due to the rapid diffusion of AI technologies and the increasing reliance on AI-equipped devices. When using automated systems, users frequently need to assess the appropriateness of either depending on the system or taking control over it. For efficiently managing that cognitive process, users need to form a mental model of AI systems, which is determined by elements such as the perceived reliability and operating principles of the system, as well as the context of usage [4].

The meaning of trust in a human–AI context has been widely discussed in many different studies, yet it remains vague, heterogeneous, and fragmented. Current literature on trust in AI systems often focuses merely on the properties believed to influence trust formation rather than on the actual construct of trust itself. The notion of trust is also frequently conflated with dependence, reliance, and other dimensions. Within the scope of AI systems, trust is thus conceptualized as a subjective belief, attitude, or intention that can be based on either prior experience (such as perceived performance, reliability, and transparency) or perceived properties of the AI system (such as its role, objectives, and decision-making criteria) [2]. Depending on trustworthiness factors and performance, trust can also be anticipated to evolve from a high level of initial trust toward a more situation-dependent state. The internal mental model of a trust-aware AI system is here further formalized using a recursive and decentralized trust model. Therefore, trust is viewed as a human’s belief about the behavior and reliability of another individual [3].

Considerable research exists on defining and delineating trust across various disciplines, including sociology, psychology, and management. Trust is defined as the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other party will perform a particular action important to the trustor [5]. Although the party granting trust (the truster) and the party receiving trust (the trustee) may differ between individual and organizational contexts, the interpersonal nature of the trust relationship remains constant even as the number of intervening parties increases.

Philosophers typically distinguish between two different types of trust: general trust and particularized trust. General trust refers to the beliefs that individuals have regarding other people in general, whereas particularized trust refers to the beliefs that individuals have regarding a specific person or social group. This duality of trust can also apply within a macro or micro context, where macro trust involves entire institutional or cultural systems and micro trust involves small interpersonal networks. The various interdependencies stemming from the action of one party can thus be differentiated according to the party granting trust and the party receiving trust.

Enabling flexible, autonomous vehicles that interact safely and predictably with pedestrians, cyclists, and other vehicles remains a daunting scientific and engineering challenge. Such vehicles must monitor their operating environment before starting, continuing, or stopping their progression, enabling them to control their motions without impeding the movements of other road users. Safe, predictable, and comfortable vehicular travel in a diverse socio-technical environment is a shared, collective societal objective where road users depend on intimate, direct, and transparent interaction with each other. Continuous interaction is needed between operators and vehicles in certain applications—e.g., driverless taxis, shared vehicles, and last-mile multi-modal solutions—so the identification of appropriate temporal and spatial frames of reference is vital to achieve truly autonomous travel.

Transitive trust can operate on significantly different timeframes. First, users may express trust in communal transit systems as temporary participation based on a much larger footprint of community compliance, aggregation, and congestion—a far wider footprint than the vehicle itself. Second, an individual vehicle must build trust according to the period of operation or intervention when operating independently of the user. These are fundamentally different levels of analysis applicable individually and sequentially. Engaging, fostering, and developing trust-building interactions remain key for the deployment of shared, mobile vehicle systems in society today [5].

Certain user-centered aspects such as ergonomics, accessibility, ease-of-use, and overall user experience (UX) play a fundamental role in shaping the human-transportation devices interaction, and consequently their initial and continuous trust toward these automated systems. Although increased investment in the technological aspects of transportation devices is evident and continues to increase, a corresponding investment in user-centered factors is still to be observed. Transportation devices are typically considered large horizontal 3D spaces that can occupy entire rooms or even outdoor spaces. User-centered considerations such as the integration of devices within existing facilities or their proper maintenance by users are far more important than aspects related to the transportation technology as such [6]. The devices should satisfy ergonomic, reachability, and material requirements in demand for today’s population, and be operable without any advanced information technology (IT) skills [1].

**METHODS**

Smart transportation devices improve mobility and safety through various forms of artificial-intelligence (AI) technology. The AI capabilities involved in smart transportation raise new challenges and considerations for modeling human trust—challenges not sufficiently captured by existing models of trust in automation. To explain these challenges, the human–AI interaction relationships unique to smart transportation are categorized according to three device types: traffic-management interfaces, autonomous-driving assistants, and connected-mobility ecosystems.

Modeling trust in devices equipped with various AI capabilities requires addressing specific considerations. A conceptual framework is proposed incorporating device-type categories. Within each device type, the system identifies trust-in-device variables, classifies them into a taxonomy comprising three components (trust determinants, trust states, and trust-related actions), delineates the expected relationships among them, and formulates corresponding hypotheses. Trust determinants comprise nine variables classified into two groups: human and device characteristics, shaped further by eighteen contextual factors corresponding to nine driving situations. Trust states include three variables reflecting different trust aspects (trust level, trust calibration, and trust stability), influencing three trust-related actions (trust adaptation, trust expression, and trust transition).

Since the operation of smart transportation devices has a significant role in the safety and efficiency of transportation systems, human–AI trust in these devices is a critical consideration. A systematic framework and conceptual model for studying human–AI trust in smart transportation devices are developed. Different classes of smart transportation devices are examined, including traffic management interfaces, autonomous driving assistants, and connected mobility ecosystems. Notable AI capabilities found in such devices are identified—deep learning-based perception and prediction, model predictive control, optimization, and automated decision-making. A review of theoretical models of trust formation in human–AI systems is conducted to explore the primary cognitive, affective, motivational, and sociotechnical factors that influence human–AI trust. An integrated conceptual framework is proposed that classifies trust antecedents along four hierarchical layers (device, driver, service, and environment) and differentiates between trust in device operation, information sharing, and decision authority. The study aims to advance knowledge of the dynamics of human–AI trust in transportation systems [7, 8].

aim to optimize transportation systems by regulating vehicle flows through traffic lights and providing travel time estimations with variable message signs [9]. They analyze traffic conditions using detection methods, automate decisions through control logics, and disseminate information to vehicles at intersections and on roads. Several functions are included, such as system status presentation, estimation of the efficiency of control logics, and diagnosis of the system's faults. সHumen factors have a large weight in the design of traffic management interfaces because drivers are responsible for complying with the advice provided.

Smart transportation devices, such as autonomous driving assistants, present novel challenges for the formation and calibration of human–AI trust. Trust in these systems influences experimental interactions across a spectrum of contexts: from a fully attentive and interactive engagements to a mere monitoring or standby roles. The emergence of traffic jams or situation that require the driver to take over often exposes the human to a multitude of AI recommendations and information, making a general evaluation of the AI agent’s overall helpful index crucial. The design of measures to develop large-scale and unobtrusive collection of real-world human–AI interactions in smart transportation settings is therefore important to ensure confidentiality and relevance [10] ; [5, 11].

In connected mobility ecosystems, significant research focuses on urban platforms integrating public transport and micro-mobility services to optimize user experience. Additional interface features support traffic flow prediction and other auxiliary services [12]. Automated vehicles are gradually becoming commonplace in urban settings amid continuing efforts to advance safety. Despite efficient operation in restricted environments, human drivers often find themselves responsible for safety-critical decisions, necessitating assistance from the driver assistance system [15]. The deployment of advanced driver assistance systems raises questions about their role as a trust mediator in scenarios where users engage with autonomous vehicles.

User's work explores the natural interactions between humans and artificial intelligence (AI) systems in smart transportation devices, while they are capable of fully autonomous operation. It investigates how people form and update trust towards AI in transportation contexts, especially when an operation is partially relinquished to AI. Several theoretical models of trust formation have been proposed in the literature. A first category—cognition-based models—scholarly addresses AI trust formation in sequential, dynamic tasks, as encountered in smart vehicles and related interfaces. Psychological models describing the influence of affective and motivational factors represent a second category. Recent findings identify anthropomorphism and social cues as means for humans to perceive transportation devices as social entities and for forming trust in human–AI cooperation. The assumption of a sociotechnical perspective based on the causality extends these models by considering the human and the environmental dimensions along with the AI technology capability. It aligns with ideas of the Smart Transportation area that trust in transportation systems is built not only on the AI automatic capabilities but also on the user–device interaction and the larger transportation modality.

Trust formation is an essential factor in the acceptance of smart transportation systems that rely on interpersonal forms of interaction between humans and AI. A systematic and conceptual framework depicts the variables influencing human trust formation towards AI in smart transportation devices, proposes new corresponding hypotheses, and identifies relevant data sources and measurements within the urban mobility domain [16].

Cognition-based modeling of human trust in AI systems focuses on understanding and predicting mental processes during interactions with automation. Mathematical models enable the theoretical exploration of the factors that determine trust formation and its evolution over time. Cognitive modeling applied to human–AI trust can take various forms: it can rely on probabilistic processes to capture trust dynamics in human–robot collaboration; it can address perceived risk concerning driving automation; or it can focus on the gradual build-up of trust based on prior experience, supporting practical applications such as intelligent-speed assistance or lane-keeping support. In the context of human–AI trust, dynamic models have been proposed to formalize the role of experience in trust formation, a topic studied also in relation to multi-agent systems and team trust. Moreover, mental-model-based frameworks are gaining traction in machine learning, enabling inferences about users’ trust grounded in latent representations of human mental models of AI capabilities. Such approaches identify the relative reliability of AI and the expected gain from using the system, thus formalizing the psychological assumptions involved in trust perception [17].

Cognition-based modeling can emphasize not only decision-making mechanisms but also the influence of attention on task execution and trust dynamics. Eye-tracking techniques have been applied in rather different contexts to analyze trust patterns in human–AI interactions and how those patterns correlate with reliance and performance. Automated analysis methods have been proposed to automatically detect adjustments in attention distribution when switching from an AI-driving assistant to full control and elaborate a user-centric understanding of foundational human–AI safety in autonomous driving. Insightful theoretical frameworks characterize human reliance on AI and how that reliance interacts with normative machine assessments of user performance. Apart from trust, several related concepts can also be modeled in conjunction with reinforcement learning: users’ understanding of the system’s operational principles, the appropriateness of the AI’s decisions, and the estimation of personal risk when engaging with the system [13] ; [4].

Under the affective perspective, trust in intelligent systems can be interpreted as a user’s disposition to rely upon the system, depend upon its functions, tolerate its inconsistent performance, and experience trust-related emotions. Studies on users’ emotional responses to new systems have emphasized their impact on users’ attitudes toward the systems. User experiences comprising pleasure or other basic attitudes, such as satisfaction and enjoyment, motivate users to keep using the systems. Studies on social robots and AI-enabled agents underline the role of emotion and trust in fostering the acceptance of such systems [1]. Affective states can drive user acceptance of human-AI collaboration in diverse situations and thus affect user readiness to adopt transportation systems supported by AI [14].

Motivational factors indirectly influence trust through a set of individual user goals, such as the desire to reach a destination, minimize travel time or keep vehicles in a good condition. The anticipation of emotional satisfaction drives the intention to keep using automated or AI-enabled devices. Keeping connected to the devices, meanwhile, the desire to travel safely, is generally considered a characteristic of driving situations directly affecting activities and events [18].

Factors associated with the sociotechnical system and contextual environment also shape human–AI trust in smart transportation devices [8]. Smart transportation systems consist of physical components (e.g., vehicles, communication networks), data flow (intended or unintended), and human users (drivers, operators, passengers, and pedestrians) [3]. A connected subset varies by market segment and service design. The prevalent “one user–one device–one data source” paradigm remains insufficient as new markets emerge. Contextual and sociotechnical factors are general prerequisites for trust—not specific to AI. In trust models, the interaction of system, regulatory, and sociocultural settings with device design, determined by norms, practices, and policies, becomes paramount. Ad hoc analysis by the International Federation of Automatic Control classified these conditions [1].

**RESULTS**

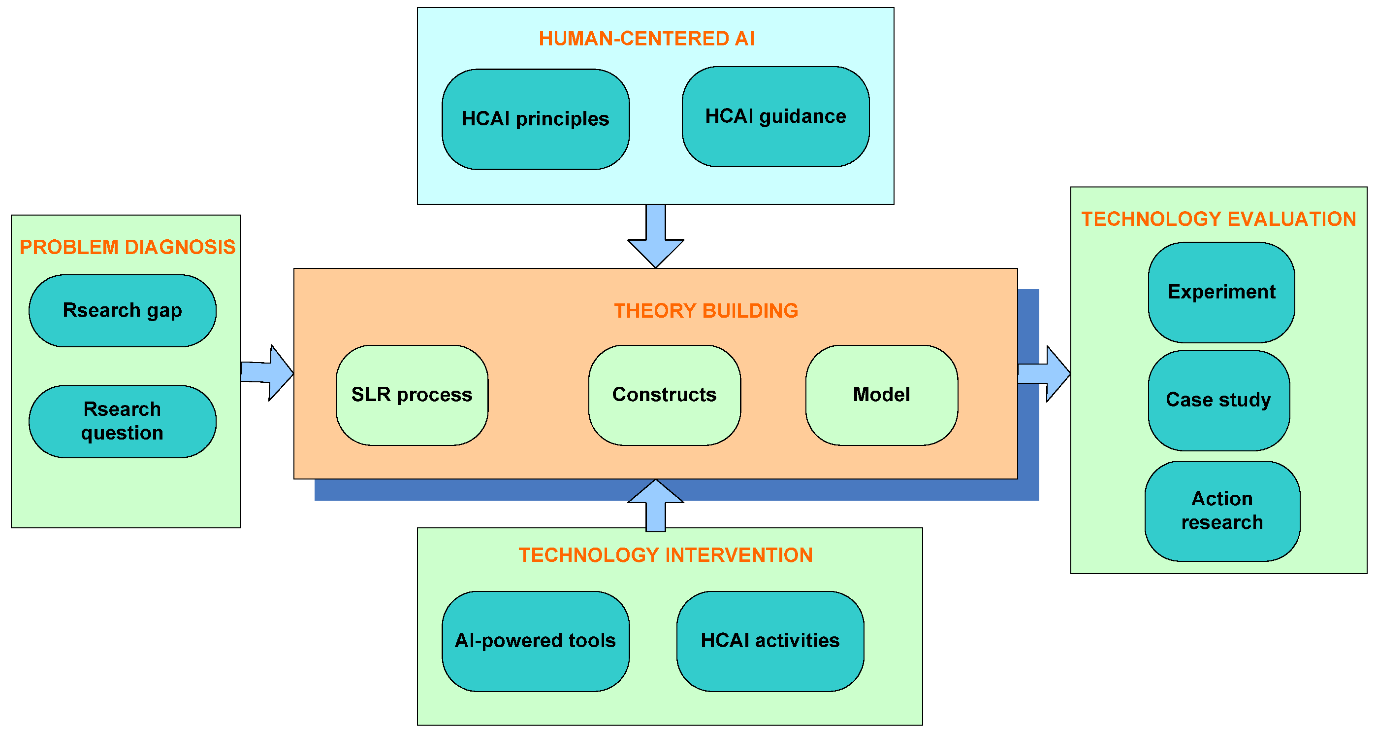
The broad objective of the proposed research is to provide a systematic framework for the study of human–AI trust in smart transportation devices and to propose specific research questions for (empirical and computational) model validation. A typology of transportation devices, highlighting their specific AI capabilities, guides the definition of candidate antecedent and consequent trust variables, whose categorization into a conceptual framework reflects the main cognitive, motivational, affective, and sociotechnical theories of human–AI trust formation. The resulting human–AI trust model includes 29 variables organized in up to 5 layers reflecting the level of abstraction of the variables; 12 expected relationships between the variables, accompanied by 12 related research hypotheses; 42 validated measurement instruments compatible with the variables; and notes on data sources. Methodological issues concerning these model components, differentiation of trust and its antecedents, and the treatment of trust as a contextualized temporal phenomenon are also discussed [5]. Research in human–AI trust is fast evolving but remains fragmented; the research questions formulated extend prior work that has primarily focused on safety-related aspects of the user experience to design and design principles relevant to transportation devices, achievable through human–AI trust frameworks and models.

**TABLE 1.** Structure of the Proposed Human–AI Trust Model for Smart Transportation Devices

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Layer (Level of Abstraction)** | **Variable Category** | **Key Variables (Examples)** | **Measurement Instruments / Sources** | **Expected Role in Trust Formation** |
| Layer 1: Contextual Conditions | Environmental & Situational Factors | Traffic density, system criticality, time pressure, operational risk | System logs, contextual scenario descriptors | Define baseline trust conditions |
| Layer 2: System-Related Variables | AI Capability & Transparency | Explainability, reliability, predictability, autonomy level | System performance metrics, XAI indicators | Shape perceived system competence |
| Layer 3: Human Cognitive Variables | Cognition-Based Trust Antecedents | Perceived usefulness, mental workload, situation awareness | NASA-TLX, Trust in Automation Scale | Enable rational trust evaluation |
| Layer 4: Affective & Motivational Variables | Emotional & Motivational States | Anxiety, confidence, perceived control, engagement | PANAS, motivation inventories | Modulate trust intensity and stability |
| Layer 5: Trust Outcomes | Behavioral & Intentional Outcomes | Reliance, compliance, override behavior, long-term adoption | Behavioral logs, intention-to-use scales | Manifest trust in action |

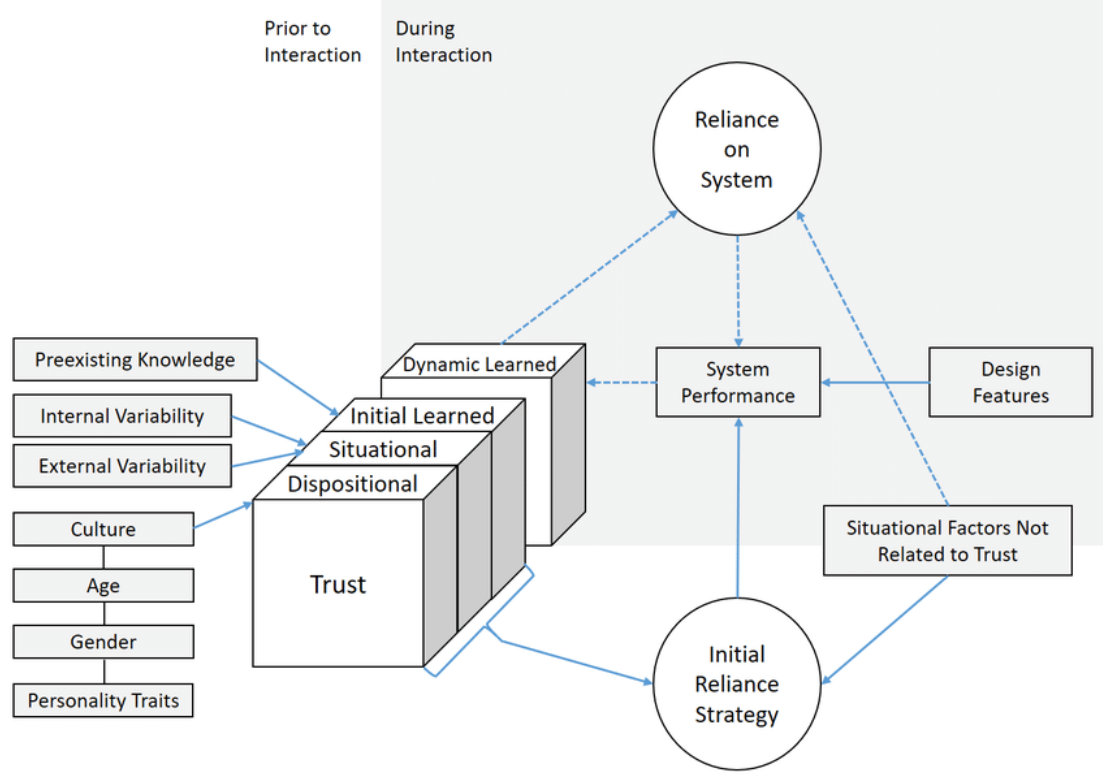
The results indicate that human–AI trust in smart transportation devices is best represented as a **multi-layered construct**, where contextual and system-level variables indirectly influence trust outcomes through cognitive, affective, and motivational mediators. The identified structure supports modeling trust as a **dynamic, contextualized, and temporally evolving phenomenon** rather than a static user attitude.

Trust is a key factor when humans interact with AI systems that increasingly make critical real-world decisions for us. AI-augmented smart transportation devices evolve across a spectrum of capabilities, from recommending traffic routes and travel schedules to assisting with driving and coordinating connected vehicles. A systematic approach is thus required to characterize and model the trust that humans place in such systems. Drawing from existing literature, a conceptual framework identifies 11 key contextual, system, and user variables influencing the formation of trust in these devices. The framework elucidates interactions among these variables and distinguishes time, event, and status dimensions within the trust-development process. A variety of measurement instruments and data sources are proposed to operationalize the framework for empirical validation [5] ; [13].

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**FIGURE** **1**. Conceptual framework illustrating the multi-layered structure of human–AI trust formation in smart transportation devices (A)

Modern search and rescue (SAR) operations have been significantly improved by the adoption of Airborne Ground-penetrating Radar (AGPR) systems. These systems, currently evolving towards full autonomy, detect landmines and metal objects while providing photos of the ground surface, 3D bathymetric surface maps, photos of the water surface and detailed photos of above-water objects. Effective communication between human operators and these devices is therefore imperative. Trust plays a vital role in ensuring that information provided to operators is properly interpreted and that follow-up actions are taken optimally.



**FIGURE** **2**. Conceptual framework illustrating the multi-layered structure of human–AI trust formation in smart transportation devices (B)

Trust characterization is a fundamental first step towards enabling appropriate human–AGPR trust levels. The advanced ecological area on the trust between humans and AGPR systems is modeled and adapted for the transportation domain where AGPR systems operate. The trust evolution model is opened, allowing consideration of any number of influencing variables. Research works at the intersection of transportation and machine autonomy have addressed the need to enhance human–machine cooperation and communication. Two well-defined categories of information that shape trust levels in human–machine systems have been considered: information that enables the understanding of machine capacity and information pertaining to machine intentions. The complexity of directing the future of transportation systems with the evolving advent of Autonomous transportation is acknowledged.

The development of smart transportation devices, such as traffic management interfaces, autonomous driving assistants, and connected mobility solutions, increases the importance of researching user trust in these technologies. Multimodal traffic management interfaces lead to trust in multiple sub-systems [5]. When the traffic information transmitted between systems and users is either high or low, priority information on the system’s traffic flow is transparent. Besides, traffic information about average speeds, congestion levels, and travel times can facilitate user trust on the diagrams presented by the system. Automated driving assistants deliver routes and provide estimation travel times to indicate required comprehension levels to users. A connected mobility ecosystem refers to a situation where users share their travel journey between facilities such as public transport, commercial vehicle, and shared vehicle. A connected mobility ecosystem not only gives spontaneous information on the route travelled by users, but also additional information about traffic and expected arrival times from vehicles.

Smart transportation devices, which either exhibit high autonomy or support users in performing transportation activities, employ a wide array of artificial intelligence (AI) capabilities. Existing taxonomies clearly delineate various AI activities relevant to domain tasks, ranging from strategic planning to situation monitoring and perceptual interpretation. Such systems include traffic management interfaces, autonomous driving assistants, and connected mobility ecosystems. Although they address different mobility-related activities, human–AI collaboration remains pivotal across these use cases.

Two broad classes of theoretically grounded human–AI trust models shed light on the formation of trust in smart transportation devices. Cognition-based models elucidate the processes by which users construct trust following the initial interaction [5]. Two key conclusions emerge from this line of research: first, trust evolves in predictive cycles, driven by users’ expectations regarding the AI’s performance; second, these predictive cycles interplay with a range of intrinsic affective, motivational, and contextual drivers that give rise to distinct modes of system engagement. Such affective and motivational considerations constitute a crucial complement to cognition-based accounts, suggesting that human–AI trust involves more than mere evaluative attribution and highlighting the importance of ongoing engagement over time.

In the validation methodology, it is important to underline the appeal of a widely used research model. The theoretical foundation offered by the Unified Theory of Acceptance and Use of Technology is complemented by human–AI trust that adds a relevant component to elicit timely feedback from users on their daily experience and accepts that AI involves high uncertainty. The affirmations made by Walker and co-authors point to the need for a clear understanding of the particulars of human–AI trust before a careful selection of constructs and trust-forming processes [19].

**DISCUSSION**

The primary objective of our work is to provide a conceptual framework for studying trust in human–artificial intelligence (AI) systems applied to smart transportation devices. This framework draws on a systematic review of existing literature and describes the relationship between the various drivers of trust and the corresponding control variables that can be manipulated by system designers, operators, or policy makers. The need for such a framework stems from the appropriate application of advanced AI capabilities to traffic management, autonomous driving, and connected mobility. In addition, trusted smart devices must be designed and implemented with consideration for user and societal needs. This paper, therefore, focuses on providing a comprehensive characterisation of trust formation in the context of smart transportation devices. These devices can assist drivers, share information on traffic and road conditions, and provide guidance on travel options. Human behaviour, however, remains a critical determinant for improving transportation efficiency, reducing accidents, and mitigating environmental impact. Addressing the growing integration of AI-based solutions into the transportation system, insufficient trust toward these technologies can undermine their societal benefits at both the user and system levels [5].

The rapid evolution of traffic management and smart mobility systems that involve artificial intelligence (AI) makes it imperative to model trust across multiple human–AI interaction contexts. Applications include traffic-management interfaces for intelligent traffic lights and dynamic routing guidance, driving-listening scenarios (human driving with driver-assistant systems), and mobility eco-systems featuring autonomous vehicles. These factors necessitate developing a conceptual framework that maps the relevant characteristics of smart transportation devices to existing theoretical models of trust formation. Such a framework will be crucial to conducting empirical studies across diverse scenarios and for formulating design principles, policy recommendations, and evaluation charters. The three classes of existing models—cognition-based, affective/motivational, and sociotechnical/contextual—directly inform variable selection and relate to trust’s layered architecture [5].

Trust develops and changes over time in a complex, multi-layered manner influenced by experience in varying situations. The quality, rather than just the quantity, of experience shapes trust, with rare or unexpected events having a strong impact. Proper assessment requires evaluating how experience and situation types influence trust and reliance. Current methods of quantifying trust often lack objectivity and reliability, highlighting the need for clearer definitions and better measurement tools. Future research should focus on understanding the psychological processes behind trust variables, how information influences expectations, and the role of specific experiences, especially rare events, in developing trust [5].

A layered approach for modeling trust in smart transportation devices (STDs) is proposed. Trust is analyzed based on four levels: human factors (variables related to the user), trust dimensions (encompassing the specific facets of trust), device qualities (factors describing the STD), and contextual aspects (situational characteristics affecting the user–STD interaction).

A human–AI trust framework for STDs has been conceived, comprising two key pillars. First, a structured human–AI trust variable taxonomy identifies the main factors influencing the trust establishment process. This multidimensional view of trust reflects the specific characteristics of STDs and distinguishes different trust dimensions. Furthermore, interrelations among trust dimensions are mapped based on the trust component literature. The second pillar proposes a set of viable approaches for measuring both trust and the proposed influential factors. Various data sources and techniques are suggested according to each variable, providing valuable options for practical implementation [4].

The layered framework depicts the main STDs trust variables across these four levels (Figure 2). At the lowest tier, human characteristics, device properties, and situational elements represent critical aspects regulating the human–AI trust process. System, reliability, and transparency dimensions emerge as the main facets of trust influenced directly by these components. System variables refer to the ability of an STD to deliver information, suggestions, or decisions adapted to the user’s context. Reliability accounts for the consistency of an STD’s performance over time and varying situations. Transparency captures the clarity of information, decisions, and uncertainties provided by the STD to the user. Finally, these three trust dimensions affect the overall trust degree toward STDs.

Trust in smart transportation devices evolves throughout their use, and its dynamics depend on contextual aspects. Contextual trust is defined as trust influenced by cues external to the target system, such as urban settings or weather conditions [13]. The context of trust formation is fundamental in human-AI systems, particularly in smart transportation, where devices operate in diverse contexts, ranging from restricted environments, such as toll booths, to activity-specific contexts, such as logistics or vehicular maintenance, and broader-system settings. Dynamic trust in ground transportation spans several time intervals, with influences occurring when a change happens in the automated functions of the system [5].

Trust is subject to momentary fluctuations and systematic re-calibrations throughout extended periods of intermittent exposure. It develops during the initial and facilitates system efficiencies that are significantly faster or safer. The aspect of extended time, in particular, is critical to driver interaction with vehicles in shared settings, such as parking, where trust increments over time without human intervention. The higher the need for the system to operate autonomously to complete the goal without relinquishing control, the earlier the driver’s initial trust is established. In smart machinery, such as pick-and-place robots, which can execute tasks without direct indication or command, the establishment of goal-trust assumes a pivotal role.

Trust levels are also influenced by other contextual variables, each depending on the specific task to accomplish, as well as users’ experiences with previous alternative automated systems. In user versus system–requested workflow interaction, the configuration of task-trust evolves differently and may not operate in the same direction. An innovative consideration is the propagation of trust loops among main agents within the system rather than focusing solely on the primary target.

Adoption of automated solutions for transportation and mobility has reached a critical point, bringing expert and public interest to system-wide trust calibration and the configuration of user–system interactions. Elements that support human–AI uptake include enhanced transparency in operations and behavior, precise specification of expected device capacities versus limitations, and clarity of input–output relationships. Trust in mediated systems encounters complexity when users, devices, and environments mutually influence one another and where time lags affect saliency. Addressing these shared concerns, the field has begun to explore how trust among an ensemble of interlinked socio-technical actors emerges, persists, facilitates, and may impede intended outcomes. A representative study employed a conceptual model to elicit trust and attitude variations within the often-automated bus and shuttle context and so defined modeling construction principles, identified influential variables, specified feedback loop dynamics, and produced instrument design recommendations aligned with complementary measures of socio-technical influences [5]. A parallel investigation defined physical events, communications, agent attributes, and contextual factors shaping trust and related dimensions across users, devices, and environments and thereafter elaborated a comprehensive MDF. The study fully recognizes that numerous complex devices influence transportation systems and that distinct feedback loop arrangements will arise in dissimilar scenarios [1].

An initial scoping review identified relevant literature and led to the selection of candidates that form a systematic, conceptual model of trust for smart transportation systems [5]. The resulting framework combines existing parties, processes, and contextual factors in an ecosystem that informs trust in associated services or technologies. It recognizes the potential for changing levels and attributes of trust across time and conditions. Systems and agents both play distinct roles in the formulation of proposals, whose attributes and context further contribute to trust and instigate feedback on the proposal originator. Simultaneously, features, situations, and other elements arise from interactions with multiple actors, scenarios, environments, parts, or systems.

Trust in pertinent applications is crucial, given the safety-critical nature of related systems that impose traffic rules and manage system integrity, privacy, and sustainability. Such operations are typically exerted via multiple interconnected agents and ecosystems—covering traffic information and coordination algorithms—that modulate control activities, recommend routes in hybrid modalities, enable travel-time predictions, and classify or convert requests among diverse transport modes.

Trust relationships in transport devices are characterized by three dimensions: the information at their core, the user characteristics, and the context of the transport device itself. Diversification of trust related to the context recognizes that devices offering similar AI functionalities may still require different approaches to foster trust. Traffic management interfaces, autonomous driving assistants, and connected mobility ecosystems provide illustrative examples of context-sensitive considerations affecting such relationships. Various relationships between SMART transportation context variables are proposed, with explanatory indicators offered for modeling each. Such models can be developed with appropriate datasets, existing measurement scales, and established or dedicated methodologies from the appropriate literature [5].

Extensive theoretical literature concerning trust formation in AI systems has emerged, including various frameworks and models. Cognition-based models posit that trust comprises different layers or dimensions. Such models have been tailored to consideration of AI systems, but Affective and motivational considerations remain significant factors influencing trust in human–AI systems and merit explicit acknowledgement and exploration, particularly for SMART transportation devices K10. Societal trust perceptions of AI technologies are established by regulations, laws, policies, and moral and ethical standards situated within cultural contexts. Such sociotechnical and contextual factors mould individual attitudes and subsequent trust development in any specific system, device, or agent. A comprehensive understanding of these diverse factors and relationships is essential for the design and deployment of effective, compliant, and trust-fostering SMART transportation devices and processes [1].

Shaping policy and regulation for the safe development and deployment of smart transportation devices is an urgent priority. Effective governance requires facilitating the transition to these technologies while ensuring the continued protection of human rights and prioritization of safety. Having the right mix and level of policy instruments and enabling regulation is critical to achieve these dual objectives.

This need is underscored by the launch of the United Nations initiative on Smart Cities and Urban Mobility, which highlights both the promise and potential pitfalls of smart transportation technologies involving artificial intelligence. Although many transportation systems have benefited from adopting artificial intelligence, achieving and maintaining public trust continues to hamstring the deployment of connected devices, autonomous vehicles, and governance capabilities in urban mobility. This challenge extends to such smart devices more generally, emphasizing the necessity of a systematic approach to understanding trust related to mobility and urban issues [10].

Trust in artificial intelligence depends on the quality of experiences interacting with those systems and the risk those systems present to users [3]. Too expansive an array of devices that reduce the need for users to dedicate attention to routing and congestion further complicates transportation trust issues. Establishing trust policies in smart transportation devices also demands developing effective evaluation frameworks and benchmarks. Such frameworks must accommodate the dynamic and distributed nature of trust involving multiple users and devices [5].

Trust in smart transportation devices refers to users’ confidence in the systems’ functionality and operation within various ecosystems such as Traffic Management (TM), Autonomous Driving Assistance (ADA), and Connected Mobility (CM). Representing a prerequisite for the digital transformation of transportation systems, trust is crucial to achieving full vehicle automation. Nonetheless, trust in smart transportation systems remains under-explored due to the complex interplay of factors across multiple levels, driving the need for conceptual frameworks that suit the system’s specificities [5]. The goal is to develop a systematic and conceptual framework modelling trust in smart transportation systems. The approach consists of delineating a system that unpacks the structure of smart transportation systems and identifies the trust-related variables, including users’ characteristics (such as sociodemographic, prior knowledge, and previous experience), vehicle characteristics (like perception accuracy, location privacy, reliability, and travel comfort), and the environment (such as user proximity to judiciary, norms, and authorities). The study later maps the relationships between these variables and establishes a set of corresponding hypotheses to guide empirical inquiries. Finally, the framework proposes an overview of measurement scales and instruments, as well as potential data sources for quantitative and qualitative approaches to support comprehensive validation of the model.

**CONCLUSION**

Designing sociotechnical systems, such as smart transportation devices that use AI, requires appropriate models for the user-agent relationship. Building trust in such systems, like in other safety-critical applications, is crucial for successful adoption. Trust in AI systems can be defined as the willingness of an agent to be vulnerable to AI actions and decisions based on the belief that the AI will act as intended. Building trust comprises two processes: initial trust formation and trust re-evaluation, which operate continuously throughout the relationship duration and across numerous interfaces. Delivering reliable, safe, and timely output encourages greater reliance over time. Transport AI comprises various functions across an itinerary, illustrating the need for a comprehensive model spanning AI capabilities, operating contexts, usage phases, and trust interactions.

The study offers a systematic review and a conceptual framework for modeling trust in smart transportation devices, addressing a crucial sociotechnical design challenge of significant economic and social importance. The systematic review identifies 98 relevant articles and 154 unique variables influencing the trust-formation process, accommodating device capabilities like driving assistance, traffic-optimization suggestions, and congestion avoidance. The identified variables classify into 7 high-level categories (user, agent, context, experience, capability, transparency, and safety) and 29 first-order subcategories (including responsibility, dependency, system knowledge, and risk). Capabilities drive behaviors that generate user experiences linked to trust, forming a complex system at the intersection of human, artificial, and environmental agents. The framework informs the design of transport-related smart devices. [5].

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