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Encouraging Residents to Save Energy by Using Smart Transportation: Incorporating the Propensity to Save Energy into the UTAUT Model

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Abstract: The rapid urbanization and technological advancements of the recent decades have increased the need for efficient and sustainable transportation solutions. This study examines the acceptance of smart transportation systems (STSs) among residents in Polish cities and explores the impact of these systems on energy-saving behaviors. Using the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model, which includes the propensity to save energy, this research seeks to understand the determinants of STS adoption. The primary research was conducted using Computer-Assisted Web Interviewing (CAWI). The sample was controlled for gender and place of residence. A sample of 471 individuals meeting the criteria of living in a city with over 200,000 residents and using smart transportation solutions in Poland were selected from the research panel. SmartPLS 4 software was used to analyze the collected data. The findings reveal that the propensity to save energy significantly influences perceived usefulness, ease of use, social influence, and hedonic motivation toward STSs. Perceived usefulness and ease of use were found to be strong predictors of the intention to use STSs, while perceived costs had a negative impact on it. This study also identified the moderating role of personal innovativeness in mitigating cost concerns. These insights underscore the importance of emphasizing energy conservation benefits and user-friendly features in promoting the use of STSs. This study concludes that aligning technological innovations with user motivations for energy conservation can enhance the adoption of sustainable transportation solutions, contributing to smarter and more sustainable urban environments.

Keywords: smart city; smart transportation solutions; ITS; Poland; UTAUT2

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1. Introduction

In the face of rapid urbanization and technological advancements, cities worldwide are grappling with the dual challenges of managing growing populations and mitigating environmental impacts. By 2050, two-thirds of the global population is projected to reside in urban areas, which will significantly increase the demand for efficient and sustainable transportation solutions. The anticipated rise in the number of vehicles, expected to

reach 2.9 billion by 2050, exacerbates concerns related to traffic congestion, pollution, and energy consumption.

In response, the concept of "smart cities" has emerged, incorporating intelligent transportation systems (ITSs) that leverage cutting-edge technologies such as artificial intelligence (AI), the Internet of Things (IoT), blockchain, and big data. These systems aim to optimize urban mobility, reduce environmental footprints, and enhance the quality of life for residents. A crucial aspect of these innovations is their potential to promote energy conservation, aligning with the global efforts to combat climate change and achieve sustainability targets.

The primary focus of this article is to analyze the acceptance of smart transportation solutions and their impact on energy-saving behaviors among residents of Polish cities. Understanding the determinants of technology acceptance is vital for the successful implementation of ITSs. This study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating the propensity to save energy as a key variable influencing technology adoption.

This research is situated within a broader context of smart city development, where the integration of advanced technologies into urban infrastructures is not without controversy. There are competing hypotheses regarding the environmental benefits versus the potential drawbacks, such as privacy concerns and data security risks [1,2]. Social resistance, particularly from older or less tech-savvy populations, further complicates the adoption process. Additionally, the significant investments required for infrastructure development pose economic challenges and raise questions about city budget allocations [3].

The most pressing challenges facing cities in every part of the world today pertain to rapid urbanization. The United Nations estimates that by 2050, 68% of the global population will be residing in cities. This shift to city living can thus create fast-growing energy consumption and increasing congestion on highways, especially with the projected growth of vehicles on the road—a total of 2.9 billion by 2050. The environmental consequences are boundless. Cities already account for a large percentage of global greenhouse gas emissions, much of which has to do with the transportation systems within them. Monzon [3] underlines that the infrastructure of smart cities—ITSs, in this case—can indeed respond to all these challenges; however, successful deployment is plagued by a set of barriers, which include large-scale infrastructure investments, privacy and data security concerns, and a lack of public acceptance, particularly among populations less familiar with modern technologies.

In light of the above, the importance of this study consists in the fact that its focus is placed precisely on smart transportation solutions and their influence on the manifestation of energy-saving behavior. Cities today are pursuing a shift toward more sustainable models of development, and the integration of STSs could provide one viable solution for reducing energy consumption as a means of minimizing environmental damage. However, according to Monzon, such systems can be really effective not only due to technological infrastructure but also due to the degree of residents' readiness to use that very infrastructure. Though ITSs have significantly improved, their ultimate success still relies on public acceptance, which, in turn, depends upon a number of factors entailing perceived ease of use, social influence, and personal motivation toward energy conservation.

This study fills a critical gap in the literature to date by researching the perception and adoption of smart transportation technologies in Polish cities, focusing specifically on their disposition toward being energy-saving. It extends the theoretical framework of UTAUT2 by including motivational variance for energy saving; it hence offers a greater subtlety in the understanding of how environmental concerns are interpreted within technology adoption.

This study employs the extended UTAUT2 model, which includes aspects of hedonic motivation, price value, and habits, to investigate the acceptance of smart transportation technologies. By incorporating the propensity to save energy, this research aims to provide a more nuanced understanding of how energy conservation motivations influence technology adoption.

This article proceeds with a literature review on smart cities and transportation systems, followed by an explanation of the research model and methodology. The results section presents findings from a survey conducted among city residents, highlighting the factors that affect their acceptance of smart transportation solutions. The discussion contextualizes these findings within the existing body of literature, addressing practical implications, limitations, and avenues for future research.

In conclusion, this article contributes to the field by elucidating the complex interplay between energy-saving behaviors and technology acceptance in the realm of smart transportation. It underscores the importance of aligning technological innovations with user motivations and environmental goals to foster sustainable urban development.

2. Literature Review

2.1. Smart Cities and Smart Transportation

Over the past century, there have been remarkable advancements in the quality of life, particularly in terms of access to various services. Despite this progress, administrators, architects, and urban planners are now confronted with a significant challenge brought about by rapid industrialization and the increasing populations in metropolitan regions. The pace of global urbanization continues to accelerate, with projections indicating that the world's population will reach approximately ten billion by 2050, with over two-thirds of people residing in urban areas [4]. In 2030, the world's urban population will reach about 4.9 billion [5]. The United Nations (UN) predicts that 68% of the global population will live in cities by 2050 [6]. As the population grows, so will the number of cars. It is predicted that 2.9 billion vehicles will be on the road by 2050 [7]. With the development of technologies of the Fourth Industrial Revolution, and the growing popularity of Industry 4.0, more and more smart solutions are being used in people's everyday activities, including when moving from place to place. Traditional automobiles and traditional public transport have come to an end [8]. New travel technologies have entered transport systems, allowing for a more flexible way of travelling. Flexible lifestyles combined with the sharing economy and the development of information technologies encourage the reconfiguration of transport systems [9]. When designing transport systems, it is essential to consider the needs of urban users and operators. As the number of participants in the system increases, cities require more complex and sophisticated systems. Consequently, smart cities are focusing on the development of intelligent transport systems (I/STSs). With a growing population leading to more vehicles on the roads, authorities must take measures to reduce congestion and plan new, environmentally friendly route optimizations—the key drivers for the advancement of intelligent transport systems. Emerging technologies such as AI, IoT, blockchain, and big data will play pivotal roles as primary entry points and foundational elements, fostering innovative solutions that will transform the current transport infrastructure into a smart system [10]. In smart cities, there is a rising demand for new algorithms to optimize routes for both vehicles and pedestrians, advanced traffic management systems to alleviate congestion, and enhanced optimization of transportation processes for goods and people. The integration of smart technologies with mobility will bring about significant changes in the coming years, such as optimizing traffic flow through "Mobility as a Service" (MaaS), which will convert existing cities into smart ones. In this manner, smart transport will become an integral part of the smart city ecosystem [11].

Developing a smart transport infrastructure for fast-growing cities is a necessity to ensure the mobility of people and the supply of goods [12,13]. Many countries invest considerable sums of money to transform their existing, traditional cities into modern and smart ones. A smart transportation system is an integral part of these developments. Advances in the IoT and information and communications technology (ICT) play a key role in the development of smart cities [14]. The IoT, which connects different smart devices, allows technologies to communicate with each other and exchange data seamlessly [15–17]. In smart cities, where growth has been accelerating since 2010, IoT technologies are used to perform many urban functions and everyday activities, including transportation [18,19].

The IoT can facilitate a set of benefits to the drivers in smart cities by the following means: improved navigation, conditions of the roads, and critical alerts. In view of the structure of the IoT, sensors and devices embedded into roadways, traffic signals, and vehicles, real-time data with regard to flow and congestion in traffic can be easily acquired. The information derived can be further used in optimizing traffic signals, changing speed limits, and routing detours, helping to minimize congestion and improving the general flow of vehicles. This real-time traffic management could prevent delays, save fuel, and make journeys smoother for drivers [1].

Another major advantage is the improvement in logistics. The IoT enables intelligent tracking of the movement of goods within smart cities for the optimization of delivery routes based on the real-time flow of traffic and the schedule. It provides great opportunities for fleet management companies, enabling them to enhance the utilization of delivery times and resources. The use of the IoT reduces delays and makes the transportation of goods more efficient, thus reducing operational costs for logistics companies and leading to timely delivery for customers. Other key benefits of the IoT in smart cities include an effective parking system. Sensors installed in parking spots and smart devices can communicate to drivers when there is a parking space available—no more driving around to look for it. Smart parking systems reduce congestion, lower emissions due to idling, and save time for drivers. Besides this, some cities have integrated payment systems where drivers can pay for parking via their smartphones to make everything even smoother.

The IoT provides various advanced security functions for drivers. With connectivity, the system can analyze road conditions and even identify accidents. The IoT can automatically notify emergency services in the case of a vehicle being involved in a crash. Furthermore, public places can also be taken care of with the help of installing surveillance cameras and sensors that are IoT-capable. Safety for drivers and pedestrians will also be enhanced in this way. The systems can assist in crime reduction, the monitoring of potential hazards, and real-time response to emergencies, hence creating a safer environment for urban transportation [5].

Smart technologies (AI, machine learning (ML)) and mobile communication enable the creation of intelligent systems. The term "intelligent system" is used to describe a set of cognitive operations such as perception, action control, interaction, and accessibility. Various systems can be distinguished when such capabilities are disabled or lacking, and one of them is the ITS, i.e., intelligent transport system [20]. Intelligent transportation makes it possible to disable transportation system technologies to ensure urban mobility efficiency [21]. The US Department of Transportation defines the ITS as "a set of tools that facilitates a connected, integrated, and automated transportation system that is information-intensive to better serve the interests of users and be responsive to the needs of travelers and system operators" [2]. Intelligent transportation systems, or smart transportation systems, involve the application of advanced sensors, computing, electronics, and communication technologies, along with management strategies, in a cohesive and integrated way to enhance the safety and efficiency of surface transportation networks [22,23].

The passengers and physical goods in smart transportation systems all interconnect under one umbrella made possible by the IoT. IoT-enabled devices are at the very core of this infrastructure as these serve as core mechanisms of data acquisition about so many key factors that impinge on transportation. These periodically capture live information on volumes of traffic, road conditions, passenger movements, and other important parameters that may have far-reaching consequences on urban mobility. The IoT allows connectivity between vehicles, traffic infrastructure, and passengers for the facilitation of a continuous flow of data between them so that the transport systems become dynamic and responsive [21].

Once the data are collected, high-performance computers such as supercomputers or cloud-based computing systems process the information. These technologies provide much-needed processing power to analyze vast amounts of information in real time. Advanced algorithms, very often with the use of machine learning and AI, further provide more

efficient management of transport. This encompasses such aspects as route optimization for vehicles and foreseeing congestion points and ways to avoid them, thus substantially improving passengers' safety and comfort. The more significant the dataset processed in these systems and the faster the computations, the more urban transportation networks will be adaptive, even proactive, in responding in real time to changes [22].

For example, IoT-enabled devices detect sudden variations in traffic flow due to accidents or road repairs and notify a central system in real time. Further, the system can take over to divert traffic and thus reduce delays and the congestion of roads. Similarly, data gathered about passengers' movements can help schedule public transport so that buses or trains are deployed more usefully in line with real-time demand. The result of this is to provide not only a more convenient experience with shorter wait times but also one that is more energy-efficient due to optimized vehicle usage. Also, with the integration of the IoT with cloud computing, cities can store and access large datasets without facing local hardware limitations [23]. The result is a distributed processing power that enables continuous improvement in transportation services through the refinement of predictive algorithms and machine learning models. In other words, this system actually becomes increasingly adept at anticipating and addressing user needs over time, thus allowing for more reliability and efficiency in urban transportation [24]. As Monzon [3] noted, while smart city infrastructure and technology are fundamental, the true intelligence of the system will depend on the level of connectivity and integration across all its components. Taking care of the efficient movement of residents, special applications or real-time monitoring of the situations on city roads are solutions that are constantly being improved. Cities are introducing smart urban traffic management. Communication standards are constantly being improved and shared mobility is being promoted: bike sharing, scooter sharing, or electric car sharing [20,21].

Basic smart transportation systems are based on several advanced technologies and infrastructures in the smart city environment: high-speed communication networks, such as 4G, 5G, or anything to that effect, will provide the necessary bandwidth with very low latency to help in real-time data transfer and communication amongst various components of the transport network [25,26]. These networks further facilitate the incorporation of various technologies that ensure efficient connectivity and coordination across vehicles, infrastructure, and management systems [27].

Other essential constituents in this ITS are Global Positioning Systems. Their location data alone are important for navigation, route optimization, and even real-time traffic management. Besides GPS, V2V and V2I communications are at the heart of intelligent transportation systems [28]. This communications technology allows vehicles to communicate with each other and the surrounding infrastructure, including but not limited to traffic lights, in-pavement sensors, and toll stations. This sharing of information enhances road safety, cuts congestion, and smooths out the flow of traffic through cities [29,30].

Therefore, the IoT may constitute a basis for smart transportation systems in that it enables various devices and transport means or structures to connect. IoT platforms are highly integrated with cloud computing to enable the collection, processing, and analysis of large volumes of data in real time [31]. The application of IoT technologies allows data-driven management such that decision-making and response mechanisms in managing urban transport networks are empowered. For example, supply chain management based on the IoT will promote the timely delivery of goods and services, ensuring minimum delays in transport routes [32].

Smart transport is further manifested in the contribution of remote sensing to the real-time monitoring of road conditions, whether in terms of weather or congestion. This kind of information may be updated from various points based on the overall connectivity of the infrastructure and could thus afford cities the opportunity to manage any flow of traffic proactively and estimate potential issues well in advance to prevent major disruptions. Real-time vehicle monitoring systems ensure input from roadside cameras and toll systems for round-the-clock surveillance of the movement of vehicles, building confidence on the streets [33].

The other vital parts of intelligent infrastructure in transportation are driver management systems and advanced scheduling algorithms. These systems ensure the highest performative level for drivers and vehicle usage and fend off any inefficiency in the entire management of urban mobility. Along this line of thought, a road maintenance system can predict and tackle infrastructural wear and tear through sensors in real-time monitoring, enabling maintenance to be proactive, with reduced downtime [34]. This is a part of the technology that requires an embedded system in an autonomous vehicle, a highly contributing factor to smart transportation. An autonomous car with this technological system can process a wide range of data from sensors, GPS, and V2V or V2I communications about complicated urban conditions. In smart cities, autonomous cars will play a key role in minimizing congestion by ensuring safety, saving energy through routing optimally, and avoiding accidents through effective communication between vehicles and infrastructure [35].

In the coming years, the digitization of transportation, particularly in the realm of ITSs, is anticipated to advance significantly. As part of the Digital Single Market Strategy (COM, 2015), the European Commission plans to increasingly utilize ITS solutions to enhance the management of transportation networks for both passengers and businesses. These systems will be employed to improve operations and crossings in specific and multimodal transport scenarios [36–38]. Additionally, the European Commission is laying the foundation for the next generation of ITSs by deploying Cooperative ITSs (C-ITSs), which are systems facilitating efficient data exchange through wireless technologies, enabling vehicles to connect with one another, road infrastructure, and other road users. The Commission is collaborating with the member states, industries, and public authorities to address various implementation challenges and bottlenecks. It also supports innovative ITS initiatives through financial instruments and ensures a coordinated deployment of ITSs across Europe via legislative measures [39].

Smart transportation benefits societies and economies by creating opportunities for sustainable development. Cities equipped with smart technologies have the potential to mitigate climate change and support the transition to a more sustainable world. As many countries aim to achieve carbon neutrality by 2050, cities play a key role in the implementation of the Paris Agreement Agenda by keeping the global temperature rise well below 2.0 degrees Celsius in this century (above the pre-industrial-era level) and continuing efforts to limit the temperature increase to 1.5 degrees Celsius [40]. Smart cities are key to supporting dynamic population growth and alleviating tensions between economic development and sustainable development. Smart transport can help to reduce the amount of energy used for transportation by up to 20%. Conventional transport is the second largest source of carbon dioxide emissions due to its low efficiency [18]. Cities need electric and hybrid vehicles. The conversion of existing petrol vehicles into electric vehicles also plays a key role in smart transport system development. Cars must be energy-efficient, and public transport must function better. Intelligent Transport Systems contribute to short-term energy efficiency by optimizing traffic flows, reducing congestion, and promoting the use of electric and autonomous vehicles. These initiatives lead to immediate reductions in fuel consumption and emissions. Intelligent street lighting and infrastructure respond to environmental conditions by adjusting brightness levels based on real-time data. This minimizes unnecessary energy consumption during periods of low activity of urban functions [41–50].

Renewable energy sources (RESs) are needed to develop ITSs and sustainable transport. The process of transition from traditional energy sources to alternative forms is called the green transformation. At the heart of the energy transition lies the technological ability to produce energy from distributed, universally available, inexhaustible, and free sources, such as solar, wind, water, or geothermal energy, entailing a profound transformation that is economic, social, environmental, and cultural. Although the share of EU countries using RESs is increasing (with many upward trends), much remains to be done. Gajdzik et al. showed that RES shares across the member states ranged from 0.0% to 53.8% in

2022 [51]. There are economic, social, legal, and other barriers in EU countries to green transformation [52,53]. Many key issues, policies, and technologies are shaping the green transformation. Even though conventional surface transportation resources remain heavily utilized and are gradually aging, transportation systems will continue to evolve, altering how people and goods navigate the smart cities of the future. Autonomous vehicles will interact with each other and urban infrastructure, leading to a profound transformation of the transport industry and its stakeholders. Smart cities that effectively implement and manage these technologies will enhance mobility, reduce pollution, and, as a result, improve the quality of life and economic performance of their communities.

Intelligent technologies applied in the context of urban mobility transform the way people navigate and experience cities. The key innovation is the deployment of intelligent displays at public transit stops (Table 1).

Table 1. Intelligent technologies concerning urban mobility.

Technology	Description
Intelligent Display of Arrival Times at Public Transit Stops [54–62]	These displays provide real-time information on the arrival times of buses, trams, and other public transport, enhancing convenience and reducing waiting times for passengers. They often use GPS and data from the transportation network.
Shared Urban Bicycles [63–67]	Shared bicycle systems allow users to rent and return bikes at various docking stations throughout cities. They provide an eco-friendly and convenient alternative for short trips, reducing traffic congestion and emissions.
Park and Ride Facilities [68,69]	Park and ride facilities enable commuters to park their cars at designated lots and transfer to public transport for the remainder of their journey. This reduces urban traffic congestion and promotes the use of public transit.
Ticket Purchase via Mobile Applications [70–75]	Mobile ticketing apps allow passengers to buy and store public transport tickets on their smartphones. This streamlines the ticketing process, reduces the need for physical tickets, and enhances user convenience.
Indication of Free Parking Spaces [76–78]	These systems use sensors and digital displays to show real-time information on available parking spaces. This reduces the time spent searching for parking, alleviates congestion, and decreases emissions from idling vehicles.
Traffic Light Countdown Displays [79–81]	Displays at intersections provide real-time countdowns for traffic lights, helping drivers and pedestrians better manage their time and navigate crossings safely, reducing anxiety and improving traffic flow.
Parking Payment via Mobile Applications [82–85]	These applications allow drivers to pay for parking using their smartphones, offering a convenient and efficient alternative to traditional payment methods. Users can extend parking time remotely, reducing the need for physical meters.
Bus Lanes for Electric Vehicles [86–89]	Dedicated bus lanes that also allow electric vehicles to use them. This encourages the use of environmentally friendly electric cars, reduces congestion in regular lanes, and promotes efficient public transportation.
City Travel Time Displays [90–93]	These displays provide real-time information on travel times across various routes in the city. They help drivers choose the fastest routes, manage expectations, and reduce congestion by distributing traffic more evenly.

Source: own preparation based on [54–93].

2.2. Acceptance of Technology in Smart Cities and Smart Transportation Using UTAUT and UTAUT2 Models

The UTAUT and its extended version UTAUT2 are influential frameworks in understanding user acceptance and usage of technology. Developed by Venkatesh et al. in 2003 [94], UTAUT synthesizes eight prominent models of technology acceptance into a unified framework. UTAUT2, introduced in 2012 [95], extends UTAUT by incorporating additional constructs and contextual factors relevant to consumer technology use. This part explores the general application of UTAUT and UTAUT2 and their specific implications in the context of smart cities, focusing particularly on smart city transportation systems.

UTAUT suggests that four primary factors influence behavioral intention and usage behavior: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). Facilitating conditions refers to an individual's belief in the presence of a supportive framework, whether administrative or technological, that aids in the implementation of smart city solutions or technologies. Performance expectancy involves an individual's confidence in a system and belief that using it will yield positive outcomes [94]. Effort expectancy pertains to how easy a particular system is to use. Social influence is defined as an individual's perception of the opinions of others regarding the adoption of a specific technology and how much these opinions influence their decision to accept and use the technology. The model takes into account the moderating effects of age, gender, experience, and willingness to use.

These determinants have been validated across various technologies and user contexts, establishing UTAUT as a robust predictive model for technology acceptance. UTAUT2 extends the original model by adding three new constructs: hedonic motivation (HM), price value (PV), and habit (HT). These additions address the evolving consumer technology landscape, where user experience and perceived value play critical roles in technology acceptance. UTAUT2 emphasizes the context-specific nature of technology use, incorporating the moderating effects of age, gender, and experience and considering the importance of the technology use context. Compared to other theories used to explain human behavior, such as the Theory of Planned Behavior, Technology Acceptance Model, and Innovation Diffusion Model, UTAUT and its extension UTAUT2 provide a more comprehensive framework for analyzing and interpretating behavioral intention to use technology-related services [96].

The rapid advancement of technology has fundamentally transformed urban living, giving rise to the concept of smart cities. These cities leverage digital technologies to enhance the efficiency of urban services, improve the quality of life for residents, and promote sustainable development. Among the various facets of smart cities, smart transportation systems stand out as critical components, aiming to address urban mobility challenges through innovative solutions such as automated road transport systems (ARTSs), ITSs, and smart public transit.

There is a limited, yet growing, body of research on the determinants of consumers' intentions to use smart city technologies. The available studies focus on the general acceptance of smart city services and technologies or investigate the intent to use specific types of technologies or services, such as mobile applications, the Internet of Things, safety systems, or smart transportation systems. A notable number of these studies are built on the theoretical foundations of the UTAUT or UTAUT2 models. Understanding the factors that influence the acceptance and use of these advanced transportation technologies is crucial for their successful implementation. In this context, UTAUT and its extended version, UTAUT2, offer comprehensive frameworks for examining user acceptance.

For example, Oliveira and Santos [97] investigated the factors influencing the acceptance of information technology (IT) in public safety within the context of a smart city. The study explored the constructs of the UTAUT model, focusing on the acceptance and use of a safety monitoring system with cameras. They found that the monitoring system's high-quality images were crucial for the effective identification of individuals, which positively influenced its acceptance. Integration with other systems was identified as ideal, indicating that ease of use and interoperability were important for user acceptance. Authorities managing the program utilized social networks to publicize their work and facilitate investigations, showing that societal influence plays a role in technology use. The participation of citizens and municipal administration was deemed essential for the successful implementation and expansion of smart city services. The findings suggest that not only the high performance and ease of integration of these technologies but also the continuous support and active involvement of citizens and local government are crucial to optimize and expand smart city services.

Popova and Zagulova [98] investigated the factors influencing the acceptance of smart city communication technologies. Their study revealed that PE, EE, SI, and FC, as well

as attitude toward the use of applications (ATA), had direct or indirect positive impacts on the intention to use technologies (behavioral intention (BI)) and/or the actual usage of these technologies (use behavior (UB)). The ease of use of these technologies was a significant factor in their acceptance, and social and peer influence was crucial in shaping user intentions. For the adoption and use of smart city communications technologies, the availability of resources and support systems was necessary. Also, positive attitudes toward using the technologies significantly influenced their adoption. The study also revealed that anxiety indirectly negatively impacted use behavior (UB) through its effect on ATA. Furthermore, the study examined the moderating effects of age, gender, and education on BI and UB. Age was identified as a significant moderator, exerting a negative influence on the relationship between FC, PE, and SI. These findings suggest that to fully engage the population in adopting communication technologies and implementing the smart city concept, it is crucial to create suitable conditions for residents, particularly through ongoing education and training.

Teng, Bai, and Apuke [99] discovered that the most significant predictor of willingness to use smart city services in Malaysia was facilitating conditions. Other factors included social influence, hedonic drive, performance expectancy, effort expectancy, and trust in government. The study also found that concerns about security and privacy were negatively correlated with the inclination to use smart city services, and trust in these services did not correlate with the intention to use them.

Bestepe and Yildirim [100] conducted a mixed methods study to explore the acceptance of IoT-based and sustainability-oriented smart city services. Their study found that users' expectations regarding the performance of IoT-based services significantly influenced their behavioral intentions. High-performance expectancy was associated with a greater likelihood of adopting smart city services. The ease of use and the minimal effort required to interact with IoT-based services were critical factors in user acceptance. Lower effort expectancy was linked to higher adoption rates. The role of social networks and peer recommendations played a significant role in shaping users' intentions to adopt IoT-based smart city services. Positive feedback and endorsement from peers enhanced acceptance. Similar to a study by Popova and Zagulova [98], it was found that the availability of resources and support systems necessary for using IoT-based services was crucial for user adoption. Facilitating conditions, such as technical support and infrastructure, positively impacted usage behavior. The results of the research confirmed that individuals with higher personal innovativeness showed a greater propensity to adopt IoT-based smart city services. Personal innovativeness refers to an individual's willingness to try out new technologies and their propensity to embrace innovation [101]. Personal innovativeness has been recognized as a direct influencing factor on behavioral intention in numerous studies [102–133]. Researchers have consistently found that individuals with higher levels of personal innovativeness are more likely to exhibit positive behavioral intentions toward adopting new technologies.

Including personal innovativeness as a moderator in the UTAUT acceptance model for smart transportation is crucial for several reasons. First, innovative users might have higher expectations regarding the benefits and performance of smart transportation technologies, thus strengthening the relationship between PE and BI. Second, innovative individuals may perceive new technologies as less complex, thereby enhancing the positive impact of EE on BI. Third, the impact of social influence on BI might be weaker for highly innovative individuals who rely more on their own judgment rather than on others' opinions. Finally, innovative users might be more proactive in seeking out and utilizing support resources, which can strengthen the relationship between FC and UB.

As for smart transportation systems, several studies focused on the acceptance of automated vehicles [104], autonomous car-sharing services [105], automated shuttles [106], and last-mile delivery using autonomous vehicles [107]. The last study extended UTAUT2 with gender as a moderator and found that trust in technology, price sensitivity, performance expectancy, hedonic motivation, social influence, and perceived risk determined behavioral intention. Some constructs were significant only for women.

Madigan et al. [108] investigated the factors influencing users' acceptance of ARTS using an adapted version of UTAUT. They found that users' enjoyment of the system significantly impacted their behavioral intentions to use ARTS in the future. The performance expectancy and availability of necessary resources and support influenced user acceptance. Moreover, the influence of others was a significant factor in users' decision-making, but effort expectancy was not. This suggests that the amount of effort required may not be a crucial determinant of users' decisions to utilize ARTS. The research offered important insights into determinants of public acceptance of automated vehicles.

Rejali et al. [109] applied the UTAUT2 model to explore public acceptance of Autonomous Modular Transit. Their results indicated that perceived usefulness was the strongest predictor of intention, followed by social influence and hedonic motivations. The level of acceptance was high despite limited prior knowledge. Furthermore, younger and more regular users of public transport showed a higher intention to use AMT. Kapousizis et al. [110] conducted a study of the acceptance of smart e-bikes in five European countries and discovered that performance expectancy, hedonic motivation, and perceived safety were the most significant factors influencing the behavioral intention to use them. The constructs of UTAUT2 exhibited significant variations across the five countries, which could be partially attributed to sociodemographic factors. However, variables such as city size, availability of suitable infrastructure, and population density did not account for the differences in user acceptance.

Previous studies on the acceptance of smart city technologies have often focused on examining solutions within a single city, typically investigating users of a specific application or technological solution. Examples of such studies include case studies of particular transportation systems or city management applications tested in limited locations and among specific user groups. These studies do not account for all the diverse conditions and contexts that may exist across different cities. To date, there has been a lack of research that attempts to demonstrate the acceptance of smart city solutions across various cities with representative samples of residents from cities with populations exceeding 200,000. Such a holistic and more diverse approach would provide a better understanding of general trends and factors influencing the acceptance of smart city technologies, considering the specific needs and preferences of residents of larger cities.

2.3. Propensity to Save Energy

In the context of adopting energy-efficient technologies, the need to incorporate more nuanced antecedent variables into established models of technology acceptance has become increasingly apparent [111]. One such variable is the "propensity to save energy", which represents an individual's attitude toward engaging in energy conservation behaviors. Although this concept is indirectly addressed in various behavioral models [112], it warrants a more explicit role as a precursor within the UTAUT framework.

The UTAUT model is a comprehensive framework that integrates several key factors influencing technology acceptance, including performance expectancy, effort expectancy, social influence, and facilitating conditions [95,113,114]. However, these factors predominantly focus on external and usability aspects, potentially overlooking deeper motivational drivers such as an individual's inherent propensity to save energy. This propensity can be conceptualized as an antecedent that influences perceptions and intentions to adopt energy-efficient technologies.

The integration of the propensity to save energy within UTAUT can be theoretically supported by the Theory of Planned Behavior (TPB) [115] and the Value–Belief–Norm (VBN) theory [116]. TPB posits that behavioral intentions are shaped by attitudes, subjective norms, and perceived behavioral control. In this context, an individual's propensity to save energy can significantly influence their attitudes toward energy-efficient technologies, thereby shaping their behavioral intentions as outlined in the UTAUT model.

VBN theory further supports this integration by linking personal environmental values and beliefs to behavioral norms. Individuals with strong environmental values are more likely to possess a high propensity to save energy, which, in turn, can influence

their performance expectancy regarding energy-efficient technologies [117,118]. They may perceive these technologies as not only beneficial but also aligned with their intrinsic values, thereby enhancing their motivation to adopt such technologies.

Within the UTAUT framework, the propensity to save energy can be positioned as an antecedent to key constructs like performance expectancy and effort expectancy. For instance, individuals with a strong propensity to save energy may have heightened performance expectancy, perceiving energy-efficient technologies as more valuable and effective in achieving their energy-saving goals. This propensity could also positively influence effort expectancy, as individuals motivated by energy conservation might be more willing to engage with technologies that require learning or adaptation.

Furthermore, the role of social influence and facilitating conditions in the UTAUT model can be extended to account for the propensity to save energy. Social norms around energy conservation, for instance, can strengthen an individual's propensity to save energy, thereby indirectly enhancing the impact of social influence on technology adoption decisions.

The need to conserve energy is today paramount. The growing demand for energy leads to environmental pressures, which are not always mitigated by technological advancements. Additionally, increased demand for energy coupled with political instability causes price surges, prompting consumers to limit their energy consumption. Reducing energy use is a direct method to address energy problems and combat climate change [119]. Energy-saving efforts span governmental, municipal, and household levels. At the individual level, they include reducing energy consumption at home and changing energy habits. Consumers' energy-saving behaviors vary from modifying the use of existing devices [120] to investing in energy-efficient equipment [121] and organizing the new form of cooperation: energy cooperatives [122].

Consumers' efforts focus mainly on in-home energy consumption, where short-term monetary effects can be relatively easily observed. Energy-saving behaviors of consumers are not yet confined to their homes only. An important area in which consumers can save energy is transportation. This can be achieved by more use of public transportation or electric vehicles. Energy conservation may require a change in long-term habits, which requires both considerable effort and some initial financial investment in new technologies or appliances. These may constitute a considerable barrier, but to limit energy consumption, consumers' habits, perceptions, and lifestyles must evolve [123,124]. However, consumers' habits are difficult to change due to resistance to change resulting from fear of a lower quality of life and reluctance to abandon what is perceived as a "comfortable" lifestyle [125]. Short-term downsizing of household energy consumption may require less use of appliances that make life more comfortable, such as air conditioning or entertainment devices. Faced with the perceived reduction in life quality and a need to modify their lifestyles, consumers may be reluctant to save energy. As a result, the degree and pace of change in energy consumption habits can be limited.

Energy-saving behaviors can be determined by multiple factors. An important factor influencing energy-saving behaviors is awareness, consisting of elements related to energy choices such as awareness of human environmental impacts and knowledge of environmental information [126]. The awareness may prompt consumers to behave in a more sustainable way, leading to limiting in-home energy consumption [127]. Awareness of the negative impacts of pollution can motivate consumers to adopt electric vehicles [128]. Conversely, low awareness levels were found to be connected to energy waste [129]. Dinca, Bucu, and Nagy-Bege [123] found that awareness positively influenced individuals to adopt energy-saving habits. Various studies indicated that awareness of issues related to energy consumption such as climate change and global warming can influence consumers' perceptions and opinions about the need to conserve energy [130]. Mezger et al. [131] found that trust in science and awareness of environmental impact may stimulate energy-saving behaviors and promote renewable energy projects. For example, Liu et al. [132] studied public acceptability of renewable energy projects and found it to be influenced by trust in scientific information.

Another studied determinant of energy-saving behavior is perceived consumer effectiveness, that is, an individual's assumption that their own capabilities can contribute to solving environmental problems [133]. Numerous studies suggest that higher perceived consumer effectiveness can lead to energy-saving behaviors [123,134–153].

Energy-saving behaviors can be influenced also by the cost of adopting an energy-saving lifestyle. Dinca, Busu, and Nagy-Bege [123] found that perceived costs have a negative and significant impact on the implementation of energy-saving behaviors. Also, resistance to change has a negative and significant impact on the implementation of energy-saving habits. A negative impact of the perceived costs of energy-saving technologies on willingness to adopt green energy technologies was found by Zheng et al. [135]. At the same time, these authors confirmed the positive impacts of environmental concern, green technology awareness, openness to experience, and green technology benefits. While financial reward and energy expenditure reductions are the main drivers behind the acceptance of sustainable energy services, high initial costs and low benefits may negatively impact the perceptions of smart and sustainable energy services and be barriers to their adoption [136].

A study by Cho et al. [137] found a relationship between cultural norms and an individual's propensity to save energy. Their results suggest that individuals with a more collectivistic worldview can be more preoccupied with environmental issues. Hence, social influence, stronger in collectivist societies, can be an important determinant of energy-saving behaviors, perceived as beneficial to society as a whole. Collectivist-oriented individuals are more likely to engage in sustainable behaviors [123]. Dinca, Busu, and Nagy-Bege [123] found that a collectivist perspective affects the implementation of energy-saving habits in a significant and positive way. A study by Ma and Liu [132] revealed two modes driving consumers' energy-saving behaviors: the personal pro-environmental characteristics-dominated mode and the environmentally friendly social atmosphere-dominated mode, which have complementary effects on energy-saving behaviors. Environmental values and social reference norms were found to be important in promoting consumers' energy-saving behaviors. The results of a study by Pothitou, Hanna, and Chalvatzis [138] indicate that individuals with positive environmental values and greater environmental knowledge are more likely to demonstrate behaviors, attitudes, and habits leading to energy saving in households.

Fleiß, Hatzl, and Raucher [139] discovered that the adoption of smart energy technologies was influenced by perceived ease of use and attitude toward the adoption of electric vehicles. This supports the findings of Zheng et al. [135] who found that discomfort with using new green technologies negatively affects the willingness to adopt them.

An investigation of factors determining the adoption of green technology by Girod, Mayer, and Nägele [140] found that subjective beliefs regarding technology had a greater influence than objective measures. The key determinants included perceived hedonic satisfaction, usefulness, habit, and facilitating conditions. Conversely, environmental norms were found to have a lesser impact compared to personal innovativeness. There is no consensus in the literature regarding the impact of hedonic values and motivations on energy-saving behaviors. As energy-saving behaviors may require additional cost and effort, they may be negatively related to these values and motivations [141]. Some studies, however, show that hedonic values may have a positive impact on intentions to use energy-efficient applications [142]. Hedonic motivations can be positively related to energy-saving behaviors [143]. For example, Hameed and Khan [144] found a positive impact of hedonic motivation on the intention to adopt electric vehicles. Hedonic values can influence sustainable behaviors through anticipated emotions evoked when purchasing pro-environmental products or services [141]. Simply put, consumers may enjoy pro-environmental behaviors. Kim and Kim [119] investigated the impact of values on energy-saving behaviors and found that hedonic values moderated the relationship between energy-saving behaviors and variables of the Theory of Planned Behavior model.

Incorporating the "propensity to save energy" into the UTAUT model for smart transportation can significantly enhance the understanding of user acceptance and behavior. This variable influences perceived usefulness, perceived ease of use, social influence, and

hedonic motivation, thereby offering a comprehensive view of technology adoption in the context of energy-saving behaviors.

The propensity to save energy refers to an individual's inclination or tendency to engage in behaviors that reduce energy consumption [145]. This factor can be integrated into the UTAUT model as a preceding variable affecting several constructs:

- Users who have a high propensity to save energy are more likely to perceive smart transportation systems as more useful because these systems often promise energy savings and environmental benefits.
- If users are motivated to save energy, they might perceive the effort needed to use smart transportation systems as lower. This is because their motivation can drive them to learn and adapt to new technologies more willingly.
- Individuals with a high propensity to save energy may be more influenced by social norms and peer behaviors that promote the use of smart transportation as a sustainable practice.
- The enjoyment and satisfaction derived from using energy-efficient technologies can enhance the perceived hedonic value of smart transportation systems for individuals inclined to save energy.

Empirical studies [146,147] support the inclusion of environmental motivations in technology acceptance models. Research demonstrates that individuals with a high propensity to save energy are more likely to adopt energy-efficient technologies, which aligns with the constructs of performance expectancy and effort expectancy in the UTAUT model. Integrating these insights into UTAUT not only broadens the model's applicability but also enhances its predictive power in contexts where environmental considerations play a critical role.

By positioning the propensity to save energy as an antecedent in the UTAUT model, this approach might provide a more holistic understanding of the factors driving the adoption of energy-efficient technologies. It shifts the focus from purely external factors to include intrinsic motivations, offering a more comprehensive framework for understanding technology acceptance in the context of global energy challenges.

2.4. Model Development

This study aimed to explore the factors influencing the intention to use smart transportation (ST) solutions as part of a smart city concept. To achieve this, we proposed an extension of the UTAUT model and identified the propensity to save energy as the new variable in the research approach. We developed a research model based on the literature review findings, as shown in Figure 1.

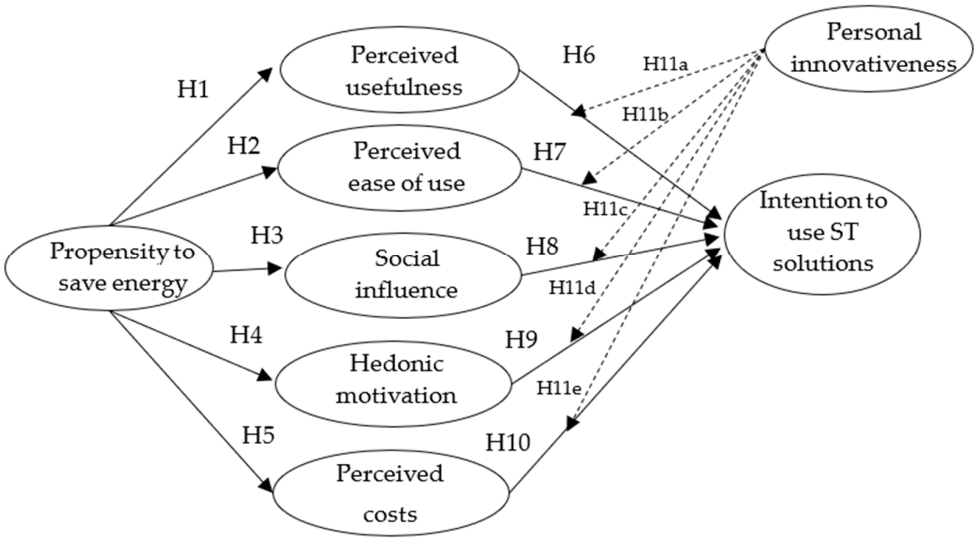


Figure 1. Conceptual research model. Source: own study.

The following research hypotheses were formulated:

H1. *The propensity to save energy positively influences the perceived usefulness of ST solutions.*

H2. *The propensity to save energy positively influences the perceived ease of use of ST solutions.*

H3. *The propensity to save energy positively influences social influence.*

H4. *The propensity to save energy positively influences hedonic motivation.*

H5. *The propensity to save energy negatively influences the perceived costs of ST solutions.*

H6. *The perceived usefulness of ST solutions positively influences intentions to use ST solutions.*

H7. *The perceived ease of use of ST solutions positively influences intentions to use ST solutions.*

H8. *Social influence positively influences intentions to use ST solutions.*

H9. *The hedonic motivation of residents positively influences their intentions to use ST solutions.*

H10. *The perceived costs of ST solutions negatively influence intentions to use ST solutions.*

H11a. *The personal innovativeness of residents moderates the impact of perceived usefulness on intentions to use ST solutions.*

H11b. *The personal innovativeness of residents moderates the impact of perceived ease of use on intentions to use ST solutions.*

H11c. *The personal innovativeness of residents moderates the impact of social influence on intentions to use ST solutions.*

H11d. *The personal innovativeness of residents moderates the impact of hedonic motivation on intentions to use ST solutions.*

H11e. *The personal innovativeness of residents moderates the impact of cost perception of ST solutions on intentions to use ST solutions.*

For these hypotheses (H11a–H11e), we tried to verify the moderating effect of the personal innovativeness of citizens on their intentions to use ST solutions.

3. Materials and Methods

3.1. Questionnaire Development

For the purpose of this research, the following scales were identified to measure aspects of encouraging residents to save energy by using smart transportation (Table 2). The design of the questionnaire was based on the literature. In 8 sections of the questionnaire, respondents made their choices based on a standardized five-point Likert scale (ranging from "strongly disagree" to "strongly agree").

The section concerning the propensity to save energy was partly based on the scale proposed by Gumz, Castro Fettermann, Oliveira Sant'Anna, and Luz Tortorella [148] and the familiarity scale based on Weisstein et al. To identify perceived ease of use, a scale proposed by Choi [149] was used. The section measuring perceived usefulness was based on Lee's scale [150]. The questionnaire also included a social influence scale, which was partially adapted from scales proposed by Nusir, Alshirah, and Alghsoon [151] and Lee [150]. The section measuring hedonic motivation was based on a scale proposed by Debesa, Gelashvili,

Martinez-Navalon, and Saura [152] and Venkatesh [95]. Personal innovativeness of respondents was assessed by the scale proposed by Alkodour, Almaiah, Shishakly, Lutfi, and Alrawad [153]. To determine perceived costs, a scale proposed by Weisstein, Kukar-Kinney, and Monroe was used [154]. In the last section of the questionnaire, intentions to use ST solutions were measured by the scale proposed by Bestepe and Yildrim [155,156].

Table 2. Measuring scales' items.

	Measuring Scales' Items
	Propensity to save energy (in the ST context) based on [148,154]
1.	I know where to find applications supporting ST solutions
2.	I know what ST solutions are available in my city
3.	I would like to use more energy from renewable sources
4.	I think that environmental issues are becoming increasingly serious in recent years
	Perceived ease of use based on [149]
1.	I find ST solutions easy to use
2.	Learning to use ST solutions is easy for me
3.	Using ST solutions does not cause any problems
	Perceived usefulness based on [150]
1.	I think the quality of my life will improve if I use ST solutions
2.	I think transportation costs will be reduced if I use ST solutions
3.	I believe that using ST solutions has a positive impact on the natural environment
4.	I believe that ST solutions improve safety in the city
	Social influence based on [150,151]
1.	I use ST solutions influenced by people around me
2.	Information available in the media affects my decision to use ST solutions
3.	Important people to me encourage me to use ST solutions
4.	I will use ST solutions if my friends use them
5.	I will use ST solutions if the city encourages these solutions
	Hedonic motivation based on [95,152]
1.	Using ST solutions entertains me
2.	Using ST solutions is a form of entertainment for me
3.	Using ST solutions gives me pleasure
	Personal innovativeness based on [153]
1.	I like experimenting with new digital technologies
2.	When I learn about a new digital technology, I try to use it as soon as possible
3.	Among my peers, I am usually the first to try out new digital technologies
	Perceived costs based on [154]
1.	The fees for using ST solutions are high
2.	I am not satisfied with the fees I pay for ST solutions
3.	The fees I pay for using ST solutions are not reasonable
4.	Using ST solutions is expensive
	Intention to use ST solutions based on [155,156]
1.	I intend to use ST solutions in the future
2.	I will try to use ST solutions in my daily life
3.	I plan to use ST solutions in the future

Source: own preparation based on selected sources.

3.2. Data Collection

To verify the hypotheses, the data were collected with the CAWI method. The choice of the CAWI method was justified by its wide reach and the ability to reach respondents living in cities with a population of over 200,000 residents across the country. The aim was to analyze the acceptance of smart transportation solutions and their impact on energy-saving behaviors among residents of Polish cities.

In the initial phase of the research, a pilot study was carried out to ensure the quality of the research instrument. Twenty-five respondents were chosen to evaluate the preliminary version of the survey, enabling an assessment of the content and validity of the questions included. As a result of this pilot study, minor linguistic adjustments were made to enhance the readability and clarity of the instrument, leading to the creation of an improved questionnaire.

Before the main study commenced, participants were presented with a declaration of anonymity and confidentiality. The objectives of the study and the way in which the results would be disseminated were outlined. Additionally, respondents were provided with the opportunity to contact researchers via email. The research was conducted from May to June 2024. This study was carried out on the Biostat Opinion Research Panel, which comprises 200,000 respondents. A sample of 1460 individuals were randomly selected from the panel who met the criterion of living in a city with a population of over 200,000 residents in Poland. The research sample was controlled for gender and place of residence. Six hundred respondents participated in this study.

After formal verification, 541 questionnaires were qualified for further analysis. Subsequently, after verification, including meeting the established criterion of using smart transportation solutions, 471 questionnaires were forwarded for further analysis.

3.3. Sample

This research focused on consumers using smart transportation solutions in cities. A random sampling method was used in this study. Ultimately, the sample size was $n = 471$. The characteristics of the study participants are presented in Table 3.

Table 3. Sample characteristics.

Characteristic	Item	%
Gender	Female	56.3
	Male	43.7
Age (years)	18–30	33.5
	31–40	31.9
	41 and above	34.6
Role in the household	Dependent on other household members	6.8
	One of the breadwinners of the household	69.4
	Sole breadwinner of the household	23.8
Place of residence	City, 201,000–500,000 residents	43.7
	City, over 501,000 residents	56.3
Use of a car at the place of residence	Yes	77.5
	No	22.5

Source: own study.

3.4. Methods of Analysis

SmartPLS 4 software was used to analyze the collected data. In total, 471 observations of respondents indicating the use of smart transport solutions were analyzed. The entire dataset comprised 471 cases and 77 analyzed variables, of which 29 variables were used for the analyses in this article. Each of the latent variables analyzed had between 3 and 5 indicators. The file had no missing data, which is a requirement for using the SmartPLS program. In the first step of the analysis, the PLS-SEM algorithm was calculated. SmartPLS using partial least squares (PLS) is a composite-based approach to structural equation modeling (SEM) that allows for the estimating of complex interrelationships between constructs and their indicator variable. As with linear multiple regression, the main objective of partial least squares regression is to build a linear model in the form of Equation (1) [157].

$$Y = X \times B + E \quad (1)$$

Y—the response matrix of n (number of cases) by m (number of variables);

X—a matrix of explanatory variables of dimension n (number of cases) by *p* (number of variables);

B—a matrix of regression coefficients of dimension *p* by m;

E—a random component of the model with the same dimensions as the Y matrix.

PLS-SEM offers the possibility to use variables whose distribution deviates from the normal distribution for modeling. This is often the case when using Likert-type scales. The reflective constructs used in the model assume that the indicators used in the model are the effect of a latent variable; for example, in our study, the propensity to use more renewable energy was the effect of the latent variable propensity to save energy.

As the measurement model was in the form of reflective indicators, the internal consistency, convergent validity, and discriminant validity of the indicators were assessed. Internal consistency determines whether the indicators accurately measure the defined latent variable. Convergent validity determines the extent to which an indicator correlates with the other indicators of the latent variable. Discriminant validity verifies whether a given latent variable is a separate construct from the other latent variables in the model [158].

The internal consistency indices should achieve Cronbach's alpha > 0.7 and composite reliability > 0.7. The convergent validity index should be AVE > 0.5. The discriminant validity for the HTMT index should be $\leq$0.85 [159]. The reliability and validity indices for the measurement model are presented in Table 4.

Table 4. The reliability and validity indicators of the measurement model.

Latent Variables	Cronbach's Alfa	Composite Reliability rho_c	Composite Reliability rho_a	Average Variance Extracted (AVE)
Propensity to save energy	0.726	0.735	0.831	0.554
Perceived usefulness	0.837	0.853	0.891	0.672
Perceived ease of use	0.903	0.909	0.939	0.837
Social influence	0.872	0.970	0.901	0.646
Hedonic motivation	0.850	0.938	0.905	0.760
Perceived costs	0.924	0.947	0.946	0.813
Personal innovativeness	0.879	0.948	0.920	0.794
Intention to use	0.920	0.923	0.949	0.862

Own calculations.

Table 5 presents the HTMT ratios for the constructs analyzed.

Table 5. Discriminant validity—heterotrait–monotrait ratio (HTMT).

Latent Variables	Perceived Usefulness	Perceived Ease of Use	Social Influence	Hedonic Motivation	Perceived Costs	Personal Innovativeness	Intention to Use	Propensity to Save Energy
Perceived usefulness								
Perceived ease of use	0.586							
Social influence	0.599	0.119						
Hedonic motivation	0.656	0.426	0.523					
Perceived costs	0.064	0.157	0.225	0.052				
Personal innovativeness	0.518	0.400	0.456	0.654	0.089			
Intention to use	0.700	0.704	0.245	0.517	0.193	0.374		
Propensity to save energy	0.659	0.458	0.382	0.454	0.106	0.405	0.579	

Own calculations.

In addition, the Fornell–Larcker criterion was checked and, in each case, the square root of the AVE for a given construct was greater than the value of the correlation coefficients between the constructs [160].

Positive verification of the measurement model allowed us to proceed to statistical verification of the structural model. The structural model illustrated the relationships between the latent variables indicated by the research hypotheses. Its verification consisted

of the assessment of collinearity (variance inflation factor (VIF)), predictive power (R^2 determination coefficients), and the significance of attrition coefficients (bootstrap method).

The assessment of the colinearity of the internal VIF model showed that they were at the desirable level of less than 4. This value of the coefficients indicated that there was no problem of colinearity between the predictors in the structural model.

4. Results

Path coefficients, R^2 values, and structural model fit indices were estimated using the PLS-SEM algorithm. The R^2 values for the construct intention to use ST technology explained by the independent variables could be considered moderate [159]. Figure 2 below presents a graphical model estimated based on the PLS-SEM algorithm.

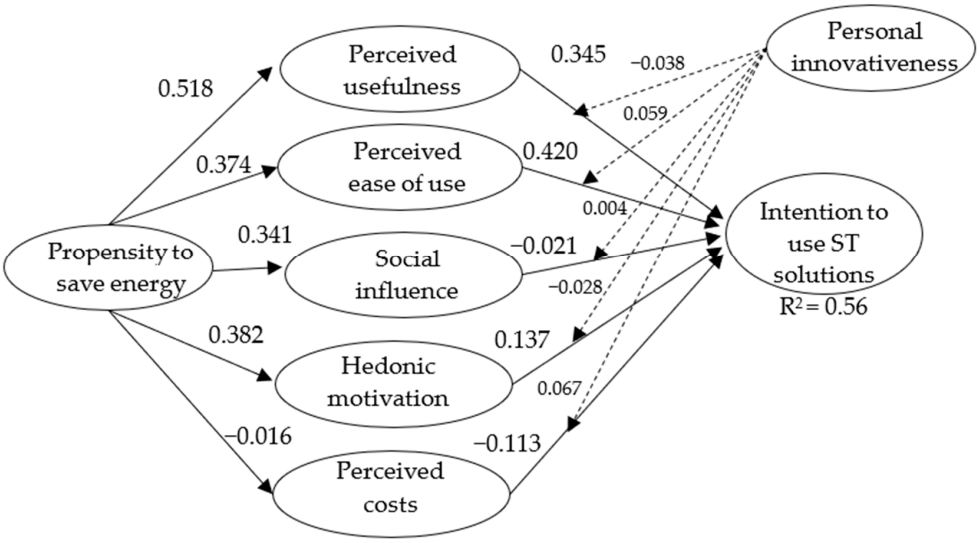


Figure 2. Path model estimated by the PLS-SEM algorithm. Source: own study.

In order to assess the statistical significance of the path coefficients, a bootstrap analysis was performed on a sample of 5000. Table 6 shows the path coefficients, t-values, significance levels, *p*-values, and confidence intervals.

Table 6. Path coefficient significance tests of the structural model.

Path	Path Coefficient	T-Value	*p*-Value	Standard Error	Confidence Interval	
					2.5%	97.5%
Propensity to save energy → Perceived usefulness	0.518	13.861	0.000	0.037	0.445	0.591
Propensity to save energy → Perceived ease of use	0.374	7.750	0.000	0.048	0.281	0.471
Propensity to save energy → Social influence	0.341	8.604	0.000	0.040	0.266	0.421
Propensity to save energy → Hedonic motivation	0.382	0.943	0.000	0.043	0.297	0.464
Propensity to save energy → Perceived costs	−0.016	0.272	0.786	0.058	−0.124	0.101
Perceived usefulness → Intention to use	0.345	6.258	0.000	0.055	0.237	0.450
Perceived ease of use → Intention to use	0.420	8.639	0.000	0.049	0.329	0.518
Social influence → Intention to use	−0.021	0.479	0.632	0.043	−0.104	0.065
Hedonic motivation → Intention to use	0.137	2.911	0.004	0.047	0.035	0.221
Perceived costs → Intention to use	−0.113	3.346	0.001	0.034	−0.181	−0.049
Personal innovativeness x Perceived costs → Intention to use	0.067	2.167	0.030	0.031	0.011	0.130
Personal innovativeness x Hedonic motivation → Intention to use	−0.028	0.655	0.513	0.043	−0.108	0.063
Personal innovativeness x Social influence → Intention to use	0.004	0.087	0.931	0.042	−0.078	0.087
Personal innovativeness x Perceived ease of use → Intention to use	0.059	0.993	0.321	0.059	−0.068	0.167
Personal innovativeness x Perceived usefulness → Intention to use	−0.038	0.666	0.505	0.056	−0.153	0.069

Own calculations.

The propensity to save energy was found to have a positive impact on a number of aspects related to the use of ST solutions (Table 7). It had the strongest impact on the perceived usefulness of ST solutions. H1 was thus confirmed. Similarly, the positive effect

of the propensity to save energy on the perceived ease of use of ST solutions (H2), social impact (H3), and hedonistic motivation to use ST solutions (H4) was verified. In contrast, the negative effect of the propensity to save energy on the perceived costs of using ST solutions was not confirmed (H5).

Table 7. Verification of research hypotheses.

Hypothesis	Direction of Influence	Estimate	*p*-Value	Verification
H1. *Propensity to save energy → Perceived usefulness*	+	0.581	0.000	Supported
H2. *Propensity to save energy → Perceived ease of use*	+	0.374	0.000	Supported
H3. *Propensity to save energy → Social influence*	+	0.341	0.000	Supported
H4. *Propensity to save energy → Hedonic motivation*	+	0.382	0.000	Supported
H5. *Propensity to save energy → Perceived costs*	−	−0.016	0.786	Not supported
H6. *Perceived usefulness of ST → Intention to use ST*	+	0.353	0.000	Supported
H7. *Perceived ease of use of ST → Intention to use ST*	+	0.413	0.000	Supported
H8. *Social influence → Intention to use ST*	+	−0.009	0.825	Not supported
H9. *Hedonic motivation → Intention to use ST*	+	0.131	0.006	Supported
H10. *Perceived costs → Intention to use ST*	−	−0.113	0.001	Supported
H11e. *Personal innovativeness x Perceived costs → Intention to use*	+	0.067	0.027	Supported
H11d. *Personal innovativeness x Hedonic motivation → Intention to use*	+/−	−0.028	0.520	Not supported
H11c. *Personal innovativeness x Social influence → Intention to use*	+/−	−0.001	0.975	Not supported
H11b. *Personal innovativeness x Perceived ease of use → Intention to use*	+/−	0.057	0.339	Not supported
H11a. *Personal innovativeness x Perceived usefulness → Intention to use*	+/−	−0.032	0.577	Not supported

Own calculations.

Referring to the other hypotheses posed in this study, it should be noted that most of the hypotheses concerning factors directly influencing the intention to use smart transport technologies were confirmed (H6–H7, H9–H10) (Table 4). Only the positive social effect on the intention to use ST solutions was not confirmed (H8). The moderating effect of personal innovativeness occurred only for the path of the impact of perceived costs on the intention to use. As shown in Figure 3, an increase in personal innovativeness has a moderating effect on its negative impact on the intention to use ST technologies.

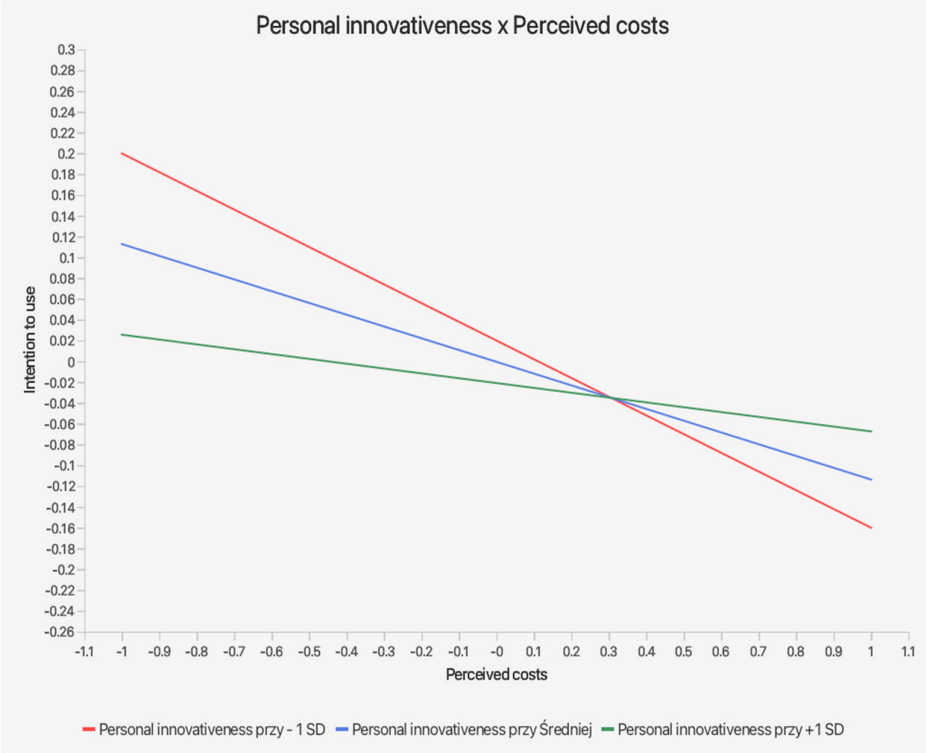


Figure 3. Perceived costs and intention to use ST technology and personal innovativeness. Source: own calculations.

5. Discussion

The results of this study provide insights into the factors influencing the adoption of ST solutions within urban environments, particularly within the framework of the smart city concept. The analysis, based on the PLS-SEM method, reveals how various variables impact the intention to use ST solutions and offers an understanding of the relationships between these factors.

The analysis shows that the propensity to save energy had a robust positive influence on perceived usefulness ($\beta = 0.518$, $p < 0.001$) and perceived ease of use ($\beta = 0.374$, $p < 0.001$), affirming its crucial role in enhancing the perceived benefits and simplicity of ST solutions. This propensity also positively affected social influence ($\beta = 0.341$, $p < 0.001$) and hedonic motivation ($\beta = 0.382$, $p < 0.001$), suggesting that individuals with a higher inclination to conserve energy are more likely to be swayed by social factors and derive pleasure from using ST solutions. However, the hypothesized negative effect of the propensity to save energy on perceived costs was not confirmed ($\beta = -0.016$, $p = 0.786$), indicating that concerns about costs are not significantly mitigated by a desire to save energy.

The findings confirm that perceived usefulness ($\beta = 0.353$, $p < 0.001$) and perceived ease of use ($\beta = 0.413$, $p < 0.001$) significantly influence the intention to use ST solutions, underscoring their importance in shaping user adoption. Conversely, social influence ($\beta = -0.009$, $p = 0.825$) did not have a significant effect on the intention to use ST solutions, suggesting that peer pressure and media influence might play a lesser role in this context. Hedonic motivation ($\beta = 0.131$, $p = 0.006$) and perceived costs ($\beta = -0.113$, $p = 0.001$) also impacted the intention to use, with hedonic motivation contributing positively and perceived costs exerting a negative effect.

The propensity to save energy was found to be a significant predictor of the perceived usefulness of ST solutions. This aligns with the hypothesis that individuals who are motivated by energy conservation view ST solutions as more beneficial. This finding underscores the importance of emphasizing the energy-saving benefits of ST solutions in promotional and educational campaigns. Additionally, the propensity to save energy positively influenced perceived ease of use, social influence, and hedonic motivation. These results suggest that individuals who are inclined to conserve energy are more likely to find ST solutions user-friendly, are affected by the social environment, and derive pleasure from using these technologies.

The hypothesis that the propensity to save energy would negatively impact perceived costs was not supported. This implies that energy-saving motivations do not necessarily lead to perceptions of high costs as a barrier. This finding could suggest that while energy conservation might be a priority for users, it does not necessarily outweigh their concerns about the costs associated with ST solutions.

Perceived usefulness emerged as a strong determinant of the intention to use ST solutions. This aligns with prior research that highlights the importance of the perceived benefits of technology adoption. Users who believe that ST solutions will enhance their quality of life and reduce transportation costs are more likely to adopt these technologies. Similarly, perceived ease of use positively affects the intention to use ST solutions, reinforcing the notion that the simplicity and user-friendliness of technology play a crucial role in adoption decisions.

The impact of social influence on the intention to use ST solutions was not statistically significant in this study. This diverges from some previous studies that have highlighted the role of social norms and peer behavior in technology adoption. The lack of support for this hypothesis could suggest that in the context of ST solutions, individuals may prioritize personal benefits or practical considerations over social pressures.

Hedonic motivation, or the pleasure derived from using technology, was positively associated with the intention to use ST solutions. This finding suggests that users who find enjoyment in the use of ST solutions are more likely to continue their use. On the other hand, perceived costs negatively impacted the intention to use ST solutions. This supports the hypothesis that high costs can deter users from adopting these technologies. However,

the negative effect of perceived costs on the intention to use ST solutions was moderated by personal innovativeness. Individuals with higher levels of personal innovativeness were less deterred by costs, indicating that they are more willing to embrace new technologies despite potential financial barriers.

This study also explored the moderating role of personal innovativeness on the relationship between various factors and the intention to use ST solutions. Among the moderating effects examined, only the interaction between personal innovativeness and perceived costs was significant. This suggests that individuals who are more innovative are less sensitive to cost-related concerns when deciding to use ST solutions. However, the moderating effects of personal innovativeness on other relationships, such as perceived usefulness and hedonic motivation, were not significant. This indicates that while personal innovativeness influences how cost perceptions impact technology adoption, it does not alter the effects of perceived usefulness or enjoyment on the intention to use ST solutions.

The results of this study can be analyzed through the lens of UTAUT, which provides a framework for understanding technology acceptance and usage. According to UTAUT, four core constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—are pivotal in shaping users' intentions to adopt and use new technologies [161]. Additionally, UTAUT identifies the role of moderating factors such as age, gender, experience, and willingness to use [162].

Performance expectancy, akin to perceived usefulness in the context of this study, was confirmed as a significant predictor of the intention to use ST solutions. This result underscores the relevance of users' beliefs that ST solutions will enhance their quality of life and reduce transportation costs. The positive impact of performance expectancy aligns with UTAUT's assertion that individuals are more likely to adopt technologies they perceive as beneficial and capable of delivering tangible improvements in their lives [163]. This study's finding that the propensity to save energy positively influences perceived usefulness further supports this, suggesting that users who prioritize energy conservation view ST solutions as offering substantial performance benefits.

Effort expectancy, comparable to perceived ease of use, also positively influenced the intention to use ST solutions. This finding is consistent with UTAUT's proposition that technologies perceived as easy to use and requiring minimal effort are more likely to be adopted [164]. This study's results demonstrate that users who find ST solutions user-friendly and straightforward are more inclined to integrate these technologies into their daily routines. This aligns with previous research suggesting that reducing perceived complexity and improving ease of use are crucial factors in increasing technology adoption rates [165–167].

Social influence, which reflects the impact of social networks and peer behaviors on technology adoption, did not significantly affect the intention to use ST solutions in this study. This finding diverges from the UTAUT model, which typically emphasizes the importance of social influence [168,169]. The lack of a significant effect in this case suggests that, within the realm of ST solutions, individual preferences and perceptions may outweigh social pressures. This could imply that while social influence can be a powerful factor in some contexts, its impact on the adoption of ST solutions might be less pronounced or overshadowed by other factors such as perceived usefulness and ease of use.

The UTAUT model includes facilitating conditions as a determinant of technology use. Facilitating conditions refers to the resources and support available to users that enable them to effectively use the technology. While this study did not explicitly measure facilitating conditions, the results relating to perceived costs and their impact on technology adoption indirectly touch on this construct [163,170]. The negative effect of perceived costs on the intention to use ST solutions reflects a limitation in available resources or support that could hinder technology adoption. The moderating effect of personal innovativeness on the relationship between perceived costs and intention to use further emphasizes how individual differences in resource availability and support can influence technology adoption decisions.

In line with UTAUT's framework, this study also explored the role of personal innovativeness as a moderating factor [170]. Personal innovativeness was found to moderate the negative impact of perceived costs on the intention to use ST solutions. This finding implies that individuals who are more innovative are less deterred by financial considerations, suggesting that personal traits can influence technology adoption [171]. However, the lack of significant moderating effects on other relationships, such as those between performance expectancy and intention to use, indicates that while personal innovativeness influences cost-related concerns, it does not uniformly affect all aspects of technology acceptance.

UTAUT2 extends the original UTAUT model by incorporating three additional constructs: hedonic motivation, price value, and habit [172]. These enhance the understanding of technology acceptance by addressing the intrinsic pleasure derived from using technology, the trade-off between the perceived benefits and costs, and the influence of habitual behaviors [171]. Analyzing the results of this study through the UTAUT2 framework provides insights into the factors affecting the adoption of ST solutions.

Hedonic motivation, which reflects the enjoyment or pleasure derived from using technology, was a relevant factor in this study. The results indicate that while hedonic motivation had a positive influence on the intention to use ST solutions, its impact was less pronounced compared to other constructs like perceived usefulness and perceived ease of use. This suggests that while the pleasure derived from using ST solutions is a contributing factor to their adoption, it may not be as decisive as the functional benefits and ease of use. This finding aligns with UTAUT2, which posits that while hedonic motivation can enhance the appeal of technology, its role is supplementary to the more fundamental drivers such as performance expectancy and effort expectancy [170,171].

The price value construct, which considers the balance between the perceived benefits and costs of using a technology, is crucial in evaluating technology adoption. This study found a significant negative impact of perceived costs on the intention to use ST solutions, which resonates with the price value dimension of UTAUT2 [169]. This indicates that users weigh the financial costs of ST solutions against their perceived benefits. The moderation effect of personal innovativeness on this relationship highlights that individuals with higher innovativeness are less deterred by costs, suggesting that they perceive greater value in the technology despite its price. This finding underscores the importance of ensuring that ST solutions offer clear and substantial benefits that justify their costs, particularly for users who are more innovative and potentially more critical of value propositions [173].

The findings of this study on smart transportation solutions resonate with research conducted in Western Europe [174–177] and North America [178–181] in several key areas. Hedonic motivation, while relevant, plays a secondary role compared to functional aspects like performance expectancy and effort expectancy. The price value construct highlights the critical importance of balancing costs and benefits, a theme consistent across different regions. Social influence shows varying impacts depending on the context, aligning more closely with North American studies in this instance.

When comparing the results of this study on ST solutions with regions characterized by less developed infrastructure or different socioeconomic conditions, several notable differences emerge. In less developed regions, where infrastructure may be limited and economic resources constrained, the adoption of ST solutions often hinges more critically on basic functional benefits and cost-effectiveness [180–183]. For instance, research indicates that in such areas, perceived usefulness (performance expectancy) tends to be a stronger driver of technology adoption than hedonic motivation or social influence, as individuals prioritize practical and essential improvements to their daily lives [184]. The impact of perceived costs is typically more pronounced in these regions, with high costs acting as a significant barrier to adoption. This contrasts with more developed regions where the availability of better infrastructure and higher disposable incomes can make users more receptive to additional features and innovations. Consequently, while the fundamental drivers of technology acceptance, such as performance expectancy and effort expectancy, remain relevant across different socioeconomic conditions, their relative importance and

the weight given to cost and enjoyment may vary significantly. In less developed areas, practical benefits and affordability take precedence, shaping technology adoption in a way that reflects the local context's infrastructure and economic realities.

6. Conclusions

This study provides an analysis of the factors influencing the intention to use ST solutions within the context of a large Polish urban population. This research, based on a sample of 471 respondents, provides insights into the determinants of ST adoption, demonstrating an interplay of various factors that align with the UTAUT2 model.

Also, this study finds that personal innovativeness moderates the relationship between perceived costs and the intention to use ST solutions ($\beta = 0.067$, $p = 0.027$), highlighting that more innovative individuals are less deterred by costs. However, no significant moderating effects were found for personal innovativeness in relation to other factors like perceived usefulness or social influence.

For individuals responsible for the implementation and promotion of ST solutions, several recommendations can be drawn from this study. It seems essential to emphasize the perceived usefulness and ease of use of ST solutions in public communications and user training programs. As these factors were found to be significant drivers of adoption, ensuring that users understand how ST solutions can enhance their quality of life and simplify their daily commutes can significantly increase uptake. Also, addressing concerns related to perceived costs should be a priority. While this study found that perceived costs did not significantly affect the intention to use ST solutions, it is still important to evaluate and address cost-related issues to prevent potential barriers to adoption. This could involve exploring cost-reduction strategies or providing financial incentives to users, which may help to mitigate concerns and enhance overall acceptance.

Given the role of hedonic motivation and social influence in promoting ST solutions, stakeholders should consider integrating features that make the use of ST solutions enjoyable and engaging. This might involve incorporating user-friendly design elements, interactive interfaces, and gamified experiences that can make the technology more appealing. Leveraging social influence by fostering community engagement and endorsements from influential figures or local leaders can also help to build a positive perception and encourage broader adoption.

It can be stated that the role of personal innovativeness in moderating the impact of perceived costs on technology adoption highlights the importance of targeting early adopters and tech enthusiasts in promotional efforts. By engaging these individuals and leveraging their enthusiasm, it might be possible to create a ripple effect that influences broader segments of the population. Overall, an integrated approach that addresses perceived usefulness, ease of use, cost concerns, hedonic elements, and social influences could be instrumental in effectively advancing the adoption of smart transportation solutions.

The main contribution of this paper lies in its exploration and empirical validation of the factors influencing the intention to use smart transportation (ST) solutions within a large urban population in Poland. By applying the UTAUT2 framework, this study provides insights into how various determinants such as perceived usefulness, perceived ease of use, social influence, hedonic motivation, and perceived costs interact to shape user intentions to use ST solutions.

We believe that the methodology used in this study, which included the use of CAWI and statistical techniques like PLS-SEM, enhances the reliability and validity of the findings. This approach not only validates the relevance of UTAUT2 constructs in a specific cultural and geographic context but also demonstrates the framework's applicability in evaluating technology adoption beyond its traditional boundaries. The empirical evidence presented offers a detailed understanding of how the propensity to save energy, as a contextual factor, influences other constructs, thus providing deeper insights into the complex interplay between user attitudes and technology adoption.

Additionally, this paper's findings regarding the moderating role of personal innovativeness in mitigating perceived costs contribute to the broader discourse on technology acceptance by revealing how individual differences can impact the adoption process. This, we believe, is important for developing targeted strategies to enhance the adoption of ST solutions, considering both practical and motivational aspects.

During the study, limitations were identified in the form of the inability to reach a wide range of a specific target group that could reliably express their opinion in the context of the research being conducted. CAWI research always has such limitations. Qualitative methods can be used to better understand the problem in the future. It is worth proposing focus group interviews or using the ST method of observing user behavior. Focus group interviews allow for an in-depth understanding of the complexity of the topics discussed, as they allow participants to freely express their opinions and share experiences. Group discussions stimulate the exchange of ideas and views, which can lead to the disclosure of new aspects and insights that may not emerge in individual interviews. Participants from different backgrounds can provide different perspectives, which could allow for a more comprehensive view of the topic under study.

Future research should consider longitudinal studies to track evolving patterns of technology acceptance and its long-term impact on energy conservation. Examining differential impacts on different demographic groups can provide more targeted insights for policy interventions. Comparative studies conducted in different regions can further elucidate the role of local contexts in shaping the acceptance and benefits of intelligent transport solutions.

As for ST itself, it is worth paying attention to the environmental and economic issues resulting from high maintenance costs. Intelligent transport solutions lead to increased energy consumption, which, in turn, may have a negative impact on the natural environment and related aspects that are important from the point of view of certain environmental protection principles.

Looking ahead, future research can contribute to the development of more efficient, equitable, and sustainable intelligent transport systems, eliminating current limitations and paving the way for innovative solutions. Research has shown that residents have a high level of trust in intelligent transport (ST). Therefore, a valuable solution would be to increase investment in order to expand the offer to a wider geographical range, e.g., smaller towns or villages. Additionally, it is worth extending or improving the smart phenomenon to other aspects of life, including smart solutions for households. By implementing smart solutions, households can improve safety, increase energy efficiency, and create a more comfortable living environment.

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