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Trust, Intention, and Behavioral Adaptation to Real Time Traffic Information Systems: A Latent Variable Model of Urban Mode Choice in Toronto

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ABSTRACT

The rapid diffusion of artificial intelligence (AI)-enabled real time traffic information systems is reshaping how urban travelers form perceptions, develop trust, and adapt their mode choice behavior. While existing transportation research has extensively examined the operational and network level impacts of intelligent mobility technologies, comparatively limited attention has been devoted to the latent cognitive and motivational mechanisms through which these systems influence individual travel decisions. This study develops and empirically tests an integrated behavioral framework that examines how AI information quality, system reliability, perceived safety, and accessibility perception are associated with system trust, travel intention, and self reported mode choice adaptation. Using survey data from 412 commuters in the Greater Toronto Area, Canada, the proposed model is estimated through Partial Least Squares Structural Equation Modeling (PLS-SEM) with bootstrapping and predictive validation procedures. The results indicate that system trust serves as a central mediating construct linking AI system attributes to travel intention, which in turn demonstrates a strong and systematic association with behavioral mode adaptation. The model exhibits substantial explanatory and predictive performance, with coefficients of determination reaching up to $R^2 = 0.64$ for key endogenous constructs. From a policy perspective, the findings highlight the role of trust centered and accessibility-oriented design of digital mobility platforms as mechanisms for reinforcing public transport strategies and promoting more sustainable travel behavior in metropolitan transport systems.

Keywords: Artificial intelligence; real time traffic information; mode choice; system trust; travel intention; urban mobility; PLS-SEM.

INTRODUCTION

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Urban transportation systems are undergoing rapid transformation driven by the integration of artificial intelligence (AI) into real time traffic information and mobility management platforms (Haghighat et al., 2020). AI-enabled systems increasingly mediate travelers' daily decisions by providing predictive congestion alerts, adaptive route guidance, and personalized multimodal travel recommendations embedded within public transit applications, navigation platforms, and smart city infrastructures (Visan, Negrea, & Mone, 2022). These systems now function as critical socio technical interfaces between transport authorities and travelers, influencing not only network efficiency but also individual behavioral responses. While prior research has extensively examined the operational and performance impacts of intelligent transportation systems, substantially less attention has been devoted to understanding how these technologies reshape travelers' latent perceptions, trust, and behavioral intentions that ultimately govern mode choice behavior in urban contexts (Alam, Ferreira, & Fonseca, 2016; Castaño-Herrera, Gomez, Garrido, Tapiador, & Vassallo, 2025; Robinsha & Amutha, 2024).

In this study, AI-enabled traffic information systems are defined as platforms that employ machine learning or algorithmic inference to generate predictive, adaptive, or personalized mobility guidance, including short term congestion forecasting, dynamic route optimization, and user specific multimodal recommendations, rather than solely providing descriptive real time status updates.

From a transport planning perspective, mode choice remains a central determinant of system sustainability, congestion mitigation, and infrastructure investment efficiency (Cheng & Lu, 2017). Classical travel demand models, including discrete choice and network equilibrium approaches, typically assume that travelers' preferences are stable and directly observable through revealed or stated preference data. However, growing reliance on AI-enabled information systems introduces new behavioral mechanisms that operate through unobservable psychological constructs such as perceived system credibility, safety assurance, and accessibility confidence (Hodge, Subramaniam, & Stewart, 2009). These latent factors can systematically alter travelers' willingness to substitute private vehicle use with public, shared, or active transport modes, thereby shaping the effectiveness of policy instruments aimed at decarbonization, congestion pricing, and transit-oriented development (Oshiro, Kainuma, & Masui, 2016; Pourhashem, Georgouli, Malichová, Straka, & Kováčiková, 2024).

Recent research in transportation has begun to examine the behavioral implications of digital mobility platforms, real time passenger information systems, and smart infrastructure investments (Galkin, 2024; Omotoye, Olusesi, & Adigun, 2025). Empirical studies indicate that information accuracy, system reliability, and perceived responsiveness significantly influence traveler satisfaction, compliance with route guidance, and continued use of digital mobility services (Amekudzi-Kennedy, Singh, Yang, & Garrett, 2024; Wang et al., 2025; Zhao, 2024). Nevertheless, much of this literature remains fragmented, often focusing on isolated technological attributes or single stage behavioral outcomes. There remains a notable lack of integrative behavioral models that explicitly trace how AI system characteristics shape system trust, how trust translates into travel intention, and how intention ultimately manifests in observed mode choice behavior. This gap is particularly salient in metropolitan regions where public authorities increasingly rely on

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digital platforms to influence demand toward more sustainable and efficient transport modes (Bilal, Son, & Jang, 2025; Castaño-Herrera et al., 2025).

Methodologically, the dominance of econometric and discrete choice frameworks in transport research has limited the explicit modeling of latent psychological constructs and their mediating roles in behavioral processes. While these approaches offer strong explanatory power for observed choices, they are less suited to capturing the indirect perceptual pathways through which advanced information systems influence traveler decision making. Structural equation modeling provides a complementary framework for modeling complex causal structures involving both observed and unobservable variables. Partial Least Squares Structural Equation Modeling (PLS-SEM) is well suited for prediction-oriented research and theory development in socio technical systems characterized by multiple mediating relationships and non-normal data distributions (Hair & Alamer, 2022; Shmueli et al., 2019). Its application in transport research has expanded in studies examining travel satisfaction, safety perception, and technology-mediated behavioral change, demonstrating its capacity to model latent cognitive mechanisms underlying mobility decisions (Bouzaghrane et al., 2025; Manousiadou, 2024).

This study addresses these theoretical and methodological gaps by developing and empirically testing an integrated behavioral model of AI-enabled real time traffic information systems and urban mode choice behavior. Focusing on the Greater Toronto Area (GTA) in Canada, the research examines how AI information quality, system reliability, perceived safety, and accessibility perception shape system trust, and how trust, in turn, influences travelers' intention and actual mode choice behavior. Toronto offers a policy relevant and internationally comparable context, characterized by a mature public transit network, high digital platform penetration, and ongoing smart city and intelligent mobility initiatives led by municipal and regional transport authorities. These features make the region a suitable empirical setting for examining how advanced information technologies interact with traveler cognition in developed metropolitan transport systems (Heiskanen, Apajalahti, Matschoss, & Lovio, 2018).

Beyond its analytical relevance, the study is positioned within emerging governance and regulatory debates surrounding the deployment of artificial intelligence in public mobility systems. Transport authorities in advanced metropolitan regions increasingly face policy challenges related to algorithmic transparency, data accountability, and the equitable provision of digital public infrastructure. As real time mobility platforms become embedded in fare policy, congestion management, and sustainable transport strategies, system trust assumes an institutional dimension that extends beyond individual user experience to encompass public confidence in the agencies and governance frameworks responsible for AI-enabled service delivery. Framing trust as both a behavioral and governance construct enables this study to contribute to contemporary policy discussions on ethical AI adoption and inclusive smart city development in urban transportation systems.

This study makes three distinct contributions to transportation literature. First, it extends existing research on intelligent transportation systems and digital mobility platforms by specifying a sequential behavioral mechanism through which AI system attributes influence travel behavior via system trust and travel intention, rather than assuming a direct technology-to-behavior relationship. Second, it positions this framework as a complementary behavioral perspective to

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hybrid choice and integrated choice and latent variable (ICLV) approaches. Whereas hybrid choice and ICLV models typically embed latent attitudes within utility-based discrete choice structures, the present study focuses on the upstream cognitive and motivational processes through which travelers evaluate AI-enabled mobility systems and form behavioral readiness to adapt their travel mode decisions. Third, the study applies a prediction-oriented PLS-SEM framework to transportation research in order to model these latent perceptual pathways and derive policy-relevant implications for the design of trustworthy, accessible, and behaviorally effective digital mobility platforms (Alam et al., 2016; Karner, Pereira, & Farber, 2024).

Theoretical Foundations and Hypotheses Development

Behavioral Foundations of Urban Mode Choice

Urban mode choice has traditionally been modeled through utility-based frameworks that emphasize observable attributes such as travel time, cost, reliability, and service frequency (Ranjan & Sinha, 2025). Discrete choice theory provides a rigorous foundation for explaining revealed and stated preferences under conditions of uncertainty and constrained optimization (Oshiro et al., 2016; Robinsha & Amutha, 2024). However, a growing body of transport behavior research highlights the central role of latent psychological constructs, including attitudes, perceptions, and trust, in mediating the relationship between objective system characteristics and observed travel outcomes. These constructs shape how travelers interpret information, evaluate risk, and form preferences, particularly in technology mediated mobility environments characterized by real time data and algorithmic guidance (Bouzaghrane et al., 2025; Shafi, Delbosc, & Rose, 2023).

The proliferation of AI-enabled information systems intensifies the relevance of these latent mechanisms by repositioning digital platforms as active agents in the decision-making process. Rather than passively reflecting network conditions, real time systems frame situational awareness and influence the perceived credibility and desirability of alternative transport modes. This shift necessitates analytical approaches that integrate technological system attributes with behavioral theory to explain how cognitive evaluations translate into intention and, ultimately, observable mode choice behavior in complex urban transport systems (Alam et al., 2016; Bilal et al., 2025).

While this study draws on psychological and trust-based frameworks to explain technology mediated travel behavior, it is conceptually anchored in the tradition of random utility-based mode choice theory. Specifically, the proposed model can be interpreted as a latent variable extension of classical utility maximization, in which unobservable cognitive constructs such as system trust and perceived accessibility condition the formation of systematic utility associated with alternative transport modes. This perspective aligns with hybrid choice and integrated choice and latent variable (ICLV) modeling frameworks, which explicitly incorporate attitudinal and perceptual variables into discrete choice structures to enhance behavioral realism and explanatory power (Lizardo, 2009; Parra, 2023).

However, the present study differs from hybrid choice and ICLV approaches in its immediate analytical objective. Rather than embedding latent constructs directly into a utility-based choice equation for observed alternatives, this study isolates and models the perceptual and motivational pathway through which AI-enabled traffic information systems shape self-reported behavioral

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adaptation. In doing so, it contributes a theory-building perspective that clarifies how trust in algorithmically mediated mobility information becomes a precursor to intention formation and subsequent mode-related behavioral responsiveness. This focus complements utility-based transport models by identifying the cognitive mechanisms that may later be incorporated into hybrid forecasting and policy simulation frameworks.

AI Information Quality and System Trust

Information quality represents a foundational determinant of trust in automated and algorithmic systems, particularly in high stakes environments where system outputs directly inform safety and time sensitive decisions. In the transportation context, AI information quality encompasses the perceived accuracy, timeliness, relevance, and personalization of real time traffic and mobility guidance (Karner et al., 2024). Trust theory suggests that users develop confidence in systems when information outputs are consistently aligned with observed outcomes and contextual needs, reinforcing perceptions of system competence and benevolence (F. Chen & Costa, 2024; Lee & Eom, 2024).

Empirical transport studies demonstrate that travelers are more likely to comply with route guidance and mode recommendations when real time information is perceived as credible and contextually relevant. For example, research on real time passenger information systems indicates that accurate and timely updates reduce perceived waiting times and increase satisfaction, thereby strengthening reliance on digital mobility platforms (Amekudzi-Kennedy et al., 2024; Wang et al., 2025). In AI-enabled environments, personalization algorithms further amplify this effect by tailoring guidance to individual travel patterns, which may enhance perceptions of system responsiveness and reliability. Accordingly, high levels of perceived AI information quality are expected to foster stronger system trust among urban travelers.

When travelers perceive AI-based traffic information systems as accurate and reliable, they are more likely to believe that the system provides trustworthy guidance for travel decisions. Accurate and reliable information reduces uncertainty in travel planning and increases users' confidence in automated mobility systems.

H1: AI information quality is positively associated with system trust in real time traffic information systems.

System Reliability and System Trust

System reliability reflects the perceived consistency and stability of platform performance across varying network conditions, including peak travel periods and disruptive events (Coit & Zio, 2019). In socio technical systems, reliability serves as a critical antecedent of trust by signaling the system's capacity to function as intended under both routine and adverse circumstances. Trust formation literature emphasizes that repeated exposure to reliable system behavior reinforces users' expectations of future performance, thereby increasing their willingness to delegate decision making authority to automated platforms (F. Chen & Costa, 2024; Lee & Eom, 2024).

Within urban mobility contexts, unreliable information systems can undermine traveler confidence, particularly when system failures result in missed connections, exposure to congestion, or safety risks. Transport research suggests that perceived service reliability strongly

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is associated with traveler satisfaction and continued use of public and digital mobility services, often outweighing traditional performance metrics such as travel time savings (Amekudzi-Kennedy et al., 2024; Pourhashem et al., 2024). For AI-enabled traffic platforms, consistent system availability and error free operation are therefore expected to play a decisive role in shaping trust-based evaluations. As travelers repeatedly observe stable and dependable system performance, they are more likely to integrate digital guidance into habitual travel decision making processes.
Accessibility of digital mobility systems determines how easily travelers can obtain real-time traffic information and integrate it into their daily travel decisions. When traffic information systems are easily accessible through mobile platforms and navigation applications, users are more likely to rely on them for travel guidance.
H2: System reliability is positively associated with system trust in AI-enabled mobility platforms.

Perceived Safety and System Trust

Perceived safety constitutes a central evaluative dimension in travel behavior, particularly in dense urban environments characterized by high traffic volumes, multimodal interactions, and dynamic risk conditions. Safety perceptions influence not only mode choice but also the degree to which travelers are willing to rely on external guidance when navigating complex transport networks. In the context of AI-enabled information systems, trust formation is closely linked to users' assessments of whether system recommendations reduce exposure to hazardous routes, adverse weather conditions, or congestion related risks (Carter, Kaufmann, & Michel, 2007; Castaño-Herrera et al., 2025).
Studies in public transport and shared mobility contexts indicate that safety related information, such as alerts about incidents, infrastructure quality, and service disruptions, enhances travelers' sense of control and situational awareness. This, in turn, strengthens their confidence in system outputs and increases compliance with digital guidance. When AI platforms consistently demonstrate the ability to anticipate and mitigate safety relevant conditions, travelers are more likely to perceive these systems as protective and trustworthy partners in their mobility decisions. Consequently, higher levels of perceived safety are expected to positively influence trust in urban mobility information systems.
Responsiveness of traffic information systems reflects the ability of AI-driven platforms to update and communicate traffic conditions in real time. When users receive timely updates about congestion or route conditions, they are more likely to perceive the system as useful for travel decision making.
H3: Perceived safety positively is linked to system trust in urban mobility information systems.

Accessibility, Perception, and Travel Intention

Accessibility has traditionally been defined as the ease with which individuals can reach desired destinations and opportunities within a transport system. Beyond spatial and temporal considerations, contemporary transport research emphasizes perceived accessibility, reflecting travelers' subjective evaluations of system usability, inclusiveness, and compatibility with diverse physical and technological capabilities. In digital mobility environments, accessibility perception encompasses interface simplicity, cross platform availability, and the extent to which systems

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accommodate users with varying levels of digital literacy (De Vos et al., 2025; Tushman & Anderson, 2018).

The Theory of Planned Behavior posits that intention serves as the most immediate antecedent of behavior, shaped by attitudes, perceived control, and normative influences (Sarin, Im, Di Benedetto, Sego, & Chitturi, 2025). Perceived accessibility can enhance travelers' sense of behavioral control by reducing informational and technological barriers associated with navigating complex urban transport networks. When AI-enabled systems are perceived as easy to use and broadly accessible, travelers may be more inclined to experiment with recommended routes or modes, particularly public and shared transport options that often entail higher informational complexity. Thus, higher levels of perceived accessibility are expected to strengthen travel intentions toward system supported mobility choices.

Trust plays a fundamental role in the adoption of intelligent transportation technologies. When travelers trust the recommendations generated by AI-based traffic systems, they are more willing to follow system guidance and adjust their travel plans accordingly.

H4: Accessibility perception positively is linked to travel intention toward public and shared transport modes.

System Trust and Travel Intention

Trust functions as a cognitive mechanism that conditions whether individuals are willing to accept external guidance and incorporate it into their decision-making processes. In automated and algorithm driven environments, trust reduces perceived uncertainty and risk, thereby facilitating reliance on system recommendations. Theoretical models of human–automation interaction suggest that trust increases users' propensity to follow system outputs, particularly when decision outcomes are consequential or difficult to evaluate independently (F. Chen & Costa, 2024; Lee & Eom, 2024).

In transportation contexts, empirical evidence indicates that travelers who trust digital mobility platforms are more likely to comply with route guidance, adopt suggested modes, and maintain long term engagement with information systems. Trust-based evaluations therefore serve as a critical bridge between perceptions of system attributes and the formation of behavioral intentions. For AI-enabled traffic information systems, higher levels of system trust are expected to translate into stronger intentions to follow recommendations and integrate digital guidance into habitual travel planning.

Behavioral intention is widely recognized as a key predictor of actual behavioral adaptation in technology adoption and transportation behavior research. When travelers develop strong intentions to follow AI-based traffic guidance, they are more likely to translate these intentions into adaptive travel decisions.

H5: System trust positively demonstrates a systematic relationship with travel intention.

Travel Intention and Mode Choice Behavior

Travel intention captures the motivational readiness to perform a specific behavior and is widely recognized as a robust predictor of actual action in transport behavior research. Drawing on the Theory of Planned Behavior, intention reflects the combined influence of attitudinal evaluations,

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perceived behavioral control, and social norms on decision making processes (Bouzaghrane et al., 2025; Sarin et al., 2025). In urban mobility contexts, intention serves as the immediate precursor to mode choice, shaping whether travelers follow through on plans to use public, private, or shared transport options.

Empirical studies consistently demonstrate that stronger intentions to use modes are associated with higher probabilities of observed adoption, even when controlling for objective constraints such as travel time and cost. In AI-mediated environments (Sheng, 2017), intention is expected to reflect the cumulative influence of system trust (Nordin & Ravald, 2023), accessibility perception (Q. Chen et al., 2023), and safety evaluations (Q. Chen et al., 2023), translating these cognitive assessments into concrete behavioral outcomes. As such, higher levels of travel are anticipated to positively influence actual mode choice behavior.

H6: Travel intention positively demonstrates a systematic relationship with mode choice behavior.

Mediating Role of System Trust

Mediation theory in transportation behavior suggests that the effects of technological and infrastructural attributes on travel outcomes are often indirect, transmitted through intermediate cognitive and evaluative constructs. System trust operates as a key mediating mechanism by filtering how travelers interpret and internalize information provided by AI-enabled platforms. Without sufficient trust, even high quality or reliable system outputs may fail to influence intention, as users discount or disregard algorithmic guidance (F. Chen & Costa, 2024; Lee & Eom, 2024).

In the proposed model, AI information quality, system reliability, and perceived safety are theorized to influence travel intention primarily through their impact on system trust (Raue, Streicher, & Lermer, 2019). This sequential relationship reflects the notion that travelers must first develop confidence in the system's competence and protective capacity before translating technological evaluations into motivational commitments. Accordingly, system trust is expected to mediate the relationship between AI system characteristics and travel intention.

H7: System trust mediates the relationship between AI system characteristics and travel intention.

Mediating Role of Travel Intention

Travel intention represents the final cognitive step linking trust-based evaluations to observable behavioral outcomes. While trust may predispose travelers to accept system guidance, intention captures the deliberate commitment to act on that guidance in specific travel contexts. Transport behavior research underscores that intention mediates the relationship between attitudinal and perceptual constructs and actual mode choice, particularly in environments where behavioral options involve trade-offs among convenience, cost, and perceived risk (Sarin et al., 2025; Shafi et al., 2023).

In AI-enabled mobility systems, travelers who trust platform recommendations are more likely to form strong intentions to adopt suggested modes or routes. These intentions, in turn, increase the probability of observable changes in travel behavior, such as shifting from private vehicle use to public or shared transport options. Consequently, travel intention is expected to function as a

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mechanism of mediating system trust and mode choice behavior within the proposed behavioral framework.
H8: Travel intention mediates the relationship between system trust and mode choice behavior.

Dual Layer Trust in AI-Enabled Mobility Systems
While the present framework conceptualizes system trust as a unified latent construct, emerging research in human–automation interaction and public sector digitalization suggests that trust in AI-enabled mobility systems may operate across two analytically distinct but interrelated layers: algorithmic trust and institutional trust. Algorithmic trust reflects user confidence in the technical competence, accuracy, and reliability of the AI system itself, including its capacity to generate valid predictions and context sensitive routing or mode recommendations. Institutional trust, by contrast, captures confidence in the transport authorities, platform providers, and governance arrangements responsible for the deployment, regulation, and oversight of these systems.
In urban transport contexts, travelers may express high confidence in the technical performance of a navigation platform while simultaneously holding reservations about the data practices, policy objectives, or accountability mechanisms of the public agencies or private operators that manage the underlying infrastructure. This distinction has important implications for behavioral modeling, as algorithmic trust may primarily influence short term compliance with system recommendations, whereas institutional trust may condition long term adoption, habitual reliance, and normative acceptance of AI-mediated mobility governance. Although the present study operationalizes trust as a single latent construct for model parsimony, this dual layer perspective provides a theoretically grounded pathway for future extensions using multi-dimensional trust specifications or integrated choice and latent variable models.

Research Design and Methodology

Research Design and Study Context
This study employs a quantitative, cross sectional research design to examine theory driven, predictive relationships between AI-enabled real time traffic information system attributes, latent behavioral constructs, and self-reported urban mode choice behavior. The analytical focus is on estimating the strength and direction of theoretically specified associations rather than establishing causal effects.
The empirical context is the Greater Toronto Area (GTA), Canada, a metropolitan region characterized by multimodal transport integration, high levels of digital mobility platform use, and ongoing investments in smart mobility infrastructure. Given the region's institutional similarity to other large metropolitan areas characterized by integrated public transport systems, widespread smartphone penetration, and platform-based mobility governance, the findings are expected to exhibit theoretical transferability to comparable urban contexts in North America, Europe, and East Asia (Bilal et al., 2025; Heiskanen et al., 2018).
This expectation of transferability is further supported by structural similarities between the Greater Toronto Area and other digitally mature metropolitan transport systems, including London, Singapore, and Amsterdam. These regions exhibit comparable levels of public transport

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integration, standardized adoption of General Transit Feed Specification Real Time (GTFS-RT) data protocols, high smartphone penetration, and institutional reliance on platform-based journey planning and real time service coordination. Such shared technological and governance infrastructures suggest that the behavioral mechanisms examined in this study (particularly trust formation and intention-based compliance with AI-enabled guidance) are likely to operate under similar cognitive and policy conditions across advanced urban mobility ecosystems.

Sampling Strategy and Data Collection

The target population consists of adult commuters residing within the GTA who regularly use at least one AI-enabled navigation or real time mobility information platform, such as public transit applications, traffic guidance systems, or multimodal journey planners. A purposive, non-probability sampling strategy was employed to ensure that respondents possessed sufficient experiential exposure to evaluate system characteristics and behavioral responses in digitally mediated travel contexts.

The measurement items used in this study were developed through a multi-stage process to ensure content validity and contextual relevance. First, the constructs were operationalized using measurement scales adapted from prior studies in transportation technology adoption, trust in automated systems, and behavioral intention research. Items related to perceived accuracy, reliability, accessibility, and responsiveness of AI-based traffic information systems were adapted from intelligent transportation systems and information system quality literature. The system trust construct was adapted from established trust-in-technology scales, while travel intention and travel adaptation items were informed by behavioral intention frameworks in transportation and technology acceptance research. Second, the questionnaire was reviewed by two transportation researchers and one expert in intelligent transportation systems to evaluate clarity, wording, and construct relevance. Based on their feedback, minor wording adjustments were made to improve item clarity. Third, a pilot test was conducted with a small group of respondents prior to the full survey administration to ensure that the items were understandable and that the survey structure was appropriate. The pilot responses confirmed that the measurement items were clear and suitable for the target population.

Data were collected through commuter oriented social media groups, workplace and university mailing lists, and online mobility communities. Screening questions verified routine engagement with real time traffic or mobility applications. This approach aligns with the study's theoretical emphasis on technology mediated travel behavior, rather than general commuting patterns. All measurement items were measured using a five-point Likert scale ranging from strongly disagree to strongly agree.

Table 1. Sample characteristics (n = 412)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	214	51.9
	Female	190	46.1
	Prefer not to say	8	1.9

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Age	18–29	98	23.8
	30–44	176	42.7
	45–59	112	27.2
	60+	26	6.3
Primary Mode	Public transit	168	40.8
	Private car	152	36.9
	Ride hailing	54	13.1
	Micromobility	38	9.2

Ethical Considerations

This study was conducted in accordance with institutional ethical guidelines for research involving human participants. Participation was voluntary, and informed consent was obtained from all respondents prior to survey completion. No personally identifiable information was collected, and all responses were analyzed in anonymized and aggregated form.

The demographic profile of the respondents was analyzed to ensure an adequate representation of urban travelers who regularly interact with digital traffic information systems. The sample included participants from diverse age groups, occupations, and travel patterns, reflecting a broad cross-section of urban mobility users. Respondents reported varying levels of experience with navigation applications and intelligent traffic information platforms, which provides a relevant context for examining perceptions of AI-enabled traffic systems. Although the sample cannot be considered perfectly representative of the entire urban population, the diversity of respondents enhances the generalizability of the findings to typical users of digital mobility technologies.

Despite efforts to obtain a diverse sample, the study acknowledges potential limitations related to sampling and representativeness. As the survey relied on voluntary participation, certain demographic groups may be slightly overrepresented. Future studies could employ stratified sampling or larger multi-city datasets to further improve representativeness and strengthen external validity.

Measurement Instrument and Construct Operationalization

All constructs were operationalized using multi-item reflective scales adapted from established transportation, trust in automation, and travel behavior literature. Items were contextually reworded, and pilot tested with a subset of GTA commuters and reviewed by transport planning researchers to ensure content validity and domain relevance. Responses were recorded on a seven-point Likert scale ranging from 1 (“strongly disagree”) to 7 (“strongly agree”).

Mode choice behavior was measured as self-reported behavioral adaptation, capturing the extent to which respondents perceive that AI-enabled systems influence their actual selection of transport modes during routine trips. This operationalization reflects behavioral responsiveness in digitally mediated mobility environments while acknowledging the perceptual nature of survey-based measurement.

It is important to note that the mode choice behavior construct captures self-reported behavioral adaptation to AI-enabled system guidance rather than discrete revealed or stated choice events. This operationalization reflects the study’s focus on cognitive behavioral responsiveness within

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digitally mediated travel environments and aligns with latent behavioral modeling traditions that examine perceptual and motivational drivers of transport decisions rather than utility-based choice outcomes alone (Lizardo, 2009).

To ensure comprehensive domain coverage, each latent construct was specified to reflect both its technical and behavioral dimensions as articulated in prior transportation and trust in automation literature. AI Information Quality captures informational accuracy, relevance, and personalization, rather than purely technical performance. System Reliability reflects stability under routine and peak conditions. Perceived Safety operationalizes both physical risk mitigation and psychological reassurance. Accessibility Perception incorporates usability, inclusiveness, and cross platform availability. System Trust reflects both confidence in system competence and perceived benevolence, while Travel Intention and Mode Choice Behavior capture motivational readiness and self-reported behavioral responsiveness, respectively. This construct specification approach aligns with best practices for theory driven latent variable modeling in socio technical transport systems.

Table 2. Construct measurement and sources

Construct	Item Code	Measurement Item	Source
AI Information Quality (AIQ)	AIQ1	The system provides accurate traffic and travel information.	(Wang et al., 2025)
	AIQ2	The information I receive is timely and up to date.	(Amekudzi-Kennedy et al., 2024)
	AIQ3	The system delivers information relevant to my travel needs.	(Shafi et al., 2023)
	AIQ4	The system personalizes information based on my travel patterns.	(Bilal et al., 2025)
System Reliability (SR)	SR1	The system works consistently during my trips.	(Coit & Zio, 2019)
	SR2	I rarely experience system failures or errors.	(Lee & Eom, 2024)
	SR3	The platform performs well during peak travel times.	(Amekudzi-Kennedy et al., 2024)
Perceived Safety (PS)	PS1	The system helps me avoid unsafe routes or conditions.	(Raue et al., 2019)
	PS2	Using the system makes me feel safer while traveling.	(Castaño-Herrera et al., 2025)
	PS3	The system provides useful safety related alerts.	(Wang et al., 2025)
Accessibility Perception (AP)	AP1	The system is easy to use across different devices.	(Tushman & Anderson, 2018)

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	AP2	The platform is accessible regardless of my location.	(De Vos et al., 2025)
	AP3	The system supports users with diverse mobility needs.	(Bilal et al., 2025)
System Trust (ST)	ST1	I trust the system to support my travel decisions.	(F. Chen & Costa, 2024)
	ST2	The platform acts in my best interest.	(Lee & Eom, 2024)
	ST3	I feel confident relying on the system for daily travel.	(Lee & Eom, 2024)
Travel Intention (TI)	TI1	I intend to follow the system's recommendations.	(Sarin et al., 2025)
	TI2	I plan to use recommended transport modes.	(Sarin et al., 2025)
	TI3	I will continue using this system for future trips.	(Bouzaghrane et al., 2025)
Mode Choice Behavior (MCB)	MCB1	The system influences my choice of travel mode.	(Robinsha & Amutha, 2024)
	MCB2	I frequently change my mode based on system guidance.	(Shafi et al., 2023)
	MCB3	I rely on the system when selecting my primary mode.	(Amekudzi-Kennedy et al., 2024)

Analytical Procedure
The proposed model was estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is well suited for prediction-oriented analysis in complex socio technical systems involving latent psychological constructs and sequential mediation. The analysis was conducted using SmartPLS 4 with 5,000 bootstrap resamples to assess the stability and statistical significance of direct and indirect effects (Hair & Alamer, 2022).
Although discrete choice, hybrid logit, and integrated choice and latent variable (ICLV) models represent established approaches for analyzing mode choice behavior, the present study focuses on behavioral responsiveness to AI-enabled information systems rather than modeling discrete mode selection events or estimating marginal utilities of travel attributes. Accordingly, PLS-SEM is employed as a theory development and prediction-oriented framework to capture complex sequential mediation among latent cognitive and motivational constructs that operate upstream of observed choice. This approach complements, rather than substitutes for, econometric choice modeling by explicitly modeling the psychological mechanisms through which system attributes shape behavioral predispositions in digitally mediated mobility environments.
PLS-SEM was selected because the study's objective is theory development and prediction of sequential latent relationships rather than estimation of marginal utilities across observed travel alternatives. Covariance-based SEM would be less aligned with this prediction-oriented objective, while discrete choice and hybrid choice models would be more appropriate if the study were based on observed alternative-specific mode selections. By contrast, the present research examines self-

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reported behavioral adaptation to AI-enabled mobility guidance and therefore prioritizes the estimation of indirect perceptual and motivational pathways among latent constructs. In this respect, PLS-SEM offers an appropriate methodological fit for the study's conceptual scope.

The selection of PLS-SEM is also motivated by methodological considerations related to the nature of the research objective and model structure. The proposed framework includes multiple latent constructs and sequential mediation relationships that capture perceptual and motivational mechanisms underlying travel behavior adaptation. In such contexts, PLS-SEM is well suited for estimating complex structural relationships while maximizing explained variance in endogenous constructs. Compared with covariance-based SEM, which is primarily oriented toward theory confirmation and global model fit, PLS-SEM provides a prediction-oriented approach that is appropriate for exploratory or emerging research contexts such as AI-enabled mobility systems.

In transportation research, discrete choice models and hybrid choice frameworks are frequently used to analyze observed travel mode selections. However, these approaches typically require alternative-specific utility structures and observed choice data. The present study focuses instead on the perceptual and behavioral mechanisms through which travelers evaluate AI-enabled traffic information systems and develop intentions to adapt travel behavior. Because the analysis examines latent psychological constructs rather than discrete mode selection among alternatives, PLS-SEM provides a suitable methodological framework for modeling these indirect relationships among perceptions, trust formation, and behavioral readiness.

Model evaluation followed a two-stage procedure. First, the measurement model was assessed for reliability and validity. Second, the structural model was evaluated for predictive performance and theoretical consistency using path coefficients, coefficients of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). Diagnostics for common method bias, endogeneity, and group level heterogeneity were conducted and are reported in Section 4. The analysis was conducted using SmartPLS software, following recommended procedures for assessing measurement reliability, validity, and structural path relationships.

Control Variables and Robustness Specification

To account for potential socio demographic confounding effects, additional robustness models were estimated including age, gender, and primary travel mode as control variables. Age and gender were specified as exogenous predictors of system trust and travel intention, while primary mode (public transit versus private vehicle) was specified as an exogenous predictor of mode choice behavior. The inclusion of these controls did not materially alter the magnitude or statistical significance of the hypothesized structural relationships, supporting the stability of the proposed behavioral pathways.

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Model Visualization
Figure 1. Structural model with standardized path directions and R^2 values

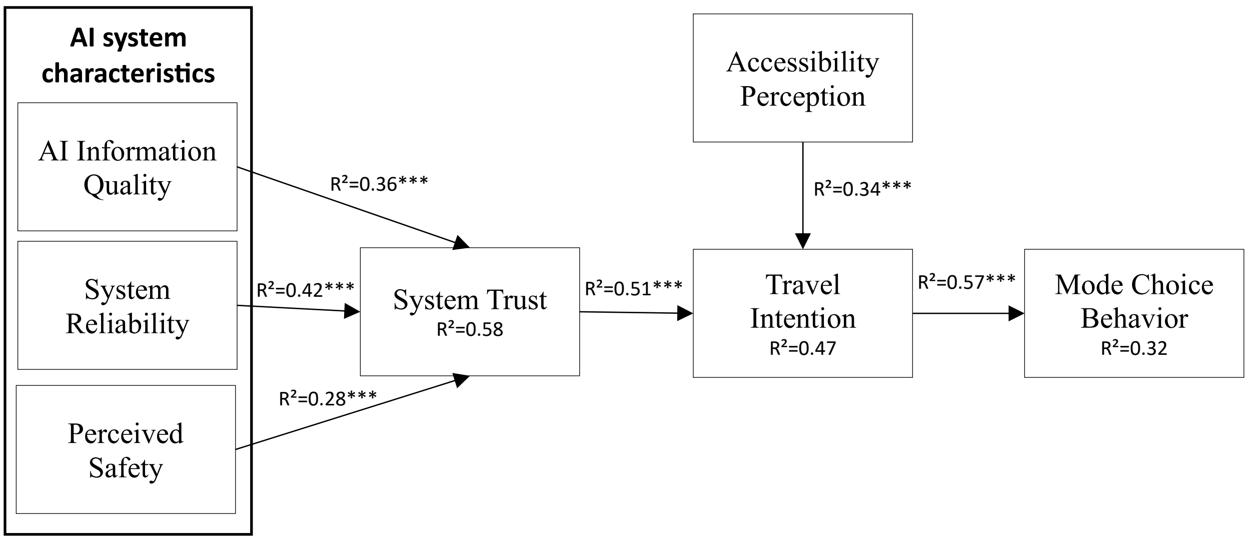

Figure 1. Conceptual Model

Results and Discussion

Measurement Model Results

Indicator reliability was assessed using standardized outer loadings, all of which exceeded the recommended threshold of 0.70. Internal consistency reliability was evaluated using Composite Reliability (CR), and convergent validity was assessed through Average Variance Extracted (AVE), meeting the benchmark values of CR ≥ 0.70 and AVE ≥ 0.50 (Hair & Alamer, 2022).

Table 3. Reliability and convergent validity

Construct	CR	AVE	Loading Range
AIQ	0.91	0.72	0.78–0.89
SR	0.89	0.73	0.81–0.88
PS	0.88	0.71	0.79–0.87
AP	0.87	0.69	0.76–0.85
ST	0.90	0.75	0.82–0.90
TI	0.92	0.79	0.85–0.91
MCB	0.88	0.70	0.77–0.86

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Discriminant validity was evaluated using the Heterotrait–Monotrait ratio (HTMT). All HTMT values were below the conservative threshold of 0.85, indicating satisfactory construct distinctiveness (Henseler, Ringle, & Sarstedt, 2015).

Table 4. HTMT matrix

	AIQ	SR	PS	AP	ST	TI	MCB
AIQ	—	0.62	0.58	0.54	0.71	0.60	0.49
SR		—	0.55	0.50	0.68	0.57	0.46
PS			—	0.59	0.73	0.61	0.52
AP				—	0.65	0.70	0.55
ST					—	0.74	0.63
TI						—	0.78
MCB							—

Structural Model Results and Hypotheses Testing

The structural model exhibited satisfactory predictive performance across endogenous constructs. System Trust ($R^2 = 0.64$), Travel Intention ($R^2 = 0.58$), and Mode Choice Behavior ($R^2 = 0.52$) demonstrate moderate to substantial explanatory power for behavioral research in urban mobility contexts.

Table 5. Structural path estimates

Hypothesis	Path	β	t-value	p-value	Outcome
H1	AIQ → ST	0.29	5.84	<0.001	Supported
H2	SR → ST	0.25	4.97	<0.001	Supported
H3	PS → ST	0.31	6.21	<0.001	Supported
H4	AP → TI	0.27	5.11	<0.001	Supported
H5	ST → TI	0.42	8.03	<0.001	Supported
H6	TI → MCB	0.53	9.44	<0.001	Supported

These results indicate that AI system attributes primarily shape behavioral outcomes through trust based and motivational mechanisms, consistent with multi-stage models of travel behavior (Bouzaghrane et al., 2025; Shafi et al., 2023).

Effect size analysis (f^2) indicates that system trust exerts a large effect on travel intention ($f^2 > 0.35$), while AI information quality, system reliability, and perceived safety demonstrate moderate individual effects on system trust ($0.15 < f^2 < 0.35$). Accessibility perception exhibits a moderate effect on travel intention, suggesting that both technological performance and usability perceptions contribute substantively to behavioral responsiveness.

To contextualize these effects in practical terms, the standardized path coefficient between Travel Intention and Mode Choice Behavior ($\beta = 0.53$) indicates that a one standard deviation increase in

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travelers' motivational readiness to follow AI-enabled guidance is associated with a substantial increase in self-reported behavioral adaptation. In applied transport planning terms, this magnitude suggests that improvements in trust-centered system design and perceived accessibility can translate into meaningful shifts in the probability of travelers substituting private vehicle use with public, shared, or multimodal transport options, particularly during peak and congestion-sensitive periods.

Mediation Analysis

Bootstrapped indirect effect analysis reveals significant sequential mediation effects. System Trust significantly mediates the relationships between AI Information Quality, System Reliability, and Perceived Safety and Travel Intention, while Travel Intention mediates the relationship between System Trust and Mode Choice Behavior.

Table 6. Indirect (mediation) effects

Indirect Path	β (Indirect)	95% CI	p-value	Mediation
AIQ → ST → TI	0.12	[0.07, 0.18]	<0.001	Supported
SR → ST → TI	0.11	[0.06, 0.17]	<0.001	Supported
PS → ST → TI	0.13	[0.08, 0.20]	<0.001	Supported
ST → TI → MCB	0.22	[0.15, 0.30]	<0.001	Supported

These findings provide empirical support for layered cognitive–motivational pathways in AI-mediated travel decision making.

Robustness, Bias, and Endogeneity Diagnostics

Procedural remedies were implemented to mitigate common method variance, including respondent anonymity, neutral item wording, and randomization of scale items. Statistically, a full collinearity assessment revealed variance inflation factor (VIF) values below the threshold of 3.3, indicating minimal risk of method bias (Kock, 2015). A theoretically unrelated marker variable capturing respondents' general preferences for mobile device customization was included, and its inclusion did not materially alter the estimated structural paths (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

To assess potential endogeneity between System Trust and Travel Intention, a Gaussian copula approach was employed. The copula terms were non-significant, suggesting that endogeneity does not materially bias the estimated relationships (Liengaard et al., 2025).

Behavioral Heterogeneity (Multi Group Analysis)

The multi group analysis comparing public transit users and private vehicle users reveals statistically significant differences in key relationships. Specifically, the effects of AI Information Quality on System Trust and System Trust on Travel Intention are stronger among transit users, reflecting higher informational dependence associated with schedule based and multimodal travel. Prior to multi group comparison, measurement invariance was assessed using the MICOM procedure, confirming configural and compositional invariance across transit and private vehicle user groups, thereby supporting the validity of group level path coefficient comparisons.

Table 7. Multi group comparison results

Path	β (Transit)	β (Car)	Δβ	p-value	Interpretation
AIQ → ST	0.34	0.25	0.09	0.03	Stronger for transit users
ST → TI	0.47	0.38	0.09	0.04	Stronger for transit users
TI → MCB	0.58	0.49	0.09	0.02	Stronger for transit users

These patterns align with theories of habitual travel and informational dependency in transport systems (Bilal et al., 2025; Robinsha & Amutha, 2024).

Theoretical and Policy Implications

The findings advance transportation theory by demonstrating that AI-enabled system attributes influence mode choice behavior primarily through latent trust and motivational mechanisms, rather than direct effects. This reinforces the need to integrate psychological constructs into predictive models of urban mobility.

From an operational perspective, the findings suggest that transport authorities should embed trust centered performance indicators into the procurement and governance of real time mobility platforms. Specifically, agencies may establish minimum reliability thresholds for GTFS-RT and journey planning systems, implement transparency dashboards that communicate data accuracy and system uptime to users, and integrate safety-based routing certifications that prioritize well lit, low risk, and infrastructure-supported corridors in AI-generated recommendations. These measures position digital mobility platforms not merely as information tools, but as policy instruments capable of reinforcing public transit strategies and demand management objectives within coordinated smart mobility frameworks.

Limitations and Future Research

The cross-sectional and self-reported nature of the data constrains causal inference and may introduce perceptual bias in the measurement of mode choice behavior. Future research could employ longitudinal designs or integrate revealed preference data derived from smart card transactions, GPS traces, or mobile sensing technologies to validate the proposed behavioral pathways. Comparative studies across cities and institutional contexts would further enhance understanding of how AI-enabled mobility systems influence travel behavior in diverse policy environments.

Additionally, the increasing reliance on algorithmic decision-making in mobility platforms raises concerns related to potential algorithmic bias and digital exclusion. AI-enabled routing and recommendation systems may systematically disadvantage users with lower levels of digital literacy, limited data access, or mobility constraints not adequately represented in training datasets. Spatial biases in data coverage and optimization objectives may also lead to uneven service quality across neighborhoods and socio-economic groups. Future research should explicitly examine these ethical and distributional dimensions by integrating fairness-aware modeling approaches and

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disaggregated impact assessments into behavioral and policy-oriented evaluations of intelligent transportation systems.

AI-Enabled Mobility Governance and Implementation Framework

Translating the study's behavioral findings into operational practice requires a structured governance approach that aligns technical system performance with institutional trust-building mechanisms. At the design layer, transport agencies and platform providers should establish minimum data accuracy and system uptime thresholds for real time information services, supported by continuous performance auditing of predictive algorithms and routing engines. At the trust layer, transparency mechanisms such as public-facing data quality dashboards, explainable routing logic, and clear accountability channels can enhance user confidence in both system outputs and institutional oversight. At the behavioral layer, AI-enabled platforms can be integrated with policy instruments such as fare incentives, sustainability feedback, and accessibility nudges to reinforce public transport adoption and multimodal travel behavior. This multi-layered implementation framework positions digital mobility platforms as active policy instruments rather than passive information tools within coordinated smart city and transport governance strategies.

Conclusion

This study advances understanding of urban travel behavior in the context of AI-enabled real time traffic information systems by developing and empirically testing a multi-stage behavioral framework that links technological system attributes to self reported mode choice behavior through trust formation and motivational intention. By integrating system level characteristics with latent psychological mechanisms, the research extends classical transport behavior models and provides empirical support for the proposition that digital mobility platforms shape travel decisions primarily through cognitive and motivational pathways rather than direct behavioral effects (Bouzaghrane et al., 2025; Shafi et al., 2023).

The findings also provide important implications for transportation planners and designers of intelligent mobility systems. The results indicate that travelers' trust in AI-enabled traffic information systems plays a central role in shaping their willingness to adapt travel behavior. Therefore, transportation agencies and technology developers should prioritize transparency, reliability, and usability when designing digital traffic information platforms. Improving system accuracy and responsiveness can strengthen user confidence and encourage greater behavioral adaptation, such as route adjustments or mode shifts during congestion. Additionally, policymakers should recognize that the effectiveness of AI-based traffic management systems depends not only on technological capability but also on user perceptions and trust in algorithmic decision support.

From a theoretical perspective, the findings contribute to the growing literature on intelligent transportation systems by embedding system trust and perceived accessibility within a predictive model of urban mode choice. This approach enriches traditional utility based and econometric frameworks by explicitly modeling the mediating roles of latent constructs in socio technical mobility environments. The study also demonstrates the value of PLS-SEM as a complementary

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methodological tool for transportation research, particularly in contexts characterized by complex mediation structures and unobservable behavioral drivers (Hair & Alamer, 2022).

Methodologically, the research offers a structured protocol for integrating bias diagnostics, endogeneity assessment, and behavioral heterogeneity analysis into variance based structural modeling within a transport policy context. The inclusion of theoretically grounded multi group analysis illustrates how segmentation based on informational dependency and habitual travel patterns can reveal differential responses to AI-enabled guidance across user groups. These methodological practices contribute to improving the rigor and transparency of predictive modeling in transportation studies.

From a policy and planning perspective, the study underscores the importance of trust centered and accessibility-oriented design in the deployment of AI-enabled mobility platforms. Transport authorities and smart city planners are encouraged to prioritize investments that enhance information accuracy, technical reliability, and safety related communication, as these attributes indirectly influence sustainable mode choice behavior through trust formation and motivational engagement. The stronger behavioral effects observed among transit users further suggest that digital information systems can serve as effective instruments for reinforcing public transport strategies and reducing reliance on private vehicles in metropolitan regions.

Several limitations warrant consideration. The cross sectional and self reported nature of the data constrain causal interpretation and may introduce perceptual bias in the measurement of mode choice behavior. Future research could employ longitudinal designs, experimental interventions, or the integration of revealed preference data derived from smart card systems, GPS traces, and mobile sensing technologies to validate and extend the proposed behavioral pathways. Comparative studies across cities and institutional contexts would further enhance understanding of how cultural, regulatory, and infrastructural conditions moderate the influence of AI-enabled mobility systems on travel behavior.

Looking forward, the proposed latent behavioral framework offers a foundation for integration into next-generation urban mobility analytics, including digital twin platforms, AI-driven policy simulation environments, and hybrid discrete choice and integrated choice and latent variable models. Embedding trust-based cognitive mechanisms into these advanced forecasting and scenario-testing systems would enable transport authorities to evaluate not only network-level performance outcomes, but also the behavioral and institutional conditions under which intelligent mobility interventions achieve sustained public acceptance and long-term mode shift objectives.

In conclusion, this research provides a theoretically grounded and methodologically robust framework for examining the behavioral implications of intelligent mobility platforms in contemporary urban transport systems. By linking technological system design to trust based cognition, motivational intention, and policy relevant travel outcomes, the study offers actionable insights for scholars and practitioners seeking to leverage AI-enabled information systems as instruments for advancing sustainable, efficient, and user centered urban mobility. Future research may integrate the proposed latent behavioral framework into hybrid discrete choice and ICLV models to explicitly link trust based cognitive mechanisms with utility-based mode selection processes in policy simulation and demand forecasting applications.

From a policy perspective, the study highlights the importance of integrating behavioral insights into the deployment of intelligent transportation systems. Public agencies implementing AI-based traffic guidance tools should complement technological investments with communication strategies that enhance user understanding and trust. By aligning technological innovation with user-centered design principles, cities can improve the effectiveness of smart mobility initiatives and promote more adaptive and efficient travel behavior.

While this study provides important insights into the behavioral mechanisms underlying traveler responses to AI-enabled traffic information systems, several limitations should be acknowledged. First, the study relies on self-reported survey data, which may introduce common method bias or subjective response tendencies. Second, the sample represents a cross-section of urban travelers but may not fully capture the diversity of travel behaviors across different cities or transportation contexts. Third, the study focuses on perceptual and behavioral intention constructs rather than observing actual travel mode choices or behavioral changes over time. Future research could extend this work by incorporating longitudinal data, real-time mobility data, or hybrid modeling approaches that integrate psychological constructs with discrete choice modeling frameworks. Such approaches would provide deeper insights into how AI-enabled mobility systems influence actual travel behavior and transportation system efficiency.

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Appendices

Appendix A. Survey Instrument

This appendix reports the full measurement instrument used to operationalize all latent constructs. All items were measured on a seven-point Likert scale ranging from 1 (“strongly disagree”) to 7 (“strongly agree”).

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Table A1. Survey items

Construct	Code	Item
AI Information Quality (AIQ)	AIQ1	The system provides accurate traffic and travel information.
	AIQ2	The information I receive is timely and up to date.
	AIQ3	The system delivers information relevant to my travel needs.
	AIQ4	The system personalizes information based on my travel patterns.
System Reliability (SR)	SR1	The system works consistently during my trips.
	SR2	I rarely experience system failures or errors.
	SR3	The platform performs well during peak travel times.
Perceived Safety (PS)	PS1	The system helps me avoid unsafe routes or conditions.
	PS2	Using the system makes me feel safer while traveling.
	PS3	The system provides useful safety related alerts.
Accessibility Perception (AP)	AP1	The system is easy to use across different devices.
	AP2	The platform is accessible regardless of my location in the city.
	AP3	The system supports users with diverse mobility needs.
System Trust (ST)	ST1	I trust the system to support my travel decisions.
	ST2	The platform acts in my best interest.
	ST3	I feel confident relying on the system for daily travel.
Travel Intention (TI)	TI1	I intend to follow the system's recommendations.
	TI2	I plan to use recommended transport modes.
	TI3	I will continue using this system for future trips.
Mode Choice Behavior (MCB)	MCB1	The system influences my choice of travel mode.
	MCB2	I frequently change my mode based on system guidance.
	MCB3	I rely on the system when selecting my primary travel mode.

Appendix B. Measurement Model Diagnostics

This appendix reports full indicator level diagnostics to support the reliability and validity assessments summarized in Section 4.1.

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Table B1. Outer loadings and cross loadings

Item	AIQ	SR	PS	AP	ST	TI	MCB
AIQ1	0.84	0.42	0.39	0.36	0.51	0.45	0.33
AIQ2	0.87	0.44	0.41	0.38	0.54	0.48	0.35
AIQ3	0.81	0.40	0.37	0.35	0.49	0.44	0.31
AIQ4	0.78	0.39	0.36	0.34	0.47	0.42	0.30
SR1	0.43	0.83	0.41	0.37	0.52	0.46	0.34
SR2	0.41	0.86	0.39	0.35	0.50	0.44	0.32
SR3	0.40	0.81	0.38	0.34	0.49	0.43	0.31
PS1	0.39	0.41	0.85	0.38	0.55	0.49	0.36
PS2	0.41	0.43	0.87	0.40	0.57	0.51	0.38
PS3	0.38	0.40	0.82	0.37	0.53	0.48	0.35
AP1	0.36	0.37	0.39	0.83	0.50	0.54	0.41
AP2	0.35	0.36	0.38	0.85	0.52	0.56	0.43
AP3	0.34	0.35	0.37	0.79	0.48	0.52	0.40
ST1	0.51	0.52	0.55	0.50	0.86	0.62	0.48
ST2	0.49	0.50	0.57	0.52	0.88	0.64	0.50
ST3	0.47	0.49	0.53	0.48	0.84	0.60	0.46
TI1	0.45	0.46	0.49	0.54	0.62	0.89	0.57
TI2	0.48	0.44	0.51	0.56	0.64	0.91	0.59
TI3	0.42	0.43	0.48	0.52	0.60	0.85	0.55
MCB1	0.33	0.34	0.36	0.41	0.48	0.57	0.84
MCB2	0.31	0.32	0.35	0.43	0.50	0.59	0.86
MCB3	0.30	0.31	0.34	0.40	0.46	0.55	0.81

Note: Diagonal loadings exceed all corresponding cross loadings, supporting discriminant validity (Henseler et al., 2015).

Appendix C. Endogeneity and Robustness Diagnostics

This appendix reports additional robustness checks referenced in Section 4.4.

Table C1. Gaussian copula test for endogeneity

Endogenous Path	Copula Term β	t-value	p-value	Endogeneity Detected
ST → TI	0.04	0.88	0.38	No
TI → MCB	0.03	0.74	0.46	No

Note: Non-significant copula terms indicate no material endogeneity bias (Liengaard et al., 2025).

Appendix D. Model Fit and Predictive Assessment

This appendix reports global model fit and predictive performance indicators to complement the R^2 and Q^2 values discussed in Section 4.

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Table D1. Model fit and predictive relevance

Metric	Value	Recommended Threshold	Interpretation
SRMR	0.061	< 0.08	Acceptable fit
Q^2 (ST)	0.41	> 0	Strong predictive relevance
Q^2 (TI)	0.38	> 0	Strong predictive relevance
Q^2 (MCB)	0.35	> 0	Strong predictive relevance

Appendix E. Additional Multi Group Analysis (Exploratory)

An exploratory multi group analysis was conducted to examine potential differences between high and low technology familiarity groups, operationalized based on self reported frequency of mobility app usage.

Table E1. MGA by technology familiarity

Path	β (High familiarity)	β (Low familiarity)	Δβ	p-value	Interpretation
AIQ → ST	0.36	0.22	0.14	0.02	Stronger for high familiarity
ST → TI	0.49	0.35	0.14	0.01	Stronger for high familiarity
TI → MCB	0.60	0.44	0.16	0.01	Stronger for high familiarity