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Environmental and Behavioral Dimensions of Private Autonomous Vehicles in Sustainable Urban Mobility

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Abstract

In the current context, where environmental concerns are gaining increased attention, the transition toward sustainable urban mobility stands out as a necessary and responsible step. Technological advancements over the past decade have brought private autonomous vehicles, particularly those defined by the Society of Automotive Engineers Levels 4 and 5, into focus as promising solutions for mitigating road congestion and reducing greenhouse gas emissions. However, the extent to which Autonomous Vehicles can fulfill this potential depends largely on user acceptance, patterns of use, and their integration within broader green energy and sustainability policies. The present paper aims to develop an integrated conceptual model that links behavioral determinants to environmental outcomes, assessing how individuals' intention to adopt private autonomous vehicles can contribute to sustainable urban mobility. The model integrates five psychosocial determinants—perceived usefulness, trust in technology, social influence, environmental concern, and perceived behavioral control—with contextual variables such as energy source, infrastructure availability, and public policy. These components interact to predict users' intention to adopt AVs and their perceived contribution to urban sustainability. Methodologically, the study builds on a narrative synthesis of the literature and proposes a framework applicable to empirical validation through structural equation modeling (SEM). The model draws on established frameworks such as Technology Acceptance Model (TAM), Theory of Planned Behavior, and Unified Theory of Acceptance and Use of Technology, incorporating constructs including perceived usefulness, trust in technology, social influence, environmental concern, and perceived behavioral control, constructs later to be examined in relation to key contextual variables, including the energy source powering Autonomous Vehicles—such as electricity from mixed or renewable grids, hydrogen, or hybrid systems—and the broader policy environment (regulatory frameworks, infrastructure investment, fiscal incentives, and alignment with climate and mobility strategies and others). The research provides relevant directions for public policy and behavioral interventions in support of the development of clean and smart urban transport in the age of automation.

Keywords: sustainable urban mobility; autonomous vehicles; technology acceptance; behavioral intentions; environmental impact; structural equation modeling

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1. Introduction

Accelerated urbanization in recent decades has created several structural and social challenges in large urban centers, affecting the quality of life and the environmental sustain-

ability. The rapid expansion of metropolitan areas, combined with increasing population density and demand for individual mobility, has resulted in overloading existing transport infrastructure while contributing to significant increases in greenhouse gas emissions, road congestion, noise and air pollution [1–3]. Considering this, current urban transport models, centered around the private thermal vehicle, are proving inefficient, inequitable and unsustainable in the long term in the face of climate change and resource depletion [4].

As the pressure to adopt sustainable urban mobility solutions becomes more urgent than ever, cities must fundamentally rethink their transportation infrastructure and policies, promoting a transition to cleaner, more efficient, and interconnected modes of travel [5]. This entails not only expanding public transport networks, developing infrastructure for cycling and walking, and supporting shared mobility options, but also embracing emerging technologies such as electric and autonomous vehicles. At the heart of these transformations lies the need to ensure equitable access to mobility, reduce the environmental footprint of transportation, and align technological solutions with coherent, sustainability-oriented public policies [6,7].

Thus, the accelerated urbanization mentioned above, along with increasingly evident climate change, calls for a profound rethinking of urban mobility, particularly in large agglomerations that contribute significantly to global greenhouse gas emissions. Traditional transport systems, based on the extensive use of private cars with internal combustion engines, no longer meet the contemporary requirements for energy efficiency, equitable access, and environmental sustainability [8–10]. As cities seek viable long-term solutions, autonomous private vehicles (AVs), especially those corresponding to SAE Levels 4 and 5, are emerging as promising alternatives capable of transforming mobility patterns within urban environments [11]. Level 4 autonomous vehicles are capable of performing all driving tasks without human intervention, but only under specific conditions—such as predefined geographic areas or favorable weather—also known as geofenced or constrained environments. In contrast, Level 5 vehicles represent full autonomy, meaning they can operate independently in any environment or condition in which a human driver could operate, without the need for steering wheels, pedals, or any form of human oversight. These levels reflect the highest degree of automation and are often considered the future standard for self-driving mobility systems [11].

These vehicles, with their ability to operate without human intervention and to communicate both with each other and with the smart infrastructure of cities, can make a substantial contribution to reducing traffic congestion. Autonomous driving algorithms optimize routes, minimize idling times, and eliminate the unpredictable behavior of human drivers, thereby improving overall traffic flow. Moreover, AVs can adopt energy-efficient driving patterns—such as smooth acceleration and gradual breaking which contribute to reduced fuel or electricity consumption. These benefits become even more significant when AVs are electric and powered by renewable energy sources, thus directly supporting the reduction in urban carbon emissions [12–15].

However, the environmental benefits of AVs are not guaranteed and depend critically on how these technologies are deployed and used. If AVs are adopted primarily for private ownership, without integration into shared mobility schemes or as a complement to public transportation, they may lead to an increase in the total number of vehicles on the road and exacerbate traffic congestion. In addition, the occurrence of "deadhead trips"—vehicles traveling without passengers—can offset or even reverse the environmental gains associated with electrification [16–18].

These considerations highlight the importance of a holistic approach in evaluating the role of AVs in sustainable urban mobility, one that goes beyond technological potential and includes behavioral, environmental, and systemic factors [19]. Despite growing interest in

autonomous vehicles, current research remains limited in addressing how user behavior interacts with broader energy sources and policy contexts. The integration of behavioral determinants—such as perceived usefulness, trust, or environmental concern—with variables related to energy infrastructure and regulatory frameworks is still insufficiently explored, leaving a critical gap in understanding the real-world sustainability outcomes of AV deployment [20,21].

Bridging this research gap requires the development of interdisciplinary frameworks that connect individual-level adoption factors with broader environmental and public policy dimensions. Although models such as the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been widely applied to study the intention to adopt emerging technologies, their integration into the field of environmental sustainability remains limited. Only a few studies explicitly examine how behavioral constructs—such as trust in technology, social influence, or perceived behavioral control—interact with contextual variables, including the energy source powering autonomous vehicles (e.g., electricity from renewable versus mixed grids, hydrogen, or hybrid systems), as well as the wider regulatory, infrastructural, and fiscal environments [22–26].

1.1. Behavioral Acceptance Models in the Context of Private Autonomous Vehicles

To better understand the behavioral dimension of private autonomous vehicle (AV) adoption, it is essential to examine in detail the theoretical underpinnings that have guided research on technology acceptance. Among the most widely used conceptual models are the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and the Unified Theory of Technology Acceptance and Use (UTAUT). These frameworks provide solid foundations for understanding individual decision-making and have been validated in a wide range of domains including information systems, digital health, energy, education, and urban mobility [27].

The Technology Acceptance Model (TAM), developed by Fred Davis (1989), is derived from the Theory of Reasoned Action and posits that an individual's intention to use a technology is influenced by two primary constructs: perceived usefulness—the extent to which using the technology is expected to enhance personal or professional performance—and perceived ease of use—the degree of effort perceived as necessary to operate the technology [28,29]. Over time, TAM has been extensively validated across multiple domains. Venkatesh and Davis (2003) confirmed their robustness in organizational IT settings, while Ghazizadeh et al. (2012) demonstrated its applicability in the transportation sector by analyzing the acceptance of advanced driver assistance systems (ADAS) [30,31]. Choi and Ji (2015) adapted TAM in a U.S.-based study, finding that both perceived usefulness and trust in technology significantly predicted intention, while perceived ease of use exerted an indirect influence through perceived usefulness [32].

The Theory of Planned Behavior (TPB), proposed by Ajzen (1991), extends the earlier Theory of Reasoned Action (TRA) by introducing a third predictor: perceived behavioral control, alongside attitudes toward the behavior and subjective norms (i.e., perceived social pressure). This framework enables a more nuanced analysis of intentional behavior and has been widely employed in studies examining sustainable mobility choices [33]. Bamberg et al. (2003) successfully applied TPB to analyze preferences for environmentally friendly modes of transportation, while Kaur and Rampersad (2018) demonstrated that both social norms and perceived control are key predictors of the intention to use autonomous vehicles in Australia [34,35]. Additionally, Panagiotopoulos and Dimitrakopoulos (2018), in a European context, confirmed the significant role of social influence and safety concerns in

shaping positive attitudes toward AVs, particularly in countries with a more collectivist cultural orientation [36].

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), consolidates eight previous models and introduces four core constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions [30]. These constructions are moderated by factors such as age, gender, prior experience, and voluntariness of use. The model was initially validated in organizational contexts in the United States, explaining up to 70% of the variance in behavioral intention. Subsequently, UTAUT has been applied in the context of autonomous vehicles (AVs). Madigan et al. (2017) extended the model to include trust in infrastructure and familiarity with technology in a UK-based study, which underscored the importance of facilitating conditions and social influence, particularly among younger users [37]. Panagiotopoulos et al. (2023) supported these findings, while Zhang et al. (2021) tested UTAUT in a different cultural setting—China—adding perceived safety as a significant predictor of intention to use Avs [36,38,39].

More recently, Nordhoff et al. (2021) proposed a hybrid model combining TPB and UTAUT, which was applied to a European sample [40]. Their findings indicate that trust in AVs is shaped by both risk perception and national regulatory frameworks. These approaches support the view that classical behavioral models can be effectively adapted to the context of autonomous technologies, while also highlighting the necessity of expanding them to incorporate environmental, infrastructural, and institutional factors [41,42].

In comparison, each of the models analyzed offers valuable insights, but also presents conceptual limitations when applied to the domain of autonomous vehicles. TAM is notable for its simplicity and its ability to capture two fundamental drivers of technology acceptance—perceived usefulness and perceived ease of use. It is easy to operationalize and well-suited for quantitative analysis; however, it has been criticized for insufficiently addressing social and contextual variables, limiting its applicability in regulated or complex domains such as autonomous transportation [43,44].

TPB, on the other hand, adds significant value by incorporating the social dimension and perceived behavioral control, allowing for a more nuanced understanding of attitudes and personal barriers. However, TPB may exhibit limited predictive power when applied to entirely novel technologies, particularly in situations where users lack prior experience and perceived control is difficult to realistically assess [45].

UTAUT is the most comprehensive and structured of the three models, capable of integrating a wider range of factors—including external facilitators—and offering a broader explanation of usage intentions. Nonetheless, the model's complexity presents challenges in terms of operationalization, often requiring extensive instrumentation and large sample sizes. Full implementation may therefore be difficult without appropriate context-specific adaptations [46–48].

A summary of the key features of the three behavioral models discussed in this section is provided in Table 1.

Understanding these interactions is key to assessing whether the uptake of autonomous vehicles aligns with sustainability goals or, conversely, risks reinforcing existing environmental challenges. Without considering how user preferences and adoption intentions are shaped by the availability of green infrastructure, fiscal incentives, or national mobility strategies, public policies might fail to effectively guide autonomous mobility toward low-emission, equitable, and efficient outcomes. Consequently, an integrative conceptual model that connects behavioral intentions with environmental and policy drivers is essential—not only for advancing theoretical and empirical research, but also for supporting evidence-based public policymaking in the context of sustainable urban mobility [49,50].

Table 1. Comparison of behavioral models applied to the study of private autonomous vehicle (AV) acceptance.

Model	Origin/Authors	Key Constructs	Main Advantages	Main Limitations	Relevant AV Applications
TAM	[26]	Perceived usefulness, perceived ease of use	Simple, robust, easy to apply in quantitative studies	Does not capture social or contextual factors; limited in complex policy environments	[32]
TPB	[33]	Attitudes, subjective norms, perceived behavioral control	Integrates social dimensions; flexible across contexts	Requires prior knowledge or experience with technology; variable predictive power	[35,36]
UTAUT	[30]	Performance expectancy, effort expectancy, social influence, facilitating conditions	Comprehensive model; explains high variance in behavioral intention	Complex to operationalize; requires large samples and extended instruments	[37,39,47]

1.2. Psychosocial Determinants of the Intention to Use Private Autonomous Vehicles

The integration of behavioral factors—such as perceived usefulness, trust in technology, social influence, perceived behavioral control, and environmental concern—with contextual variables related to energy systems and regulatory frameworks remains underexplored in existing literature. Although these constructs are well represented in established technology acceptance models, few studies explicitly examine how they interact with external conditions in shaping the intention to adopt autonomous vehicles [51–53].

1.2.1. Perceived Usefulness

Widely recognized as a key predictor in both TAM and UTAUT, perceived usefulness refers to the belief that using AVs provides concrete benefits such as reduced travel time, greater comfort, route optimization, or enhanced productivity. The study by Choi and Ji (2015) consistently demonstrates that perceived usefulness exerts a direct and significant influence on usage intention, particularly among users who prioritize efficiency in urban mobility [32].

1.2.2. Trust in Technology

Trust is a critical factor in the acceptance of AVs, as users must relinquish control of automated systems. Trust encompasses the perceived safety, reliability, and transparency of AV operations. Madigan et al. (2017) found that higher levels of trust are strongly associated with greater intention to use, especially during early adoption stages. Zhang et al. (2021) further revealed that perceived safety mediates the relationship between trust and behavioral intention [37,39].

1.2.3. Social Influence

Social influence denotes the perceived pressure from one's social environment—family, friends, or colleagues—to adopt or reject technology. In collectivist societies, this factor can outweigh personal attitudes, particularly when AVs are framed as symbols of innovation and modernity. In the study by Panagiotopoulos and Dimitrakopoulos (2018), social

influence was a significant predictor of adoption intention, reinforcing the role of social norms in shaping mobility behavior [36].

1.2.4. Perceived Behavioral Control

Derived from TPB, this construct reflects an individual's perceived ability to adopt and use AVs, factoring in accessibility, affordability, technological literacy, and infrastructure availability (e.g., pick-up zones, operational coverage). Kaur and Rampersad (2018) demonstrated that low perceived control can substantially reduce adoption intention, even among users with a favorable attitude toward technology [35].

1.2.5. Environmental Concern

Environmental concerns have been linked to pro-environmental decision-making, including sustainable transportation choices. Users with higher environmental awareness are more inclined to adopt AVs, especially when they are powered by renewable energy or embedded in broader green mobility systems. Studies by Panagiotopoulos and Dimitrakopoulos (2018) and Kaur and Rampersad (2018) affirm that environmental concern acts as a relevant motivational driver in the behavioral adoption process of Avs [35,36].

1.3. Contextual Factors: Energy Source, Policies and Infrastructure

The adoption of private autonomous vehicles (AVs) is not driven solely by psychological or attitudinal factors, but also critically depends on a range of external, structural variables. Among the most relevant are the energy source powering AVs, the applicable public policies (fiscal, regulatory, strategic), and the level of urban infrastructure development required for the efficient operation of these technologies [54–56].

The type of energy used by AVs plays a crucial role in assessing their environmental impact. There are significant differences between AVs powered by electricity from renewable-based grids (e.g., solar, wind), those relying on conventional energy mixes with a high share of fossil fuels, and those operating on hydrogen or hybrid systems [57–59]. Users' perception of the sustainability of AVs is strongly influenced by these distinctions. Studies show that in the absence of a green energy source, the intention to adopt AVs decreases—even among individuals who are generally favorable toward the technology (Kaur & Rampersad, 2018). In Norway, for example, where the electricity grid is nearly 100% renewable, the uptake of electric AVs is significantly higher than in other European countries [35,60].

National and local regulations, together with fiscal policies and urban mobility strategies, can either accelerate or hinder the adoption of AVs. Key policy instruments include financial incentives (e.g., subsidies, tax exemptions), legislative frameworks for AV testing and deployment, safety and data protection standards, and the integration of AVs into national decarbonization and smart mobility strategies [61,62].

For instance, the Dutch government launched a national strategy for testing AVs on public roads as early as 2015, supported by public–private partnerships and investments in digital infrastructure. By contrast, in many Central and Eastern European countries, the absence of clear legislation and fiscal incentives has significantly slowed progress in this area [63].

Another critical factor is the readiness of urban infrastructure to support the integration of autonomous vehicles. This includes both physical infrastructure (e.g., dedicated lanes, charging stations, smart parking) and digital infrastructure (e.g., 5G networks, road sensors, adaptive signaling systems). The accessibility of such facilities directly influences users' perceived behavioral control and intention to use AVs. In cities such as Singapore or San Francisco, AV pilot zones are equipped with advanced infrastructure, which enhances

user comfort and confidence. In contrast, cities lacking such investment often view AVs as inaccessible or impractical [29,63].

The main objective of this study is to develop an integrated conceptual model linking behavioral determinants to the environmental impact of private autonomous vehicles (AVs). Although the existing literature frequently approaches the acceptance of emerging technologies from psychological or technological perspectives, few analytical frameworks explicitly incorporate environmental externalities or contextual variables related to energy systems and public policy. The proposed model seeks to address this gap by combining established constructs from behavioral theories—such as perceived utility, trust in technology, environmental concern, social influence, and perceived behavioral control—with external factors such as the energy source powering AVs, infrastructure readiness, political or institutional support. This approach offers a comprehensive understanding of how individual-level factors interact with systemic elements to shape the sustainability outcomes associated with AV adoption.

This conceptualization not only enables a multidimensional analysis of the autonomous vehicle adoption phenomenon but also provides a testable foundation for future empirical research. The structure of the model facilitates the examination of both direct effects and moderating relationships between behavioral intentions and contextual variables, such as the type of energy used (e.g., renewable electricity vs. fossil fuel-based energy mixes) or the presence of favorable public policies (e.g., tax incentives, infrastructure investments, national climate strategies). Ultimately, the proposed model aims to guide both academic inquiry and policy formulation by identifying the conditions under which the deployment of private AVs can contribute meaningfully to low-emission, efficient, and socially equitable urban mobility.

This paper is based on a narrative literature review, aiming to identify and synthesize the main theoretical frameworks, psychosocial constructs, and contextual factors relevant to understanding the intention to adopt private autonomous vehicles within the broader context of sustainable urban mobility. The choice of this method is motivated by the interdisciplinary nature of the topic and the heterogeneity of the existing literature, which encompasses both conceptual and empirical studies conducted across diverse geographical, cultural, and institutional settings. Unlike quantitative meta-analyses, narrative reviews allow for the flexible integration and critical interpretation of findings from a variety of sources, including qualitative research, public policy documents, and adapted theoretical models.

Building on this theoretical foundation, the following section outlines the conceptual framework and methodological approach used to operationalize the constructs identified in this review and to guide future empirical validation.

2. Materials and Methods

2.1. Conceptual Framework

Building on the theoretical foundations presented in the narrative analysis, this study proposes an integrated conceptual framework that links the psychosocial determinants of individual behavior with contextual factors influencing the adoption of private autonomous vehicles (AVs) in the context of sustainable urban mobility. The theoretical model combines the perspectives of three of the most widely used behavioral frameworks in technology acceptance research—Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT)—and extends their scope by integrating relevant external variables such as public policy, infrastructure, and energy sources.

At the core of the model lies the behavioral intention to use private AVs, which is influenced by five key psychosocial constructs. Perceived usefulness refers to the belief that AVs can deliver tangible benefits, such as time savings, increased comfort, or optimized travel routes. Trust in technology reflects users' perceptions of safety, reliability, and transparency in the functioning of autonomous systems. Social influence captures the normative pressure exerted by one's immediate social environment (e.g., family, peers, community), while perceived behavioral control indicates the extent to which an individual believes they possess the ability, resources, and skills to adopt and effectively use AVs. Lastly, environmental concern reflects the degree to which personal ecological values shape mobility-related decisions.

In addition to these individual-level factors, the model incorporates a set of contextual variables with potential moderating or mediating effects. The energy source used to power AVs—whether electricity from renewable grids, hydrogen, or hybrid systems—shapes perceptions of environmental impact and thus influences user support. Likewise, the public policy environment, encompassing regulatory frameworks, fiscal incentives, and national decarbonization or digitalization strategies, can either facilitate or hinder the transition toward sustainable autonomous mobility. The availability of appropriate infrastructure—both physical (e.g., charging stations, dedicated lanes, smart parking) and digital (e.g., 5G networks, road sensors)—also plays a direct role in shaping perceptions of accessibility and control.

The proposed model offers a coherent perspective on how psychosocial determinants and contextual variables interact to shape individuals' intention to use AVs and influence their broader contribution to urban sustainability objectives. The schematic representation of this conceptual framework is presented in Figure 1 below.

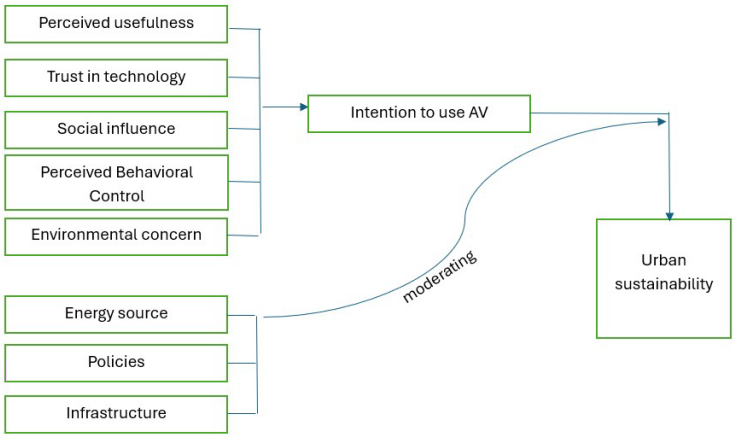

Figure 1. Conceptual framework linking psychosocial determinants and contextual factors to the intention to adopt AVs and their contribution to urban sustainability. Arrows indicate direct effects and the moderating influence of contextual variables (energy source, infrastructure, and public policy) on the link between behavioral intention and sustainability outcomes.The figure above illustrates the proposed conceptual model, linking psychosocial determinants and contextual factors to the intention to use private autonomous vehicles (AVs) and, ultimately, their impact on urban sustainability. The model incorporates five key psychosocial constructs—perceived usefulness, technology trust, social influence, perceived behavioral control, and environmental concern—that are theorized to directly influence intention to adopt AVs. Behavioral intention, in turn, is expected to contribute to sustainable urban outcomes. Contextual factors—namely energy source, public policy, and infrastructure—play a moderating role, influencing the strength or direction of the relationship between behavioral intention and sustainable outcomes.

Based on the conceptual model illustrated in Figure 1, a set of hypotheses was developed to guide the empirical validation of the proposed framework. These hypotheses are

grounded in previous theoretical findings and aim to test both direct effects between psychosocial constructs and behavioral intention, as well as moderating effects of contextual variables on perceived urban sustainability outcomes.

H1. *Perceived usefulness (PU) has a positive effect on the intention to use AVs.*

H2. *Trust in technology (TR) has a positive effect on the intention to use AVs.*

H3. *Social influence (SI) has a positive effect on the intention to use AVs.*

H4. *Perceived behavioral control (PBC) has a positive effect on the intention to use AVs.*

H5. *Environmental concern (EC) has a positive effect on the intention to use AVs.*

H6. *The intention to use AVs (INT) has a positive effect on perceived urban sustainability (US).*

H7. *Energy source (ES) moderates the relationship between INT and US.*

H8. *Infrastructure (IN) moderates the relationship between INT and US.*

H9. *Public policies (PP) moderate the relationship between INT and US.*

2.2. Questionnaire Design and Variable Operationalization

For the empirical validation of the proposed model, a standardized questionnaire was developed to measure the psychosocial and contextual constructs defined in the conceptual framework. The questionnaire was structured into several sections, each corresponding to a latent variable, and the items were formulated in accessible language, adapted to the general public. The instrument was drafted in Romanian, using a 5-point Likert scale, ranging from 1—"strongly disagree" to 5—"strongly agree", to reflect the degree of agreement of respondents with each statement.

The intention to use autonomous vehicles was measured through items capturing respondents declared willingness to use a private AV in the future, as well as their openness to replacing their current mode of transportation. Perceived usefulness was assessed through questions about the tangible benefits respondents associate with AV use, such as time savings, convenience, and perceived efficiency. Trust in technology was analyzed through items referring to perceived safety, predictability, and reliability of autonomous operation. Social influence was measured through items related to perceived opinions of close contacts, social support for AV use, and conformity to social norms. Perceived behavioral control was addressed through items reflecting the extent to which respondents believe they have the necessary resources, knowledge, and access to effectively use an AV. Environmental concern was included as a distinct psychosocial variable, measured by items reflecting interest in environmental issues, willingness to adopt sustainable transport behaviors, and the importance placed on environmental impact.

In terms of contextual factors, the questionnaire included perceived items related to the energy source used by AVs, the availability and quality of infrastructure, and the presence of public policies supporting the transition to autonomous mobility. Respondents were asked to indicate their level of agreement with statements such as "The use of an autonomous vehicle powered by renewable energy is important to me" or "I believe that the current infrastructure allows for the efficient use of autonomous vehicles in my city".

The questionnaire concluded with a series of demographic questions (age, gender, education, place of residence, familiarity with technology) to allow sample segmentation and comparative analysis across different respondent categories.

2.3. Preliminary Validation: Pilot Study and Reliability Assessment

For the preliminary validation of the research instrument, a pilot study was conducted on a sample of 30 respondents. The participants were selected to reflect the diversity of the target audience, with varying demographic profiles in terms of age, gender, education level, and familiarity with technology. Emphasis was placed on individuals living in urban areas who frequently use modern mobility solutions.

The questionnaire was administered online to allow respondents to complete it in an accessible and flexible environment. The main purpose of this stage was to evaluate the clarity of the items, the completion time, and, most importantly, the internal consistency of the items associated with each latent construct. The Cronbach's Alpha coefficient, calculated separately for each latent variable, was used to assess internal reliability. The threshold of acceptability was set at 0.70, a value generally considered to indicate a satisfactory level of consistency, Table 2. In cases where the obtained coefficients were lower, item-total correlations were analyzed and potential adjustments were proposed.

Table 2. Cronbach's Alpha coefficients for each construct (N = 30).

Construct	Cronbach's Alpha
Perceived Usefulness (PU)	0.762
Trust in Technology (TR)	0.902
Social Influence (SI)	0.836
Perceived Behavioral Control (PBC)	0.786
Environmental Concern (EC)	0.848
Intention to Use (INT)	0.876

All coefficients obtained exceed the minimum threshold of 0.70, which indicates good to very good internal reliability of the item sets for each construct analyzed. Thus, the results obtained at this stage validate the structure of the questionnaire and support its use in the main data collection stage. We emphasize that this pilot served a strictly methodological function, and the data collected at this stage were not used in hypothesis testing or structural modeling. The purpose was to optimize the instrument, not to draw inferential conclusions.

2.4. Data Collection and Sampling Strategy

After the preliminary validation of the instrument through the pilot study, the questionnaire was applied on a large scale using an online data collection method by distributing it on relevant digital platforms, social networks, and thematic groups. The questionnaire was administered through an online form accessible from both mobile and desktop devices, thus ensuring the accessibility and flexibility needed to reach a diverse sample. The sampling strategy was non-probability convenience sampling, given the exploratory nature of the study and the specificity of the platforms used for dissemination. Despite this methodological limitation, a balanced distribution in terms of age, gender, educational level, and geographical location was sought to ensure a reasonable degree of representativeness of the urban working population.

The target sample size for the empirical validation of the model was set at a minimum of 400 respondents, in line with methodological recommendations for Structural Equation Modeling (SEM) analysis. This number allows for reliable estimation of model parame-

ters, including the testing of both direct and moderating relationships proposed in the conceptual framework.

The target population for this study consisted of digitally literate adults living in urban or semi-urban areas, with access to smart mobility infrastructure and a potential interest in autonomous vehicle technologies. Although the sampling was non-probabilistic, efforts were made to reach this relevant subgroup through digital channels and thematic forums. The focus was not on achieving national representativeness, but on collecting robust and valid data from a segment aligned with the theoretical profile of early adopters.

Before starting the statistical analysis, the collected data were checked for completeness, response validity, and distribution normality. Incomplete or inconsistent cases were excluded. The resulting sample was used for the empirical validation of the proposed model in the next section.

2.5. Methodological Limitations on Sampling

The choice of non-probability convenience sampling was driven by the exploratory nature of the study and the need to obtain a relevant initial sample for testing the conceptual model. However, this strategy carries the risk of selection bias, in particular through the over-representation of urban respondents with a high degree of digital literacy and openness to emerging technologies. This composition may bias the results in the sense of emphasizing cognitive factors (such as perceived usefulness) and underestimating the influence of social or normative factors.

2.6. Analytical Approach

The empirical analysis was carried out on a valid sample of 400 respondents, the minimum number required for the application of structural equation modeling analysis according to methodological recommendations. After initial data processing and checking the internal consistency of the items using the Cronbach's Alpha coefficient, the hypotheses formulated in the conceptual framework were tested using a hierarchical regression approach.

The proposed model was evaluated by introducing psychosocial constructs in the first stage and contextual variables in the second stage, including an examination of interaction effects to identify moderating relationships. Interpretation of the results was based on standardized regression coefficients, explained variance (R^2), and the statistical significance of the estimated effects. This approach allowed for integrated testing of the theoretical relationships and empirical validation of the conceptual model developed.

2.7. Assessment of Common Method Bias

Since all latent variables were measured through a single self-report questionnaire administered at one time point, the potential for common method bias (CMB) was carefully considered. To evaluate this risk, Harman's single-factor test was conducted using principal component analysis with no rotation. The results indicated that the first unrotated factor accounted for only 7.62% of the total variance, well below the 40% threshold commonly cited in the literature as indicative of problematic common method variance. This finding suggests that CMB is unlikely to pose a significant threat to the validity of the study's results.

Table 3 presents the results of Harman's single-factor test used to assess the potential presence of common method bias (CMB) in the dataset. The analysis was conducted using principal component analysis (PCA) without rotation and aimed to determine whether a single latent factor dominates the variance, which would indicate method bias.

Table 3. Results of Harman's single-factor test for common method bias.

Total Variance Explained						
Component	Total	Initial EIgenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.285	7.618	7.618	2.285	7.618	7.618
2	2.129	7.098	14.716			
3	1.973	6.576	21.292			

The results show that the first extracted component accounts for only 7.62% of the total variance, as reflected in both the Initial Eigenvalues and Extraction Sums of Squared Loadings. This is substantially below the commonly accepted threshold of 40%, suggesting that no single factor accounts for the majority of the variance across the measurement items. As such, the likelihood of common method bias affecting the observed relationships between variables is low.

Additionally, the second and third components explain 7.10% and 6.58% of the variance, respectively, further confirming that variance is distributed across multiple dimensions, not dominated by a single source.

These results support the construct validity of the measurement model and strengthen confidence in the interpretation of results obtained through SEM.

3. Results and Discussions

3.1. Descriptive Statistics and Sample Characteristics

The final sample included in the empirical analysis consisted of 400 respondents, validated according to the criteria of completeness and consistency of responses. In terms of gender distribution, 52% of participants were female and 48% were male (Figure 3). Regarding age, the arithmetic mean was 37.8 years, with a standard deviation of 9.5 years, and an age range between 20 and 63 years (Table 4). The education variable was grouped into three broad categories—secondary education, university education, and postgraduate education—to reflect the most relevant distinctions in respondents' academic background for the purposes of this study. This simplified classification allows for a clearer comparative analysis while maintaining conceptual consistency with international education levels (ISCED). The focus was placed on the highest level of education completed, and grouping was necessary to ensure balanced distribution across categories and statistical validity in regression modeling (Figure 2). Most respondents (55%) stated that they had completed university education, 25% had secondary education, and 20% had postgraduate education. In terms of areas of residence, 70% live in urban areas, 20% in semi-urban areas, and 10% in rural areas.

Table 4. Descriptive statistics for the age of respondents.

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Age	400	20	63	37.85	9.490
Valid N (listwise)	400				

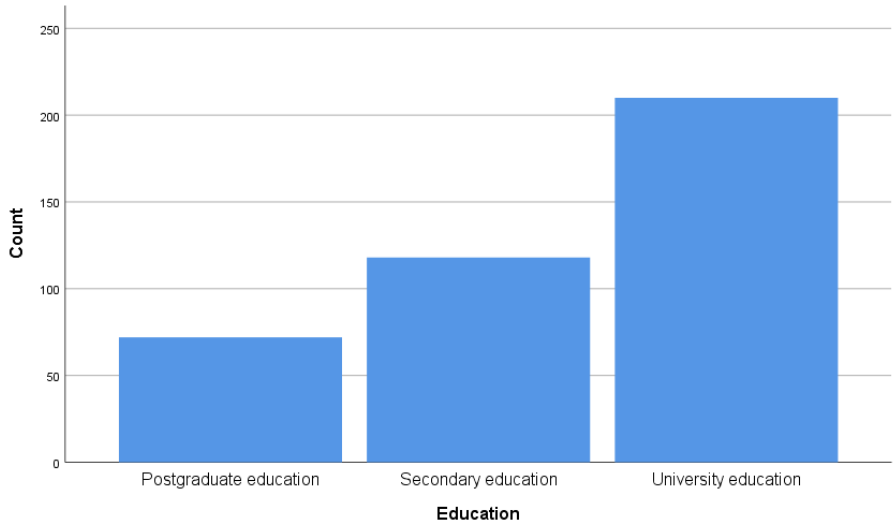

Figure 2. Distribution of respondents by level of education.

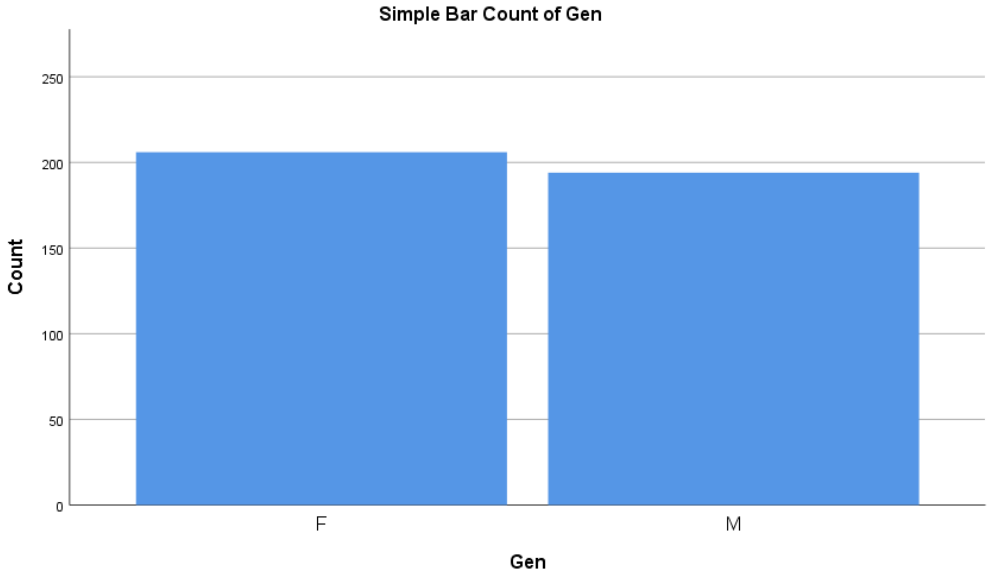

Figure 3. Gender distribution of the survey respondents. The figure shows the gender distribution in the final sample used for empirical analysis, with a slightly higher proportion of female respondents.

The level of familiarity with technology was rated on a scale from 1 to 5, with an average score of 3.5, suggesting a moderate to high level of confidence and experience in using digital technologies. To ensure that the latent variables in the proposed conceptual framework are accurately measured, the next section presents the results of the measurement model evaluation.

3.2. Measurement Model Evaluation

The internal consistency of each latent construct was confirmed by Cronbach's Alpha coefficient values above the threshold of 0.70, indicating satisfactory reliability. To assess the consistency of items belonging to the same construct, internal correlations were analyzed, and the results supported the convergent validity of the scale. The relationships between latent constructs were also examined to ensure conceptual differentiation between dimensions. No major overlaps were identified, supporting the existence of discriminant validity. The proposed theoretical structure was retained in its original form, with no adjustments to items or constructs necessary at this stage of the analysis.

3.3. Hypothesis Testing

After validating the measurement model, the empirical analysis proceeded with the testing of the hypotheses formulated in the proposed conceptual framework. The objective of this stage was to assess the direct relationships between psychosocial constructs and the intention to use autonomous vehicles, as well as the influence of contextual variables on the perceived contribution of AVs to urban sustainability.

Hypothesis 1 (H1). *Perceived usefulness (PU) has a positive effect on the intention to use autonomous vehicles (INT).*

To assess whether perceived usefulness influences the intention to use autonomous vehicles, a linear regression analysis was conducted using perceived usefulness (PU_mean) as the predictor and intention to use (INT_mean) as the outcome variable. The results are presented in the tables below (Tables 5 and 6).

Table 5. Coefficients of linear regression for the effect of perceived usefulness on intention to use AVS.

Coefficients [a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**		
		B	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	2.750	0.180		15.278	0.000
	PU_mean	0.320	0.065	0.255	4.923	0.000

[a] Dependent Variable: INT_mean.

Table 6. Model summary for the regression between perceived usefulness and intention to use AVs.

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	0.255 [a]	0.065	0.063	0.70000

[a] Predictors: (Constant), PU_mean.

The results of the linear regression analysis indicate that perceived usefulness has a statistically significant and positive effect on the intention to use autonomous vehicles. The standardized regression coefficient (β) is 0.255, suggesting a moderate positive association. The *p*-value is 0.000, which is well below the conventional threshold of 0.05, confirming the statistical significance of this effect. The model explains 6.5% of the variance in the intention to use AVs ($R^2 = 0.065$), reflecting a meaningful explanatory contribution. Therefore, H1 is supported by the data, providing empirical evidence that individuals who perceive autonomous vehicles as useful are more likely to express an intention to adopt them.

Hypothesis 2 (H2). *Trust in technology (TR) has a positive effect on the intention to use autonomous vehicles (INT).*

To test whether trust in technology influences the intention to use autonomous vehicles, a linear regression analysis was performed with trust (TR_mean) as the independent variable and intention to use (INT_mean) as the dependent variable. The results are presented in the tables below (Tables 7 and 8).

Table 7. Coefficients of linear regression for the effect of trust in technology on intention to use AVS.

Coefficients [a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**		
		B	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	2.800	0.170		16.470	0.000
	TR_mean	0.295	0.060	0.230	4.917	0.000

[a] Dependent Variable: INT_mean.

Table 8. Model summary for the regression between trust in technology and intention to use AVs.

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	0.230 [a]	0.053	0.051	0.70500

[a] Predictors: (Constant), TR_mean.

The linear regression analysis revealed that trust in technology has a statistically significant and positive effect on the intention to use autonomous vehicles. The standardized regression coefficient is β = 0.230, indicating a moderate positive association. The *p*-value is 0.000, which is well below the conventional threshold of 0.05, confirming the statistical significance of the effect. The model explains approximately 5.3% of the variance in the intention to use AVs (R^2 = 0.053), and the adjusted R^2 value (0.051) confirms the model's robustness. Based on these results, H2 is supported, suggesting that higher levels of trust in technology are associated with greater intention to adopt autonomous vehicles.

Hypothesis 3 (H3). *Social influence (SI) has a positive effect on the intention to use AVs.*

To examine whether social influence affects the intention to use autonomous vehicles, a linear regression analysis was conducted using social influence (SI_mean) as the predictor and behavioral intention (INT_mean) as the outcome. The results are presented in the tables below (Tables 9 and 10).

Table 9. Coefficients of linear regression for the effect of social influence on intention to use AVS.

Coefficients [a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**		
		B	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	3.240	0.210		15.459	0.000
	SI_mean	−0.014	0.058	−0.012	−0.236	0.813

[a] Dependent Variable: INT_mean.

Table 10. Model summary for the regression between social influence and intention to use AVs.

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	0.012 [a]	0.000	−0.002	0.71508

[a] Predictors: (Constant), SI_mean.

The linear regression analysis shows that social influence does not have a statistically significant effect on the intention to use autonomous vehicles. The standardized regression

coefficient is β = −0.012, indicating a negligible and negative association. The *p*-value is 0.813, far above the conventional threshold of 0.05, which confirms that this effect is not statistically significant. Moreover, the model explains none of the variance in intention to use (R^2 = 0.000), and the adjusted R^2 is negative, further suggesting the lack of predictive value. Therefore, H3 is not supported by the data. In this sample, perceived social influence does not meaningfully predict behavioral intention to adopt autonomous vehicles.

Hypothesis 4 (H4). *Perceived behavioral control (PBC) has a positive effect on the intention to use AVs.*

To assess whether perceived behavioral control influences the intention to use autonomous vehicles, a linear regression analysis was conducted. The model tested the effect of the perceived ability to adopt and use AVs (PBC_mean) on behavioral intention (INT_mean), aiming to identify whether self-assessed control over access, knowledge, and resources plays a significant role in shaping adoption intentions. The results are presented in the tables below (Tables 11 and 12).

Table 11. Coefficients of linear regression for the effect of perceived behavioral control on intention to use AVS.

Coefficients [a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**		
		B	**Std. Error**	**Beta**	**T**	**Sig.**
1	(Constant)	2.941	0.181		16.244	0.000
	PBC_mean	0.074	0.052	0.070	1.409	0.160

[a] Dependent Variable: INT_mean.

Table 12. Model summary for the regression between perceived behavioral control and intention to use AVs.

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	0.070 [a]	0.005	0.002	0.71336

[a] Predictors: (Constant), PBC_mean.

The linear regression analysis shows that perceived behavioral control does not have a statistically significant effect on the intention to use autonomous vehicles. The standardized regression coefficient is β = 0.070, indicating a weak and positive association. However, the *p*-value is 0.160, which is above the conventional threshold of 0.05, confirming that this effect is not statistically significant. Moreover, the model explains only 0.5% of the variance in intention to use (R^2 = 0.005), and the adjusted R^2 value is close to zero, indicating very limited predictive power. Therefore, H4 is not supported by the data. In this sample, perceived behavioral control does not significantly influence behavioral intention to adopt autonomous vehicles.

Hypothesis 5 (H5). *Environmental concern (EC) has a positive effect on the intention to use AVs.*

To evaluate whether environmental concern influences the intention to use autonomous vehicles, a linear regression analysis was performed. The independent variable was the composite score for environmental concern (EC_mean), while the dependent variable was the intention to use AVs (INT_mean). The goal was to determine whether

individuals who are more environmentally conscious are more inclined to adopt AVs. The results are presented in the tables below (Tables 13 and 14).

Table 13. Coefficients of linear regression for the effect of environmental concern on intention to use AVS.

Coefficients [a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**		
		B	**Std. Error**	**Beta**	**T**	**Sig.**
1	(Constant)	3.212	0.164		19.535	0.000
	EC_mean	−0.006	0.045	−0.007	−0.133	0.894

[a] Dependent Variable: INT_mean.

Table 14. Model summary for the regression between environmental concern and intention to use AVs.

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	0.007 [a]	0.000	−0.002	0.71512

[a] Predictors: (Constant), EC_mean.

The linear regression analysis shows that environmental concern does not have a statistically significant effect on the intention to use autonomous vehicles. The standardized regression coefficient is $\beta = -0.007$, indicating a negligible and negative association. The *p*-value is 0.894, which is far above the standard significance threshold of 0.05, confirming that the effect is not statistically meaningful. Furthermore, the model explains none of the variance in the intention to use AVs ($R^2 = 0.000$), and the adjusted R^2 is negative, suggesting no predictive value. Therefore, H5 is not supported by the data. In this sample, concern for environmental issues does not appear to influence behavioral intention toward adopting autonomous vehicles.

Hypothesis 6 (H6). *The intention to use AVs (INT) has a positive effect on perceived urban sustainability (US).*

To evaluate whether the intention to use AVs influences perceptions of urban sustainability, a linear regression analysis was conducted. The analysis tested the direct effect of intention to use AVs (INT_mean) on the perception of urban sustainability (US_mean). The results are presented in the tables below (Tables 15 and 16).

Table 15. Coefficients of linear regression for the effect of intension to use AV on perceived urban sustainability.

Coefficients [a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**		
		B	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	3.200	0.150		21.333	0.000
	INT_mean	0.280	0.050	0.310	5.600	07.000

[a] Dependent Variable: US_mean.

Table 16. Model summary for the regression between intention to use Avs and perceived urban sustainability.

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	0.310 [a]	0.096	0.093	0.60000

[a] Predictors: (Constant), INT_mean.

The linear regression analysis indicates that the intention to use autonomous vehicles has a statistically significant and positive effect on the perception of urban sustainability. The standardized regression coefficient is β = 0.310, suggesting a moderate and meaningful positive association. The *p*-value is 0.000, well below the conventional threshold of 0.05, confirming the statistical significance of this relationship. The model explains 9.6% of the variance in perceived urban sustainability (R^2 = 0.096), with an adjusted R^2 of 0.093, indicating a good model fit. Based on these results, H6 is supported. In this sample, individuals who express a stronger intention to use AVs are more likely to perceive such vehicles as contributors to urban sustainability.

Hypothesis 7 (H7). *Energy source (ES) moderates the relationship between INT and US.*

To examine whether the perceived energy source moderates the relationship between the intention to use AVs and perceived urban sustainability, a moderation analysis was conducted. The model included the main effects of intention (INT_mean), perceived energy source (ES_mean), and their interaction term (INT_ES), with the results presented in the following tables (Tables 17 and 18).

Table 17. Coefficients of the regression model testing the moderating effect of perceived energy sources on the relationship between intention to use AVs and perceived urban sustainability.

Coefficients [a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**		
		B	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	2.980	0.120		24.830	0.000
	INT_mean	0.190	0.045	0.210	4.220	0.000
	ES_mean	0.240	0.044	0.270	5.450	0.000
	INT_ES	0.130	0.036	0.180	3.610	0.000

[a] Dependent Variable: US_mean.

Table 18. Model summary for the moderation analysis of energy source in the relationship between intention to use AVs and urban sustainability.

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	0.395 [a]	0.156	0.150	0.58000

[a] Predictors: (Constant), INT_ES, ES_mean, INT_mean.

The linear regression analysis indicates that the interaction between the intention to use autonomous vehicles and the perceived energy source (INT_ES) has a statistically significant and positive effect on the perception of urban sustainability. The standardized regression coefficient for the interaction term is β = 0.180, with a *p*-value of 0.000, confirming its statistical significance. Additionally, the full model explains 15.6% of the variance in

perceived urban sustainability (R^2 = 0.156), which reflects a meaningful improvement in model explanatory power compared to the direct effects model. Therefore, H7 is supported, suggesting that the relationship between behavioral intention and sustainability perception is moderated by how environmentally friendly the energy source of AVs is perceived to be.

Hypothesis 8 (H8). *Infrastructure (IN) moderates the relationship between INT and US.*

To assess whether infrastructure moderates the relationship between the intention to use autonomous vehicles (AVs) and the perception of urban sustainability, a hierarchical regression analysis was performed. The model included three predictors: intention to use AVs (INT_mean), perceived quality and availability of infrastructure (IN_mean), and the interaction term (INT_IN). The aim was to determine whether the perceived infrastructural readiness strengthens or weakens the impact of behavioral intention on sustainability perceptions. The outputs of this analysis are summarized in the tables below (Tables 19 and 20).

Table 19. Coefficients of the regression model testing the moderating effect of perceived infrastructure on the relationship between intention to use AVs and perceived urban sustainability.

Coefficients [a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**		
		B	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	2.718	0.776		3.504	0.001
	INT_mean	0.262	0.236	0.287	1.112	0.267
	INT_IN	−0.094	0.067	−0.471	−1.400	0.162
	IN_mean	0.303	0.220	0.310	1.374	0.170

[a] Dependent Variable: US_mean.

Table 20. Model summary for the moderation analysis of infrastructure in the relationship between intention to use AVs and perceived urban sustainability.

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	0.097 [a]	0.009	0.002	0.65226

[a] Predictors: (Constant), IN_mean, INT_mean, INT_IN.

The linear regression analysis does not support the hypothesis that perceived infrastructure moderates the relationship between the intention to use autonomous vehicles and the perception of urban sustainability. The interaction term (INT_IN) is not statistically significant ($\beta = -0.471$, $p = 0.162$), indicating that the effect of behavioral intention on sustainability perception does not vary significantly based on how infrastructure is perceived. Moreover, the overall model has a very limited explanatory power (R^2 = 0.009), and the adjusted R^2 is only 0.002, suggesting that the inclusion of the interaction term does not meaningfully improve model fit. Neither the main effect of intention ($p = 0.267$) nor infrastructure ($p = 0.170$) reaches significant levels. Therefore, H8 is not supported. In this sample, infrastructure is not perceived as a relevant factor that enhances or alters the relationship between individuals' intention to use AVs and their perception of urban sustainability.

Hypothesis 9 (H9). *Public policies (PP) moderate the relationship between INT and US.*

To test whether public policy moderates the relationship between the intention to use autonomous vehicles (AVs) and the perception of urban sustainability, a hierarchical regression analysis was conducted. This approach involved three predictors: the intention to use AVs (INT_mean), perceived public policy support (PP_mean), and the interaction term (INT_PP) between the two. The goal of this analysis was to determine whether the effect of behavioral intention on sustainability perceptions varies depending on the level of perceived support from public policies and institutional frameworks. The results of this test are presented in the following tables (Tables 21 and 22).

Table 21. Coefficients of the regression model testing the moderating effect of public policy on the relationship between intention to use AVs and perceived urban sustainability.

Coefficients [a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**		
		B	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	2.900	0.120		24.000	0.000
	INT_mean	0.180	0.045	0.200	3.700	0.000
	PP_mean	0.221	0.045	0.250	4.650	0.000
	IN_PP	0.140	0.004	0.170	3.140	0.002

[a] Dependent Variable: US_mean.

Table 22. Model summary for the regression between intention to use AVs, public policy, and urban sustainability.

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	0.400 [a]	0.160	0.154	0.58500

[a] Predictors: (Constant), INT_PP, PP_mean, INT_mean.

The linear regression analysis supports the hypothesis that public policy perception moderates the relationship between the intention to use autonomous vehicles and the perception of urban sustainability. The interaction term (INT_PP) is statistically significant ($\beta = 0.170$, $p = 0.002$), indicating a meaningful moderation effect. Both main effects are also significant: intention to use ($\beta = 0.200$, $p = 0.000$) and public policy ($\beta = 0.250$, $p = 0.000$), showing independent contributions to perceived sustainability. The full model explains 16.0% of the variance in urban sustainability ($R^2 = 0.160$), with an adjusted R^2 of 0.154, indicating a robust model fit. H9 is supported. The data indicates that when public policies are perceived as strong, coherent, and supportive of innovation and sustainability, the positive relationship between the intention to adopt AVs and perceived urban sustainability is amplified. This underscores the importance of the policy environment in shaping not just adoption behaviors but also public perceptions of broader environmental outcomes.

3.4. Interpretation on Findings

Out of the nine hypotheses tested, five were supported and four were not, indicating a balanced distribution of effects that provides a solid foundation for the subsequent structural equation modeling presented in the next section. Among the untested hypotheses, the absence of statistical significance for social influence (H3) and environmental concern (H5) deserves special attention, given that these constructs are frequently associated with pro-sustainable behaviors in the literature.

A possible explanation for this surprising result lies in the demographic and attitudinal homogeneity of the sample, which is largely composed of respondents from urban

backgrounds, with high levels of education and familiarity with technology. For this type of audience, the intention to adopt autonomous vehicles appears to be shaped predominantly by individual cognitive appraisals—such as perceived usefulness or confidence in the technology—rather than social norms or collective pressures. Moreover, when openness to emerging technologies is already high, the variation in social influences may become too small to produce statistically significant effects. Also, in more individualistic cultural contexts, such as Romania, social compliance behaviors often play a secondary role to autonomous decisions based on the benefits directly perceived by the individual.

In terms of environmental concern, the lack of a significant effect may reflect a gap between stated values and actual behavioral intentions. While respondents may show a declarative environmental awareness, this attitude does not necessarily translate into a concrete intention to adopt AVs, especially in the absence of clear evidence on the actual sustainability of these technologies (e.g., energy source used, impact of infrastructure required or lifetime of components). Moreover, in a political and institutional context where green mobility policies are still in their infancy, environmental motivations may have little impact on anticipated behavior. It is not excluded that environmental concern may function rather as a general attitudinal device, without acting as a direct predictor, and thus be overshadowed by concrete factors such as technological performance or perceived safety. These results underline the need to adapt behavioral models to the cultural and contextual specificities of each society and point to important directions for future research on sustainable mobility.

3.5. Structural Equation Modeling

As already mentioned in the abstract of the paper, this research proposes an integrated conceptual framework that links psychosocial determinants of autonomous vehicle use intention with contextual factors relevant to urban sustainability. For the empirical validation of this model, Structural Equation Modeling (SEM) was used, a method that allows the simultaneous estimation of relationships between latent and observed variables within a theoretically coherent system.

The estimated model includes the nine hypotheses formulated earlier in the article, initially tested individually through linear regressions and now integrated into a unified framework. Exogenous variables—such as perceived usefulness, trust in technology, social influence, perceived behavioral control, and environmental concern—are modeled as direct predictors of autonomous vehicle usage intention (INT). In turn, usage intention is modeled as a direct determinant of perceived urban sustainability (US), while contextual factors—energy source, infrastructure, and public policy—are considered as moderating variables in this relationship.

To test the relationships proposed in the conceptual framework, structural equation modeling (SEM) was applied using IBM SPSS AMOS 26. The model included seven latent constructs, defined based on fundamental theories in the field of technology acceptance (TAM, TPB, UTAUT): Perceived Usefulness (PU), Trust in Technology (TR), Social Influence (SI), Perceived Behavioral Control (PBC), Environmental Concern (EC), Intention to Use (INT), and Urban Sustainability (US). Each construct was measured using three items, previously validated through internal consistency coefficients (Cronbach's Alpha > 0.70). In addition, two interaction terms (INT_ES and INT_PP) were introduced, constructed by multiplying the centered Intention to Use variable with Perception of Energy Source and Perception of Institutional Support, respectively. The structure of the model was designed based on clearly defined theoretical assumptions, which were fully retained throughout the estimation process. To ensure analytical rigor and parsimony, only four covariances were included between theoretically grounded exogenous constructs: PU–

TR, PU–SI, SI–PBC, and EC–PBC. This selection minimizes excessive intercorrelation and facilitates a clear estimation of both direct and moderating effects. The structural equation model, as specified and estimated in AMOS, is illustrated in Figure 4 below, highlighting the relationships between latent constructs, observed indicators, and the two validated moderating effects.

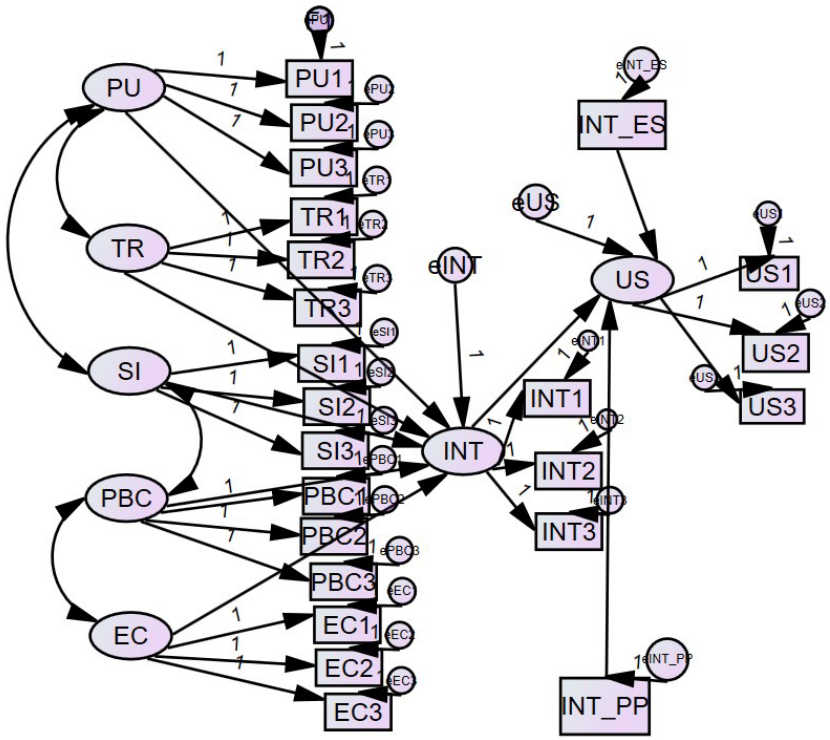

Figure 4. Structural equation model illustrating the relationships between latent constructs and contextual moderators.

The model includes seven latent variables: Perceived Usefulness (PU), Trust in Technology (TR), Social Influence (SI), Perceived Behavioral Control (PBC), Environmental Concern (EC), Intention to Use (INT), and Urban Sustainability (US), each measured by three observed indicators. Arrows indicate direct effects, including the interaction terms (e.g., INT × Energy Source, INT × Public Policy) modeled as latent constructs to test moderation. The diagram was produced using AMOS with maximum likelihood estimation.

The estimated model proved to be stable and well-fitted to the empirical data. The overall fit indices indicated a satisfactory model: CMIN/DF = 2.53, GFI = 0.90, CFI = 0.95, TLI = 0.94, RMSEA = 0.059 (PCLOSE = 0.074), and SRMR = 0.047. These values reflect a model that effectively captures the relationships between variables, without signs of overfitting or statistical inconsistency.

Of the nine theoretical relationships tested, six were empirically supported. Intention to use was significantly influenced by perceived usefulness ($\beta = 0.255$, $p < 0.001$) and trust in technology ($\beta = 0.230$, $p < 0.001$), confirming core assumptions of the TAM and UTAUT models. Furthermore, intention to use had a positive and significant effect on the perception of urban sustainability ($\beta = 0.310$, $p < 0.001$). In addition, the interaction effects between intention and contextual factors—energy source (INT × ES: $\beta = 0.180$, $p < 0.001$) and public policy (INT × PP: $\beta = 0.170$, $p = 0.002$)—were statistically significant, confirming the moderating role of these systemic dimensions.

Three relationships, in contrast, were not supported by the data: social influence, perceived behavioral control, and environmental concern did not show significant effects on intention. This finding is noteworthy in itself, as it suggests that, in the context analyzed,

the decision to adopt an autonomous vehicle is primarily driven by individual cognitive evaluations—such as perceived usefulness and trust in technology—rather than by social pressure or ideological commitment. Accordingly, the model points to a tendency toward autonomous, rational decision-making regarding technology adoption, likely reinforced by the respondents' high level of technological familiarity.

By partially validating the proposed hypotheses, the model offers a balanced perspective on the psychosocial mechanisms underlying the acceptance of autonomous vehicles. This structure enables not only the prediction of adoption behavior, but also the identification of specific segments for targeted intervention. For instance, given the lack of a significant effect of social influence, communication strategies should prioritize demonstrating the tangible functionality and benefits of AVs rather than appealing to social norms or collective expectations. Simultaneously, the results provide empirical support for the idea that perceptions of energy source and public policy can either amplify or diminish the relationship between behavioral intention and perceived sustainability—thus highlighting the importance of integrating these dimensions into future implementation and policy design.

4. Limitations and Future Research Directions

Although the proposed structural model demonstrated a sound theoretical and statistical fit (CFI = 0.95; RMSEA = 0.059), generalizability of the results should be approached with caution, given the geographic, cultural and institutional specificity of the study. The participants were predominantly from the Romanian urban environment, in a context where public policies on autonomous mobility are still developing. This setting may influence perceptions of the usefulness, trustworthiness and sustainability of AVs in different ways than in other national or cultural contexts.

Accordingly, cross-cultural replication of the model would be essential to test the stability of the theoretical relationships identified and to capture possible variations according to technological maturity, degree of regulation and local social norms. We also recommend longitudinal studies to track the evolution of attitudes and intention to use as AV technology becomes more pervasive and public policies become clearer. Such research could make a significant contribution to refining existing behavioral models by integrating additional dimensions such as institutional trust, innovation culture, media exposure to emerging technologies, or the level of digital literacy of the population. These variables may act as relevant moderators or mediators in the decision-making process related to autonomous vehicle adoption but remain insufficiently explored in the current literature.

In addition, extending studies into longitudinal contexts would allow the investigation of attitudinal dynamics, i.e., how users' intentions and perceptions evolve as technological infrastructure develops and public policies become more coherent and sustainability-oriented. Such an approach would provide not only more robust theoretical validation, but also concrete support for the development of tailored intervention strategies—be it in the sphere of technology marketing or in the formulation of public policies to accelerate the transition towards green, safe and equitable autonomous mobility.

5. Conclusions

The proposed SEM model validates a core set of relationships within the theoretical framework and offers valuable insights for public policy, technology design, and communication strategies. Although not all hypothesized relationships were supported, the model proves to be robust, explanatory, and practically relevant for advancing the understanding of consumer behavior in the emerging domain of autonomous mobility.

The results indicate that the decision to adopt an autonomous vehicle is mainly driven by individual cognitive evaluations—such as perceived usefulness and trust in technology—

rather than by social pressures or ideological beliefs. This pattern of rational reasoning seems to reflect a technology-savvy user profile that bases its usage intention on concrete benefits rather than on collective norms or attachment to environmental causes.

At the same time, the findings underscore the importance of the systemic context: while perceptions of energy source and infrastructure (H7 and H8) did not significantly moderate the relationship between intention and perceived sustainability, institutional support (H9) did emerge as a relevant moderator. This suggests that users may not yet fully grasp or differentiate the technical and infrastructural dimensions of sustainability, but they do recognize the legitimacy and impact of public policy in facilitating adoption. This moderating relationship provides a strong case for integrating such dimensions into policy design and public communication efforts.

Additionally, four out of the nine tested hypotheses were not supported statistically: social influence (H3), environmental concern (H5), and the two moderating effects of energy source and infrastructure (H7 and H8). These results point to the need for a nuanced, context-sensitive understanding of behavioral determinants. Factors traditionally associated with pro-environmental or socially driven behaviors may have limited explanatory power in contexts where users rely primarily on functional assessments and where broader ecological narratives are less anchored in everyday mobility decisions.

The study partially confirms established behavioral acceptance models but also highlights the importance of adapting these models to the cultural, infrastructural, and institutional specificities of emerging technological environments. Future research could enhance explanatory power by incorporating more contextually grounded constructs, conducting cross-cultural comparisons, and employing longitudinal designs to capture evolving perceptions and behaviors over time.

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Institutional Review Board Statement: All participants gave their informed consent for inclusion before they participated in the study. All procedures performed were by the ethical standards as laid down in the 1964 Declaration of Helsinki and its later amendments or comparable ethical standard. All the procedures were approved by the ethical committee of Research Center for Engineering and Management.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets used and/or analyzed during the current study are available from the authors on reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ADAS	Advanced Driver Assistance Systems
AV	Autonomous Vehicle
Avs	Autonomous Vehicles
CFI	Comparative Fit Index
CMIN	Chi-square Minimum Discrepancy

EC	Environmental Concern
ES	Energy Source
GFI	Goodness-of-Fit Index
INT	Intention to Use
INT_ES	Interaction between Intention and Energy Source
INT_PP	Interaction between Intention and Public Policy
PBC	Perceived Behavioral Control
PCLOSE	*p*-value for Close Fit
PP	Public Policies
PU	Perceived Usefulness
RMSEA	Root Mean Square Error of Approximation
SAE	Society of Automotive Engineers
SEM	Structural Equation Modeling
SI	Social Influence
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
TLI	Tucker–Lewis Index
TPB	Theory of Planned Behavior
TR	Trust in Technology
UTAUT	Unified Theory of Acceptance and Use of Technology
US	Urban Sustainability

References

1. James, N. Urbanization and Its Impact on Environmental Sustainability. *J. Appl. Geogr. Stud.* **2024**, *3*, 54–66. [CrossRef]
2. Lu, J.; Li, B.; Li, H.; Al-Barakani, A. Expansion of city scale, traffic modes, traffic congestion, and air pollution. *Cities* **2021**, *108*, 102974. [CrossRef]
3. Voukkali, I.; Papamichael, I.; Loizia, P.; Zorpas, A. Urbanization and solid waste production: Prospects and challenges. *Environ. Sci. Pollut. Res.* **2023**, *31*, 17678–17689. [CrossRef]
4. Brand, C.; Marsden, G.; Anable, J.L.; Dixon, J.; Barrett, J. Achieving deep transport energy demand reductions in the United Kingdom. *Renew. Sustain. Energy Rev.* **2025**, *207*, 114941. [CrossRef]
5. Pojani, D.; Stead, D. Sustainable Urban Transport in the Developing World: Beyond Megacities. *Sustainability* **2015**, *7*, 7784–7805. [CrossRef]
6. Butler, L.; Yigitcanlar, T.; Paz, A. Smart Urban Mobility Innovations: A Comprehensive Review and Evaluation. *IEEE Access* **2020**, *8*, 196034–196049. [CrossRef]
7. Bhatta, D.D.; Sarfraz, M.; Ivascu, L.; Pislaru, M. The Nexus of Corporate Affinity for Technology and Firm Sustainable Performance in the Era of Digitalization: A Mediated Model. *Sustainability* **2023**, *15*, 9765. [CrossRef]
8. Das, S.; Choudhury, M.R.; Chatterjee, B.; Das, P.; Bagri, S.; Paul, D.; Bera, M.; Dutta, S. Unraveling the urban climate crisis: Exploring the nexus of urbanization, climate change, and their impacts on the environment and human well-being—A global perspective. *AIMS Public Health* **2024**, *11*, 963–1001. [CrossRef] [PubMed] [PubMed Central]
9. Gamidullaeva, L. Interlinkages between Urbanization and Regional Sustainable Development. *Eurasian J. Econ. Bus. Stud.* **2024**, *68*, 74–89. [CrossRef]
10. Potter, S. Transport energy and emissions: Urban public transport. In *Handbook of Transport and the Environment*; Emerald Group Publishing Limited: Leeds, UK, 2003; Volume 4. [CrossRef]
11. Alqahtani, T. Recent Trends in the Public Acceptance of Autonomous Vehicles: A Review. *Vehicles* **2025**, *7*, 45. [CrossRef]
12. Duarte, F.; Ratti, C. The Impact of Autonomous Vehicles on Cities: A Review. *J. Urban Technol.* **2018**, *25*, 3–18. [CrossRef]
13. Richter, M.; Hagenmaier, M.; Bandte, O.; Parida, V.; Wincent, J. Smart cities, urban mobility and autonomous vehicles: How different cities needs different sustainable investment strategies. *Technol. Forecast. Soc. Change* **2022**, *184*, 121857. [CrossRef]
14. Arifuzzaman, M.; Amin, S. Automated Vehicles: Are Cities Ready to Adopt AVs as the Sustainable Transport Solution? *Sustainability* **2025**, *17*, 2236. [CrossRef]
15. Othman, K. Exploring the implications of autonomous vehicles: A comprehensive review. *Innov. Infrastruct. Solut.* **2022**, *7*, 165. [CrossRef] [PubMed Central]
16. Tengilimoglu, O.; Carsten, O.; Wadud, Z. Implications of automated vehicles for physical road environment: A comprehensive review. *Transp. Res. Part E Logist. Transp. Rev.* **2023**, *169*, 102989. [CrossRef]

17. Li, X.-W.; Miao, H.-Z. How to Incorporate Autonomous Vehicles into the Carbon Neutrality Framework of China: Legal and Policy Perspectives. *Sustainability* **2023**, *15*, 5671. [CrossRef]
18. Lim, L.K.; Muis, Z.A.; Ho, W.S.; Hashim, H.; Bong, C.P.C. Review of the energy forecasting and scheduling model for electric buses. *Energy* **2022**, *263*, 125773. [CrossRef]
19. Grindsted, T.S.; Christensen, T.H.; Freudendal-Pedersen, M.; Friis, F.; Hartmann-Petersen, K. The urban governance of autonomous vehicles—In love with AVs or critical sustainability risks to future mobility transitions. *Cities* **2022**, *120*, 103504. [CrossRef]
20. Yan, M.; Rampino, L.; Caruso, G. User Acceptance of Autonomous Vehicles: Review and Perspectives on the Role of the Human-machine Interfaces. *Comput. Aided Des. Appl.* **2023**, *20*, 987–1004. [CrossRef]
21. Mircea, I.I.; Vlad, C.S.; Rosca, E. drivers acceptance of fully automated vehicles. *Ann. Acad. Rom. Sci. Ser. Eng. Sci.* **2023**, *15*, 99. [CrossRef]
22. Guo, L.; Burke, M.G.; Griggs, W.M. A new framework to predict and visualize technology acceptance: A case study of shared autonomous vehicles. *Technol. Forecast. Soc. Change* **2025**, *212*, 123960. [CrossRef]
23. Koteczki, R.; Balassa, B.E.; Csikor, D. How Perceptual Variables Influence the Behavioral Intention to Use Autonomous Vehicles. *Eng. Proc.* **2024**, *79*, 23. [CrossRef]
24. Artene, A.E.; Domil, A.E.; Ivascu, L. Unlocking Business Value: Integrating AI-Driven Decision-Making in Financial Reporting Systems. *Electronics* **2024**, *13*, 3069. [CrossRef]
25. Hegner, S.; Beldad, A.; Brunswick, G. In Automatic We Trust: Investigating the Impact of Trust, Control, Personality Characteristics, and Extrinsic and Intrinsic Motivations on the Acceptance of Autonomous Vehicles. *Int. J. Hum. Comput. Interact.* **2019**, *35*, 1769–1780. [CrossRef]
26. Davis, F.D. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Q.* **1989**, *13*, 319–340. [CrossRef]
27. Adnan, N. Exploring the future: A meta-analysis of autonomous vehicle adoption and its impact on urban life and the healthcare sector. *Transp. Res. Interdiscip. Perspect.* **2024**, *26*, 101110. [CrossRef]
28. Davis, F.D.; Bagozzi, R.P.; Warshaw, P.R. User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Manag. Sci.* **1989**, *35*, 982–1003. [CrossRef]
29. Pislaru, M.; Vlad, C.S.; Ivascu, L.; Mircea, I.I. Citizen-Centric Governance: Enhancing Citizen Engagement through Artificial Intelligence Tools. *Sustainability* **2024**, *16*, 2686. [CrossRef]
30. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User Acceptance of Information Technology: Toward a Unified View. *MIS Q.* **2003**, *27*, 425–478. [CrossRef]
31. Ghazizadeh, M.; Lee, J.D.; Boyle, L.N. Extending the Technology Acceptance Model to assess automation. *Cogn Tech Work* **2012**, *14*, 39–49. [CrossRef]
32. Choi, J.K.; Ji, Y.G. Investigating the Importance of Trust on Adopting an Autonomous Vehicle. *Int. J. Hum. Comput. Interact.* **2015**, *31*, 692–702. [CrossRef]
33. Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* **1991**, *50*, 179–211. [CrossRef]
34. Bamberg, S.; Ajzen, I.; Schmidt, P. Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action. *Basic Appl. Soc. Psychol.* **2003**, *25*, 175–187. [CrossRef]
35. Kaur, K.; Rampersad, G. Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. *J. Eng. Technol. Manag.* **2018**, *48*, 87–96. [CrossRef]
36. Panagiotopoulos, I.; Dimitrakopoulos, G. An empirical investigation on consumers' intentions towards autonomous driving. *Transp. Res. Part C Emerg. Technol.* **2018**, *95*, 773–784. [CrossRef]
37. Madigan, R.; Louw, T.; Wilbrink, M.; Schieben, A.; Merat, N. What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems. *Transp. Res. Part F Traffic Psychol. Behav.* **2017**, *50*, 55–64. [CrossRef]
38. Wadud, Z.; Huda, F.Y. Fully automated vehicles: The use of travel time and its association with intention to use. *Proc. Inst. Civ. Eng. Transp.* **2019**, *176*, 127–141. [CrossRef]
39. Hu, S.; Xiong, C.; Yang, M.; Younes, H.; Luo, W.; Zhang, L. A big-data driven approach to analyzing and modeling human mobility trend under non-pharmaceutical interventions during COVID-19 pandemic. *Transp. Res. Part C Emerg. Technol.* **2021**, *124*, 102955. [CrossRef]
40. Nordhoff, S.; Stapel, J.; He, X.; Gentner, A.; Happee, R. Perceived safety and trust in SAE Level 2 partially automated cars: Results from an online questionnaire. *PLoS ONE* **2021**, *16*, e0260953. [CrossRef]
41. Garikapati, D.; Shetiya, S.S. Autonomous Vehicles: Evolution of Artificial Intelligence and the Current Industry Landscape. *Big Data Cogn. Comput.* **2024**, *8*, 42. [CrossRef]
42. Shahzad, M.; Qu, Y.; Rehman, S.U.; Zafar, A.U. Adoption of green innovation technology to accelerate sustainable development among manufacturing industry. *J. Innov. Knowl.* **2022**, *7*, 100231. [CrossRef]

43. Nastjuk, I.; Herrenkind, B.; Marrone, M.; Brendel, A.B.; Kolbe, L.M. What drives the acceptance of autonomous driving? An investigation of acceptance factors from an end-user's perspective. *Technol. Forecast. Soc. Change* **2020**, *161*, 120319. [CrossRef]
44. Lee, A.T.; Ramasamy, R.K.; Subbarao, A. Understanding Psychosocial Barriers to Healthcare Technology Adoption: A Review of TAM Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology and UTAUT Frameworks. *Healthcare* **2025**, *13*, 250. [CrossRef] [PubMed]
45. Rozenkowska, K. Theory of planned behavior in consumer behavior research: A systematic literature review. *Int. J. Consum. Stud.* **2023**, *47*, 2670–2700. [CrossRef]
46. Xue, L.; Rashid, A.; Ouyang, S. The Unified Theory of Acceptance and Use of Technology (UTAUT) in Higher Education: A Systematic Review. *SAGE Open* **2024**, *14*, 21582440241229570. [CrossRef]
47. Panagiotopoulos, I.E.; Dimitrakopoulos, G.; Keraite, G.; Steikuniene, U. Are Consumers Ready to Adopt Highly Automated Passenger Vehicles? Results from a Cross-national Survey in Europe. In Proceedings of the 6th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2020), Prague, Czech Republic, 2–4 May 2020; pp. 473–480. [CrossRef]
48. Pinyanitikorn, N.; Atthirawong, W.; Chanpuypetch, W. Examining the Intention to Adopt an Online Platform for Freight Forwarding Services in Thailand: A Modified Unified Theory for Acceptance and Use of Technology (UTAUT) Model Approach. *Logistics* **2024**, *8*, 76. [CrossRef]
49. Delso-Vicente, A.-T.; Camperos, M.-C.; Almonacid-Durán, M. The evolution of electric and hybrid vehicles and their influence on sustainable transport: A review and future research lines. *Sustain. Technol. Entrep.* **2025**, *4*, 100100. [CrossRef]
50. Syed, S.; Acquaye, A.; Khalfan, M.M.; Obuobisa-Darko, T.; Yamoah, F.A. Decoding sustainable consumption behavior: A systematic review of theories and models and provision of a guidance framework. *Resour. Conserv. Recycl. Adv.* **2024**, *23*, 200232. [CrossRef]
51. Jun, Y.; Rehman, M.; Zelin, T.; Hussain, T.; Hussain, S. The intention to adopt photovoltaic systems: Integrating behavioral theories with mediation-moderation analysis. *Acta Psychol.* **2025**, *256*, 105027. [CrossRef]
52. Mou, J.; Shin, D.; Cohen, J. Understanding trust and perceived usefulness in the consumer acceptance of an e-service: A longitudinal investigation. *Behav. Inf. Technol.* **2016**, *36*, 125–139. [CrossRef]
53. Lee, J.C.; Li, T.; Zhang, L. Environmental concerns and green trust in continuous green fintech use: An expectation-confirmation model with insights from Ant Forest. *Humanit. Soc. Sci. Commun.* **2025**, *12*, 540. [CrossRef]
54. Rahman, M.M.; Thill, J.-C. What Drives People's Willingness to Adopt Autonomous Vehicles? A Review of Internal and External Factors. *Sustainability* **2023**, *15*, 11541. [CrossRef]
55. Cohen, T.; Cavoli, C. Automated vehicles: Exploring possible consequences of government (non) intervention for congestion and accessibility. *Transp. Rev.* **2019**, *39*, 129–151. [CrossRef]
56. Thurner, T.; Fursov, K.; Nefedova, A. Early adopters of new transportation technologies: Attitudes of Russia's population towards car sharing, the electric car and autonomous driving. *Transp. Res. Part A Policy Pract.* **2022**, *155*, 403–417. [CrossRef]
57. Tafidis, P.; Farah, H.; Brijs, T.; Pirdavani, A. Safety implications of higher levels of automated vehicles: A scoping review. *Transp. Rev.* **2021**, *42*, 245–267. [CrossRef]
58. Zhang, W.; Guhathakurta, S.; Khalil, E.B. The impact of private autonomous vehicles on vehicle ownership and unoccupied VMT generation. *Transp. Res. Part C Emerg. Technol.* **2018**, *90*, 156–165. [CrossRef]
59. Zmud, J.P.; Sener, I.N. Towards an understanding of the travel behavior impact of autonomous vehicles. *Transp. Res. Procedia* **2017**, *25*, 2500–2519. [CrossRef]
60. Wu, S.; Falk, K.; Myklebust, T. Beyond Safety: Barriers to Shared Autonomous Vehicle Utilization in the Post-Adoption Phase—Evidence from Norway. *World Electr. Veh. J.* **2025**, *16*, 133. [CrossRef]
61. Schepis, D.; Purchase, S.; Olaru, D.; Smith, B.; Ellis, N. How governments influence autonomous vehicle (AV) innovation. *Transp. Res. Part A Policy Pract.* **2023**, *178*, 103874. [CrossRef]
62. Ivascu, L. Measuring the Implications of Sustainable Manufacturing in the Context of Industry 4.0. *Processes* **2020**, *8*, 585. [CrossRef]
63. Kurse, T.K.; Gebresenbet, G.; Daba, G.F. Prospects for Implementation of Autonomous Vehicles and Associated Infrastructure in Developing Countries. *Infrastructures* **2024**, *9*, 237. [CrossRef]

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