

Review

Sustainable Mobility and Shared Autonomous Vehicles: A Systematic Literature Review of Travel Behavior Impacts

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Abstract: Shared autonomous vehicles (SAVs) are emerging as a potential tool for sustainable transportation, yet their impact on travel behavior and environmental outcomes remains uncertain. This review evaluates the sustainability implications of SAV adoption, including its potential to reduce emissions through optimized fleet operations, enhance social equity by improving mobility access, and increase economic efficiency through resource-sharing models. This systematic literature review examines 107 articles from English and Chinese databases, focusing on SAVs' effects on total travel demand, mode choice, and in-vehicle time use. Findings indicate that SAVs could increase vehicle miles traveled due to unoccupied relocation and new demand from previously underserved demographics, though advanced booking and dispatch systems may mitigate this increase. The study identifies 59 factors influencing SAV adoption, categorized as user-centric, contextual, and psycho-attitudinal. Analysis of in-vehicle time use shows varied activities, from productivity to leisure, with contradictory findings in the value of travel time (VOT) compared to conventional vehicles: while some studies report up to 34% lower VOT for SAVs due to multitasking opportunities, others find up to 29% higher VOT. Privacy and personal space emerge as important factors, with users showing a high willingness to pay to avoid additional passengers. The review highlights underexplored variables and methodological limitations in current research, including psychological influences and mode substitution dynamics. These insights inform policymakers and urban planners on how to integrate SAVs into sustainable transportation systems by mitigating their environmental impact, promoting equitable access, and ensuring alignment with smart urban planning strategies.



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Keywords: shared autonomous vehicles; sustainable mobility; systematic literature review; urban sustainability; travel behavior; value of travel time; emerging mobility

1. Introduction

Sustainable transportation is a priority as cities face growing challenges with emissions, congestion, and equitable mobility access [1,2]. Shared autonomous vehicles (SAVs), which combine autonomous driving with shared mobility services [3], offer potential solutions to enhance environmental sustainability, improve social equity through increased accessibility, and optimize resource utilization [4]. However, their actual sustainability impact remains uncertain, particularly regarding their effects on travel behavior [4,5].

This review examines three interconnected dimensions of travel behavior that impact transportation sustainability. The first dimension examines total travel demand, measured in *vehicle miles traveled (VMT)*, which has direct implications for carbon emissions, congestion, and energy consumption in sustainable transportation. The second dimension focuses

on *mode choice and adoption*, as SAVs could either enhance or undermine sustainable mobility by shifting users from public transport or active travel modes. This has direct consequences for transport equity, accessibility, and the viability of low-carbon transport systems. The third dimension explores *travel time utilization*, as automation may transform in-vehicle productivity and leisure, influencing economic sustainability by improving efficiency in urban transport networks.

Several automotive and technology companies, including Tesla, General Motors, Ford, Toyota, Uber, and Waymo, are actively engaged in SAV development and testing [6–10], with pilot deployments already underway in cities such as San Francisco (Waymo) and Wuhan (Baidu) [11–13]. While these developments suggest potential for reducing private car dependence and emissions, concerns remain about increased vehicle miles traveled due to empty repositioning trips. Experts project, that, within the next decade, ride-hailing services will become predominantly autonomous [14,15], requiring careful policy frameworks that prioritize shared mobility and public transport integration to ensure sustainable outcomes [16,17].

SAVs combine autonomous driving technology with shared mobility services [18–20], operating without human drivers in various forms (see Table 1), including autonomous taxis, ride-sharing services, shuttles, and buses. While evidence suggests that SAVs could bring significant changes to transportation [4,5,12,21], the magnitude and characteristics of their influence on travel behavior remain uncertain and are the subject of ongoing research. The adoption of SAVs depends substantially on user acceptance mechanisms and technology trust [22]. Research demonstrates that psychological factors and perceived utility affect both users' value of travel time and mode choice decisions [23], with variations across socio-demographic segments [24].

Previous studies have examined the impact of AVs on travel behavior [15,25–29], but few have specifically focused on SAVs. The relative novelty of SAV technology and the limited real-world deployments have constrained the amount of empirical research specifically focused on SAVs compared to the broader field of AVs. For SAVs, Bala et al. [30] used a narrative approach to highlight psychological factors such as trust in technology, perceived safety and security, and social influence, which influence the adoption of SAVs. However, their investigation did not systematically address the impact of SAVs on travel demand, mode choice, and time use. By examining the impact of SAVs on travel behavior, Narayanan et al. [16] and Golbabaei et al. [14] provided insights, albeit constrained by the availability of data only up to 2020.

The existing research landscape remains fragmented, with studies often addressing narrow dimensions like travel demand or mode choice in isolation, rather than examining their combined effects on sustainable transportation. Notable gaps include limited analysis of how SAVs specifically (as opposed to AVs in general) might impact transportation sustainability through changing travel patterns and behaviors. Additionally, many studies have limited geographic scope or inadequate consideration of key psychological and socio-demographic factors that could influence sustainable adoption patterns. This fragmentation limits our understanding of how SAVs might contribute to or potentially hinder sustainable urban mobility goals.

To address the limitations in existing research, this paper conducts an extensive systematic review following PRISMA guidelines, analyzing literature in both English and Chinese. By adhering to a structured protocol for searching, screening, and analyzing relevant studies, this review seeks to provide a comprehensive synthesis of available evidence and address the following question:

How do SAVs influence travel behavior in ways that impact sustainable transportation, particularly in terms of total travel demand, mode substitution, and travel time use?

This systematic review contributes to transportation literature by analyzing SAVs' influence on sustainable transportation across three specific dimensions. Our methodology provides two advantages: It incorporates both English and Chinese research, expanding geographical scope beyond previous studies, and it develops a taxonomy of 59 adoption factors for analyzing user acceptance determinants. These contributions address significant gaps in the existing fragmented literature on sustainable SAV implementation.

In this study, SAVs refer to self-driving vehicles that combine autonomous driving technology with shared mobility services. These vehicles operate without human drivers and can be deployed in various forms, including autonomous taxis (1–4 passengers), autonomous ride-sharing services (1–4 passengers with public sharing), autonomous shuttles (1–11 passengers), and autonomous buses (1–40 passengers), offering either on-demand flexible services or scheduled fixed-route services. Unlike personal autonomous vehicles, SAVs are designed for sequential or simultaneous use by multiple users, operating as part of a public or commercial transportation service.

By synthesizing the current state of knowledge on SAVs and sustainable travel behavior while acknowledging existing research gaps, this review provides valuable insights for both researchers and policymakers seeking to understand and shape the future of sustainable urban mobility in the autonomous vehicle era. The remainder of the paper is organized as follows: The methodology section details the systematic literature review process, including the search strategy, screening criteria, and data analysis methods. The results section presents the key findings, organized into three topics: total travel demand, travel mode choice, and the use of travel time in private cars. The discussion section synthesizes the findings and identifies areas for future research. The paper concludes with a summary of the main insights and recommendations for stakeholders in the transportation sector.

Table 1. Topologies of SAV services.

	Autonomous Taxi/Robo-Taxi	Autonomous Ride-Sharing/Pooled Robo-Taxi	Autonomous Shuttle	Autonomous Bus
Vehicle Type				
Vehicle Size	1–4 pax	1–4 pax	1–11 pax	1–40 pax
Sharing	No public sharing	Ride-sharing	Public service	Public service
Service	On-demand and flexible pickup/dropoff points	On-demand and flexible pickup/dropoff points	Scheduled and Fixed pickup/dropoff points	Fixed-route scheduled or on-demand flexible service
Usage	Taxi	Ride-sharing	Short-distances and Access/Egress	Urban and long-distance transport

Note: This classification of SAV services is adapted from Hao and Yamamoto (2018) [31] and Shaheen and Cohen (2019) [3], who provided a comprehensive framework for categorizing shared mobility services.

2. Methodology

2.1. Systematic Literature Review Design

This study employs a systematic literature review approach to synthesize extant research findings, following established frameworks [32–35]. Unlike narrative reviews, systematic reviews follow a rigorous, auditable process that methodically identifies, selects, and evaluates studies based on predefined criteria [36], ensuring full replicability and minimizing bias [34,37–39]. This objective analysis is paramount in transportation research, where evidence synthesis directly informs theoretical advancements and policy formulation [25,40].

2.2. Search Strategy and Selection Criteria

The systematic review utilized four major academic databases—Web of Science (WoS), Scopus, EBSCO, and ScienceDirect—supplemented by the China National Knowledge In-

frastructure (CNKI) to include Chinese-language publications. Of the 198 Chinese-language studies initially identified in CNKI, only 3 met our inclusion criteria, as most focused on technical and regulatory aspects rather than behavioral impacts. This finding aligns with prior reviews indicating that Chinese AV research primarily emphasizes infrastructure readiness, road safety certification, and sensor technologies rather than user adoption patterns. In contrast, a larger proportion of studies from North America and Europe analyzed behavioral responses to SAVs, likely due to the greater availability of stated preference surveys and real-world trials. While sociocultural differences may influence adoption patterns, these gaps highlight a critical need for behavioral studies in Chinese megacities as SAV pilots expand.

This database selection aligns with established practices in transportation research systematic reviews [41–43] and ensures comprehensive coverage while minimizing selection bias. The review focused on peer-reviewed journal articles in English and Chinese examining Level 4 or 5 autonomous vehicles, with select peer-reviewed conference papers included for recent developments. Additionally, relevant grey literature was consulted, including industry reports (e.g., Waymo’s Safety Methodologies, California Department of Motor Vehicles’ Disengagement Reports) and real-world implementation data from commercial deployments (e.g., Baidu’s robo-taxi trials in Wuhan). The grey literature was screened based on empirical data quality, with industry reports only included when they provided verifiable operational metrics or structured pilot program results.

Search terms combined different autonomous vehicle types (e.g., robo-taxi, autonomous shuttle, driverless bus) with mobility-related terms (see Table 2 for complete search queries). The review included various methodological approaches (e.g., simulation models, observational studies from real-world deployments) to provide a comprehensive understanding of travel behavior, such as Yan et al. [44] investigating how sustainability concerns and real SAV exposure influence acceptance in China. The search was conducted in December 2024 without date restrictions.

Table 2. Search queries used in systematic literature review.

(shared OR automated OR autonomous OR driverless OR self-driving OR robo)
AND
(car OR vehicle OR taxi OR shuttle OR van OR bus OR mobility OR car-sharing OR ride-hailing)

2.3. Data Collection and Screening Process

Following the PRISMA flowchart (Figure 1), the initial search yielded 5342 records. After removing duplicates and screening titles and abstracts, 139 potentially relevant records remained. Full-text review identified 107 eligible studies, including 22 focused on travel demand and 3 in Chinese. Exclusion criteria targeted studies focusing on non-autonomous or lower automation levels (Level 3 or below), purely technical aspects (e.g., sensor development), and connected vehicles without autonomous capabilities. We also excluded papers without clear behavioral dimensions or those presenting policy recommendations without empirical evidence. Each included article was then systematically categorized by vehicle topology, research methodology, geographical focus, and analyzed variables, enabling comprehensive cross-study comparisons. A complete list of studies and their classifications can be found in Appendices A and B.

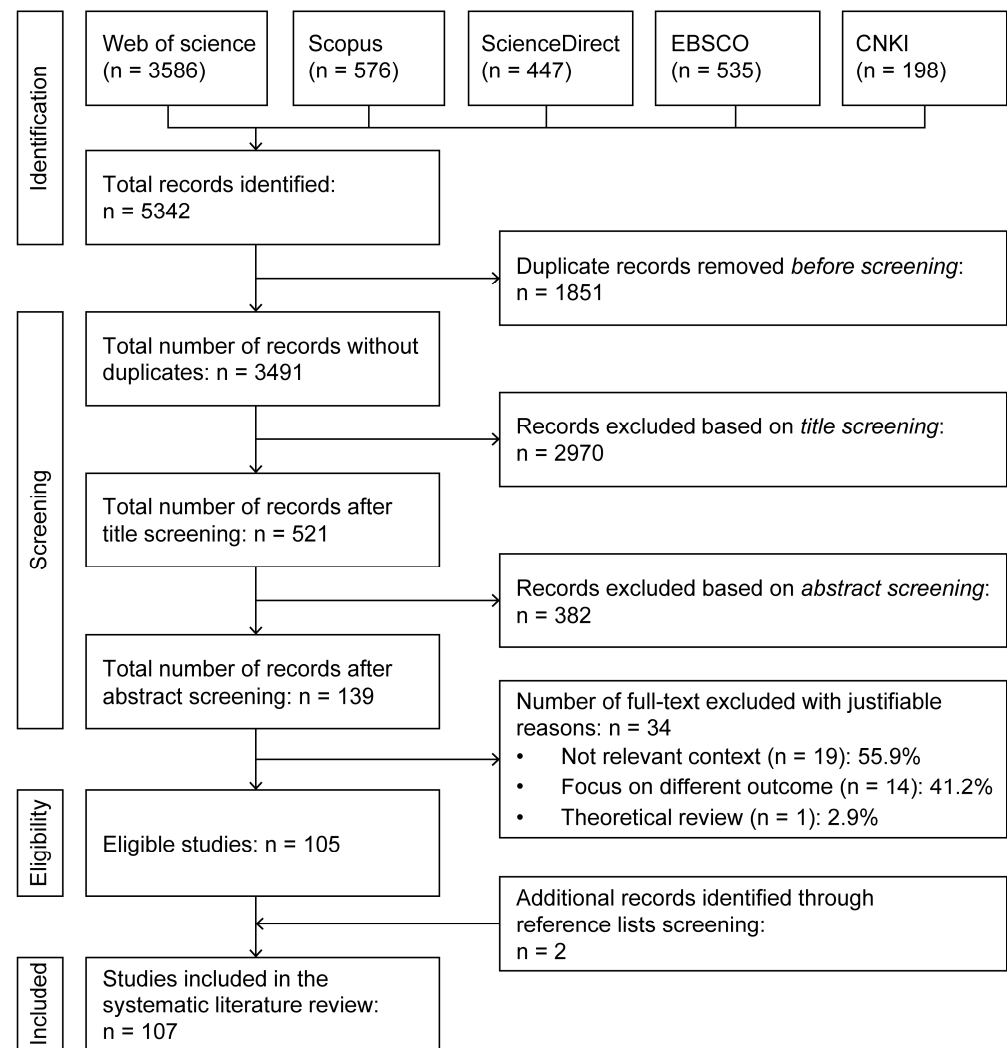


Figure 1. Data collection and screening process.

3. Findings

3.1. Descriptive Analysis

3.1.1. Temporal Distribution of Publications

Research on total travel demand emerged first in 2014, with a notable increase in 2015 (five publications) and continued presence until 2019. Studies on factors influencing travel mode choice began appearing in 2016 and showed steady growth, reaching their peak in 2020 with 15 publications. While both research streams coexisted initially, mode choice studies have dominated since 2020, with travel demand studies essentially ceasing. Publication numbers have remained relatively stable between 2020–2023 (thirteen to fourteen annually), with a slight decrease in 2024 (nine publications), though this likely reflects partial-year data (Figure 2).

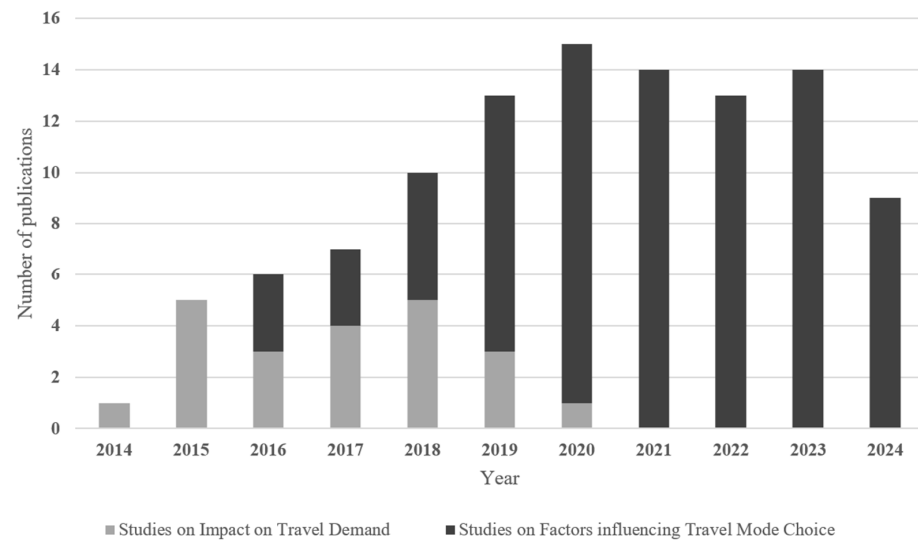
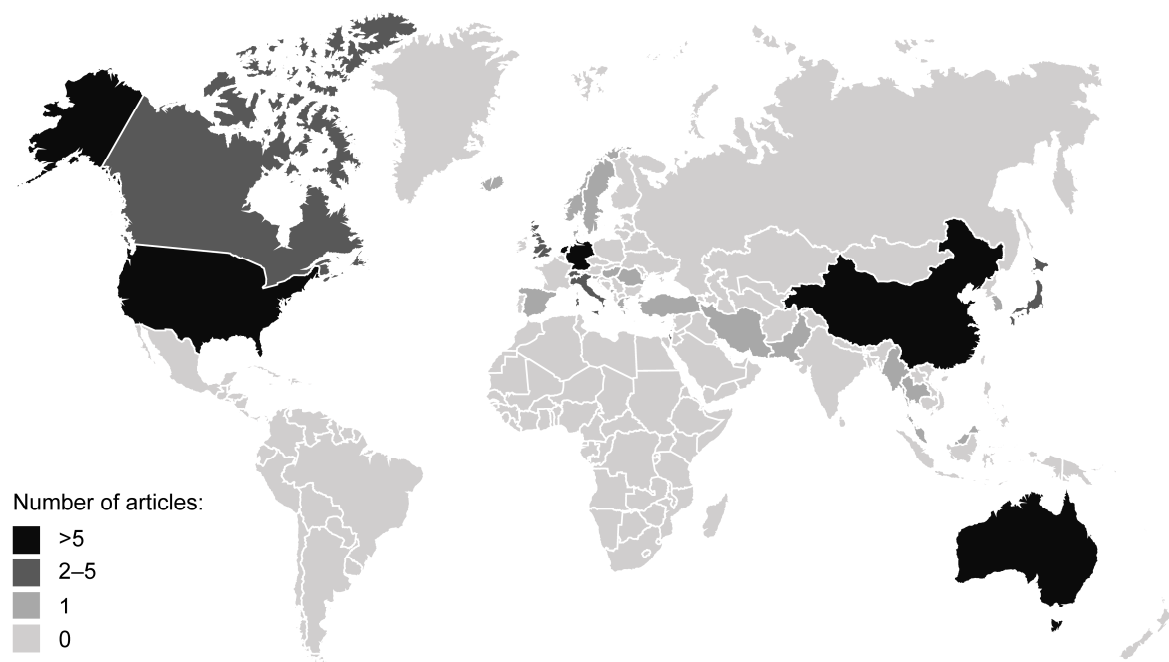


Figure 2. Publications per year.

3.1.2. Geographical Distribution

The systematic analysis reveals research spanning 30 countries across four continents, with some studies examining multiple countries, resulting in 107 country-level analyses (Figure 3). North America emerges as a prominent focal point, contributing 44 studies, trailed by Europe with 31 studies. Asia and Australia follow with twenty-nine and six studies, respectively [12,45,46]. The United States, with 40 studies [47–49], and China, with 13 [50–52], stand out as significant contributors.



Number of articles (107) by country: USA (40), China (9), Germany (7), The Netherlands (7), Australia (6), Canada (4), Japan (4), Singapore (3), Switzerland (3), Israel (2), Italy (2), UK (2), Cyprus (1), Denmark (1), Hungary (1), Iceland (1), Malaysia (1), Montenegro (1), Pakistan (1), Qatar (1), Romania (1), Slovenia (1), Republic of Korea (1), Spain (1), Sweden (1), Turkey (1), Thailand (1), Norway (1), Iran (1), Greece (1)

Figure 3. Geographical distribution of analyzed studies by country.

The literature encompasses 20 developed countries, including the United States, Australia, and several European nations such as Germany, Italy, and the Netherlands, providing

insights into transportation systems in mature economies [53–55]. The inclusion of 10 developing countries, with China as a prominent contributor, offers valuable perspectives on mobility challenges amid rapid urbanization [56,57].

The analysis further reveals a balanced distribution between national and local perspectives, with 62 studies adopting a countrywide approach and 52 studies focusing on city-specific examinations, highlighting the importance of both macro-level understanding and location-specific solutions [58,59].

3.1.3. SAV Typologies

This review categorizes SAVs into five distinct types following Hao and Yamamoto's [19,31] classification framework: robo-taxis, pooled robo-taxis, robo-shuttles, robo-buses, and a general category. This taxonomy distinguishes SAVs based on their capacity and sharing configurations, as illustrated in Figure 4.

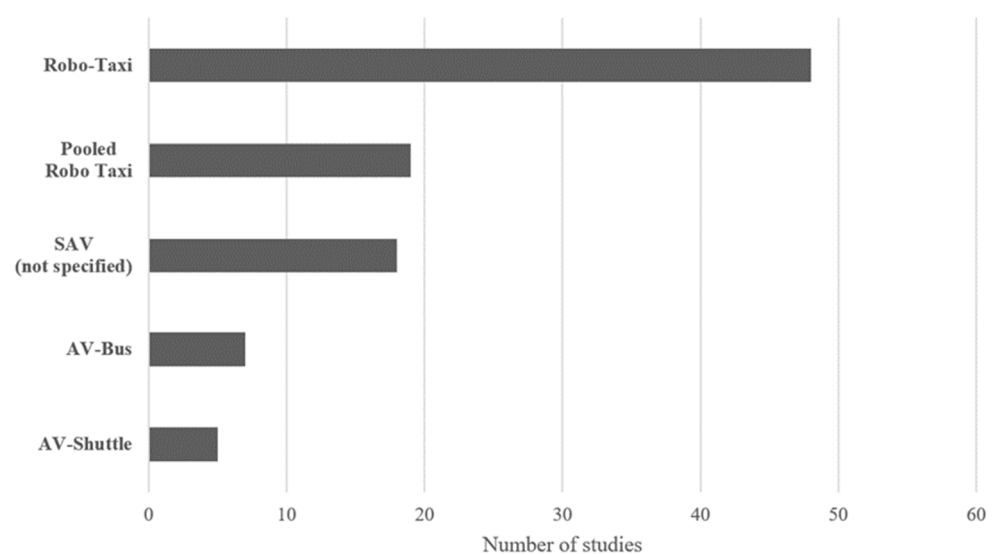


Figure 4. Occurrence of the different vehicle types in the reviewed articles.

Within the reviewed literature, robo-taxis emerged as the predominant focus, featuring in 48 out of 97 studies (49.5%), likely due to their familiarity as an autonomous extension of existing ride-hailing services. Pooled robo-taxis and general SAV studies were also well-represented, appearing in 19 (19.6%) and 18 (18.6%) studies, respectively.

Notably, larger vehicle formats received considerably less attention, with only seven studies (7.2%) examining robo-buses and five studies (5.2%) focusing on robo-shuttles. This underrepresentation may reflect the greater complexity of implementing and integrating larger autonomous vehicles into existing transportation networks.

Some publications investigated multiple vehicle types and/or geographic contexts [60–62], contributing to the total count of 97 SAV studies analyzed.

3.2. Impact on Travel Demand (Vehicle Miles Traveled)

Anticipated VMT changes under SAV adoption depend on service models (private vs. shared), policy interventions, and geospatial dynamics. While empty vehicle repositioning and induced demand from underserved populations (e.g., youth, elderly, disabled users) are key drivers of VMT growth [21,63,64]. Studies consistently project VMT, and the literature reveals two opposing pathways (see Figure 5 and Appendix B):

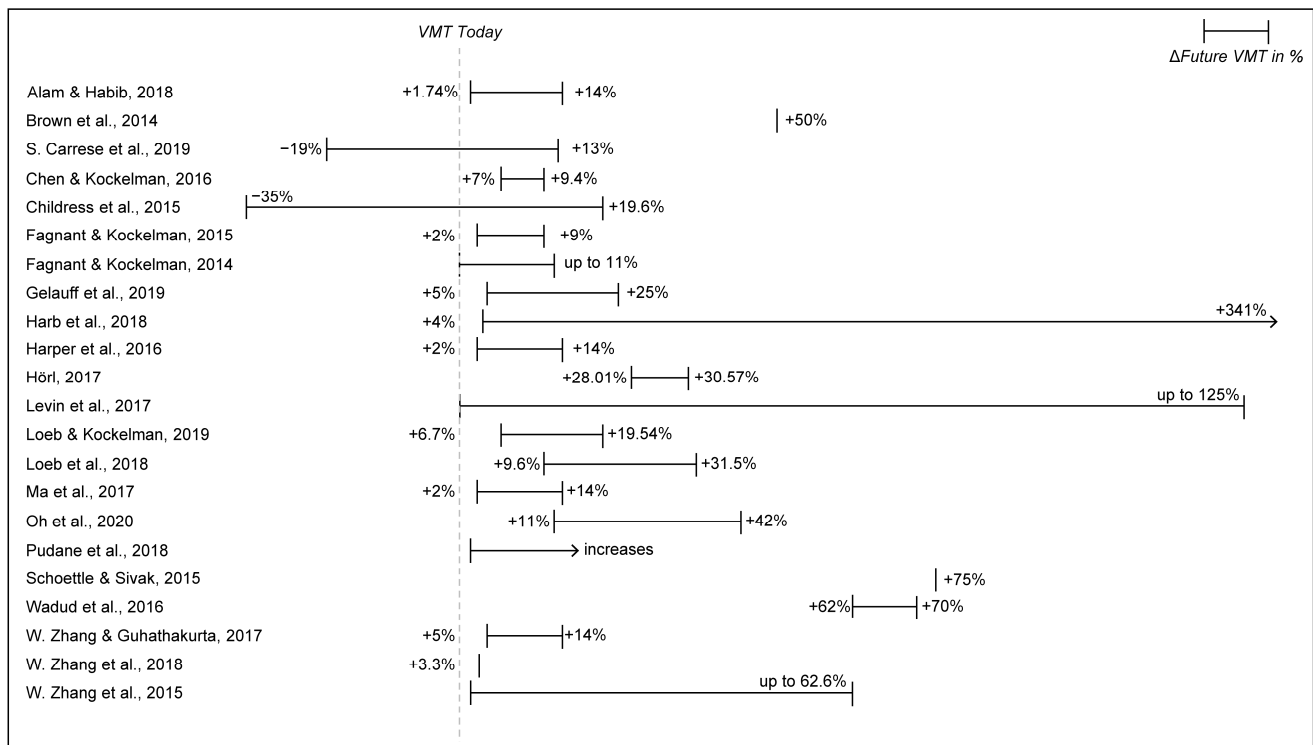


Figure 5. Overview of future travel demand due to SAV [5,21,63–82].

Private AV ownership emerges as a primary driver of VMT growth, with simulations of privately owned AVs projecting substantial increases. Levin et al. [65] estimate up to a 125% VMT increase for poorly optimized fleets in low-density areas, while Pudane [66] highlights how reduced travel stress enables multitasking, incentivizing longer commutes. Urban sprawl further amplifies these effects, as Gelauff et al. [67] note that reduced transportation costs could lengthen commutes, while Carrese et al. [68] found that 37–42% of Rome respondents would consider suburban relocation, potentially redistributing rather than reducing VMT.

Shared fleet optimization presents significant opportunities for VMT reduction. Fagnant and Kockelman [5] demonstrate modest 2–9% VMT increases in dense urban grids with optimized ride-sharing, though these benefits diminish if fleet utilization drops below 50%. Childress et al. [69] show potential 35% VMT reductions through full-cost pricing mechanisms. Advanced booking systems can reduce fleet idle time by 18–27% [70], while electrified, pooled SAVs under emission caps could counteract sprawl-induced growth [71,72].

Environmental outcomes depend on four critical factors. Vehicle ownership policy must balance mandated shared fleets in city centers against private ownership in suburbs [70]. To effectively manage demand, pricing regimes can penalize low-occupancy SAV trips during peak hours and during periods of high congestion [69]. Urban planning measures require coupling SAV policies with mixed-use zoning to offset sprawl incentives [68]. Finally, fleet electrification success relies on the strategic placement of renewable charging infrastructure in high-utilization corridors [67].

These findings highlight that SAV's impact on VMT is not predetermined—rather, it depends critically on policy decisions around sharing, pricing, and land use that will shape whether SAVs support or undermine sustainable mobility patterns.

3.3. Factors Influencing Travel Mode Choice and SAV Acceptability

This study presents a framework for examining SAV adoption determinants by categorizing 59 attributes into three main categories and seven sub-categories, synthesized from

85 research articles. With some studies investigating multiple countries and SAV topologies (as detailed in Section 3.1.2), the total individual studies analyzed amounts to 96 [83,84].

The framework comprises user-centric factors, contextual factors, and psycho-attitudinal influences. Within contextual determinants, three sub-categories emerge: operational travel attributes, SAV-specific features, and built environment, addressing external factors such as physical environment, service characteristics, and trip attributes. User-centric determinants examine individual characteristics, including socio-demographic factors and travel habits, while psycho-attitudinal influences explore internal psychological drivers.

For clarity, similar attributes were aggregated. For instance, ‘Waiting tolerance’ [85] and ‘Time sensitivity’ [86] were combined under a single sub-category, as both relate closely to the time-related aspects of travel. Similarly, ‘Environmental attitude’ (from various studies), ‘Pro-environment’ [61], and ‘Green travel pattern’ [87] were aggregated under a single attribute related to environmental consciousness. Table 3 presents all 59 attributes and their categorization (Appendices C–E).

Table 3. Factors influencing willingness to use SAV.

Categories	Factors	N
User-Centric Factors		
Socio-demographic	Age, Gender, Education, Income, Household, Employment, Disability/Impairment, Level of physical activity	8
Current Travel Habits and Mobility Needs	Driver’s License, Vehicle ownership, Common transport mode (private vehicle, public transport, active transport), Public transport card owner, car crash history, Familiarity Ride-sharing, Familiarity AV/SAV, Trip purpose (commute, leisure), Commute Time, First Class Train travel, Need to carry items, Yearly Mileage/Usage Frequency	15
Contextual Factors		
Operational Travel Factors	Travel distance, Travel time, Travel cost, Accessibility/Service, Reliability, Travel speed, Access/Egress time, Waiting time, Congestion time, In-vehicle-time, Parking time, Parking cost, Weather	13
SAV-specific Features	Vehicle interior, Chauffeur/Monitoring, Seating, Trip delay insurance, Liability holder, Preferred lane, Multitasking, Willingness-to-pay for automation, VOT	9
Built Environment	City size, Neighbourhood density, Centre vs. Rural	3
Psycho-Attitudinal Influences		
Attitude	Ride-sharing (strangers, family/friends), Safety concerns/Trust, Time sensitivity, Attitude towards public transport, Attitude towards SAV, Technology interest, Enjoyment driving, Environmental attitude, Privacy concern, Social influence	11

3.3.1. User-Centric Factors of SAV Adoption

Research has extensively examined the influence of socio-demographic variables on SAV adoption. Studies reveal several key patterns across variables.

Gender has been a topic of interest in many studies, with mixed results. Nearly half of the studies (45.45%) find that men are more inclined to use SAVs [12,45,88,89], while a similar proportion (47.47%) finds no significant effect of gender on SAV adoption [50,90,91]. These contradictory findings likely reflect methodological variations: early SAV trials predominantly sampled male early adopters, potentially skewing results toward male preferences. Additionally, studies that found no gender effect often focused on high-income urban areas where both genders prioritize convenience over cost concerns. Only a small percentage of studies (7%) report a more positive attitude towards SAVs among females [24,60,92], suggesting the need for more diverse sampling across socioeconomic strata and geographical contexts to clarify these gender dynamics.

Age influences adoption, with two-thirds of studies finding that younger people have higher intention to use SAVs [48,93–95]. However, some studies found no significant effect of age on the willingness to use SAVs. Interestingly, Piatkowski [96] highlights that the

willingness to substitute travel by foot for travel by autonomous shuttle increases with age, possibly due to the perceived inconvenience of walking for older individuals.

Education level shows divided results, with nearly half reporting more positive attitudes among higher-educated individuals [55,91,97]. For example, Alhajyaseen et al. (2021) [98] found that university students in Qatar were more likely to adopt SAVs compared to other population segments. The remaining studies found no significant effect of education on SAV adoption [95].

Income is also a significant predictor of SAV use, with studies showing that high-income individuals view SAVs more positively (income classifications varied across studies due to different economic contexts and measurement approaches). However, Gkatzorikas et al. [99] found that people with incomes higher than USD 100,000 seem to be indifferent towards using SAV ride-hailing services (with or without ride-sharing options) compared to their lower-earning counterparts, regardless of the travel scenario.

Findings regarding household size are mixed, with around 51% of studies reporting no significant effect [17,49,100], while the remaining studies are evenly split between those reporting that people with smaller household sizes are more likely to adopt SAVs [47,101,102] and those reporting that people with larger families and children are more likely to do so [103–105].

Other variables, such as employment status [49,93,100], disability/impairment [106–108], and level of physical activity [55,107,108], have been studied, but most studies found no significant effects or trends.

In summary, the profile of individuals most likely to adopt and use SAVs appears to be males with high income and high education levels [62,109,110]. However, the effect of these socio-demographic variables is often moderated by other factors, and their influence may vary depending on the specific context and study design.

Current travel habits and mobility needs emerge as stronger predictors than socio-demographic factors [111]. Public transport users, in particular, have shown a greater interest in adopting SAVs compared to other groups [11,49,92,112]. Irannezhad and Mahadevan [61] found that frequent public transit users in Australia were more likely to choose SAVs over private vehicles. This finding is consistent across multiple studies, suggesting that individuals who are already accustomed to shared mobility services are more likely to view SAVs favorably. However, the results for private vehicle users are mixed. While approximately one-third of the studies find that using a conventional car has no significant impact on the willingness to use SAVs, the remaining studies are evenly split between those reporting a positive influence [87,101,113] and those reporting a negative impact [12,97,114]. Similarly, for active transportation users, such as cyclists and pedestrians, around half of the studies do not find any significant relationship with SAV adoption, while the other half is divided between positive [55,104,112] and negative [45,106,115] influences.

Trip purpose influences adoption, with commuting and business trips favored over leisure trips [86,87,116]. This preference may be attributed to the fact that those with longer commutes tend to favor SAVs, as they appreciate the ability to use their time effectively for other tasks during the journey [111]. On the other hand, those who need to carry items are less likely to use SAVs [117], possibly due to concerns about storage space or convenience, as demonstrated by Frei et al. [118] in their study of SAV adoption in the Chicago region.

Vehicle ownership and driver's licenses generally show a negative correlation with SAV interest [93,98,100,119]. Zhou et al. [46] found that households with a higher number of licensed drivers in Australia were less likely to adopt SAVs. The effect of vehicle ownership on willingness to use SAVs is predominantly negative, with 25 studies finding a negative impact and 19 studies reporting no significant effect. Only one study found a positive relationship between vehicle ownership and SAV adoption [116]. In addition, individuals

who rarely use their private cars or have a lower yearly mileage are more likely to use SAVs [86,87,120], as shown by Yao et al. [105] in their study of SAV adoption in China. Moreover, two studies found that people with a car crash history are more willing to use SAVs, while three other studies did not find any significant effect of car crash history on SAV adoption [60,121,122].

Besides vehicle ownership, eleven studies researched the effect of owning a public transport card on SAV uptake. Eight of these 11 studies found no significant effect, while three reported a positive influence [104,118,120]. On the contrary, Yap et al. [112] highlight that first-class train travelers in the Netherlands are inclined to use SAVs for their access/egress, as they are not satisfied with their current access/egress in multimodal trips and believe that SAVs sufficiently fulfill their mobility needs.

Familiarity with AVs or SAVs is another major factor influencing adoption. Of the 33 articles that analyzed this aspect, 25 studies found that previous experience or familiarity with AVs or SAVs positively influences the choice to use them in the future, while seven studies found no significant effect. Bansal et al. [47] demonstrated that individuals in Austin, Texas, who were more familiar with AV technology had a higher willingness to pay for SAVs. Booth et al. [45] highlighted that the lack of familiarity, awareness of the service's features, and information on how to use it could be barriers to adoption. Notably, prior knowledge and experience with shared mobility services can increase the desire to use SAVs, as highlighted by all three studies that examined this aspect [24,108,123].

The early adopters of SAVs are likely to be current public transit users and individuals familiar with shared mobility services and autonomous vehicle technology [11,49,89,92], those with longer commutes or who travel for business purposes [111,116], individuals who do not own many private vehicles, do not have driver's licenses, or have a low yearly mileage [86,93,98,120]. First-class train travelers dissatisfied with access/egress options may also be attracted to SAV services [112].

3.3.2. Contextual Factors of SAV Adoption

Operational travel factors significantly shape SAV adoption decisions [12,47]. Cordera et al. [113] found that trip purpose and travel time significantly influenced the choice between SAVs and private vehicles in the Cantabria region in Northern Spain. This subcategory of studies investigates variables related to time, cost, and accessibility. A number of studies confirm that affordable and faster connections with better accessibility are strongly related to SAV usage [12,62,123,124].

Travel cost and time are the most studied variables (82% and 93% of studies, respectively), with all relevant studies showing decreased adoption likelihood with higher costs or longer times [17,49,97,125]. For example, Yao et al. [126] demonstrated that lower fares and shorter travel times increased the likelihood of choosing SAVs over traditional taxis in China. Travel time, which is sometimes further broken down into access/egress time, waiting time, congestion time, and in-vehicle time, is also a significant factor. Numerous studies confirm that faster connections are strongly related to SAV usage [54,90,127,128]. Time outside the vehicle is perceived more negatively than in-vehicle time [129–131], with studies showing higher willingness-to-pay for reducing waiting time versus in-vehicle time [52].

Accessibility improvements lead to higher SAV usage, particularly for multimodal commutes, with 24 out of 28 studies showing a positive influence [17,87,124,125]. Cai et al. [92] showed that the introduction of SAVs for first- and last-mile connections to public transport in Singapore would increase the use of public transport by up to 57%. A study conducted in Malaysia by Susilawati and Lim [94] further confirms the importance of accessibility factors like walking time in influencing SAV adoption. They found that intro-

ducing just a 2-min walking time to access an SAV reduced adoption by a substantial 50%, highlighting how sensitive travelers are to first- and last-mile inconveniences and the big potential for SAVs by providing seamless door-to-door mobility. Reliability, analyzed in settings with trip delays and detours in pooled robo-taxis, showed a negative influence on the willingness to use SAVs in four studies [88,132–134], while three others found no significance [51,52,109].

Travel distance yielded contradictory results. Out of fifteen studies, seven found that SAVs are preferred for long-distance travel [113,117,135], while seven others indicated a preference for shorter trips [106,109,121]. A study in Israel argued that travel distance alone has no significant effect on the willingness to use SAVs, differentiating between commutes over and under 20 km [136]. In contrast, Gurumurthy and Kockelman [48] investigate the impact of trip distance on willingness to use SAVs. Their findings suggest that SAV use will be particularly popular for long-distance business travel. The study revealed that Americans expect a significant portion of their long-distance travel to shift toward AVs and SAVs. Nearly 50% of trips between 50 and 500 miles are expected to eventually take place in an AV or SAV. Furthermore, the survey results indicate that some business travel under 500 miles is also likely to be completed using SAVs.

Weather effects vary, with some studies showing reduced attraction in bad weather, while Thorhauge et al. [115] found increased demand for AV shuttles in rain.

Parking-related variables were also included in SAV studies. Higher parking time due to scarcity or longer distances was investigated five times, with a clear trend indicating that higher parking time increases the willingness to use SAVs. Similarly, higher parking costs increase the interest in using SAVs, especially for commutes. Huo et al. [121] showed that parking costs significantly influence the decision to use SAV services in the future, even at different price points. They also found that individuals who pay parking fees at their workplace tend to use SAVs more frequently and are more likely to be among the early adopters of this technology.

The built environment, including factors such as density and walkability of urban development, has been extensively documented as a significant influence on transportation mode choice [104,106]. For instance, a study by Barbour et al. [109] found that individuals living in denser, more walkable areas were more likely to adopt SAVs, possibly due to the shorter distances and reduced need for private vehicle ownership in these environments. However, previous studies have yielded mixed results due to variations in geographical scales, residential self-selection, empirical contexts, and methodological approaches [118,128]. Despite the substantial body of research on this topic, the specific effect of the built environment on SAV adoption remains largely unexplored.

A study involving 1922 residents from small and medium-sized metropolitan areas in the United States revealed that individuals residing in regional and remote areas are less likely to adopt SAVs [103]. Considering the high population density in city centers, other studies corroborate this finding, indicating that population and residential land density positively impact potential SAV ridership [11,19,101]. While some researchers suggest that suburban areas could potentially have a positive impact on SAV adoption, particularly at greater distances from city centers [106,120], Zhong et al. [102] found that individuals living in suburban areas of the United States enjoy a larger reduction in the value of travel time compared to those living in urban centers. As SAVs facilitate private motorized mobility, their widespread adoption may increase the accessibility of locations and potentially contribute to urban sprawl and suburbanization by influencing the location choices of households and firms [97]. These two competing forces, urban densification and sprawl, present a complex dynamic for SAV adoption.

SAV-specific features significantly influence adoption rates. Of 22 studies examining comfort features and vehicle design [130], 19 show a positive impact on adoption willingness. Hao et al. [114] found varying interest in additional services, from 39% for device charging to 83% for short waiting times, with willingness-to-pay ranging from USD 0.22 for child tracking to USD 0.45 for longer boarding times. Three studies focused specifically on seating in SAVs, with one finding that seating has no significant effect [24]. Nickkar et al. [137] found that individuals would be willing to pay a premium for a pre-designated seat, while Etzioni et al. [136] discovered that many individuals, especially wealthier ones accustomed to traveling by car, do not favor seating in the middle between two strangers. The possibility for multitasking was examined in 12 studies, with eight finding a positive influence and four detecting no impact. Gao et al. [131] highlight that these results may reflect a lack of familiarity and comfort with driverless technology at present.

Twelve studies examined the effects of safety drivers/chauffeurs and monitoring methods on user acceptance of SAVs. Two-thirds of these studies report a positive effect of safety drivers/chauffeurs on user acceptance. For example, Sheldon and Dua [132] found that the presence of a safety driver increased the willingness to use SAVs among participants in the USA. The presence of a chauffeur monitoring the movements showed higher intentional usage, indicating that trust is higher when a person is present. However, three fail to detect any significant impact, suggesting that the presence of a human driver may not always be a universal solution for user concerns [24,55,96].

Furthermore, two studies reported that the possibility of segregated AV lanes is a successful way to increase SAV use by lowering travel time and increasing reliability [68,138], while one found no significance. A study by Guo et al. [138] in Stockholm, Sweden showed that preferential lanes increased the likelihood of using AV buses by reducing travel time and improving the service level. Nickkar et al. [137] provided the add-on of trip delay insurance in their survey, which might be a way to attract more people to adopt SAVs. Two other studies reported that liability issues significantly influence user preferences, with users generally having negative perceptions toward assuming higher personal liability in the event of crashes involving autonomous vehicles and preferring models where manufacturers or service providers bear a significant portion of the liability [60,139].

3.3.3. Psycho-Attitudinal Factors and SAV Acceptability

Psycho-attitudinal factors are fundamental determinants of SAV acceptability, reflecting both individual attitudes and broader social considerations that influence the willingness to adopt this new technology. These factors not only affect immediate adoption decisions but also shape long-term public acceptance of SAVs as a mainstream transportation option [140].

Safety and Security Acceptance

Trust in technology is a key factor influencing SAV adoption, as fully automated AVs have yet to achieve mass adoption [25]. This topic has been analyzed by 27 studies from two different angles that come to similar conclusions. Ten studies found that trust in SAVs has a positive impact on willingness to ride [11,141,142], while 13 studies highlighted that safety concerns have a negative impact on willingness to use SAVs [135,143]. Only four studies did not find any effect [91,130,144]. Kolarova and Cherchi [23] revealed that in Germany, individuals with greater trust in autonomous vehicles were not only more inclined to adopt SAVs but also placed a higher value on travel time, perceiving SAV services as safer and more reliable options. In a similar vein, Bakioglu et al. [60] found that safety concerns were a significant barrier to SAV adoption in Istanbul, Turkey, with individuals expressing hesitation about entrusting their lives to a fully autonomous vehicle.

This suggests that safety perceptions could significantly influence both mode choice and travel time utilization.

Privacy concerns have also been examined, with nine out of ten studies finding a negative impact [47,53,92,145] and one study finding no impact [48]. Fu et al. [91] conducted a survey of college students at the University of Alabama in the United States to investigate their perceptions of SAVs. The study revealed that privacy concerns are a significant barrier to SAV adoption, as respondents expressed apprehension about SAV service operators accessing their daily travel behaviors, which could lead to the collection and utilization of personal travel data.

Social Acceptance

Social influence and social norms significantly shape attitudes towards SAVs. Several studies have shown that these factors can have both positive [47,50,99,146] and negative [51,85] effects on travel mode choice. Ding et al. [50] found that high market penetration positively influenced the adoption of autonomous vehicles in China, with the degree of influence varying based on individual susceptibility levels. Younger, more educated, higher-income, and more experienced drivers were more readily influenced by their peers when it came to SAV adoption. However, Li et al. [51] found that the perceived convenience of public transit, shaped by social norms and public opinion, decreased the likelihood of choosing shared autonomous vehicles for commuting in China, especially among older, lower-income, and less educated individuals.

Pro-environmental attitudes have been studied in 13 articles, with mixed results. Only seven studies found that environmental motives have a significant positive impact on explaining SAV riding intention, while six studies did not find evidence that environmental motives explain SAV willingness [101,122,129,147]. Nazari et al. [87] found that individuals with strong pro-environmental attitudes were more likely to adopt SAVs in the State of Washington, USA, as they perceived these services as a more sustainable alternative to private vehicle ownership. One study by Asgari et al. [117] found that environmental motives might play a role in intention to use SAVs but do not fully translate into actual behavior. The study showed that although individuals perceive SAVs as environmentally beneficial, their actual usage is more strongly driven by factors like cost, convenience, and reliability rather than environmental considerations.

The role of attitudes towards ride-sharing has been extensively studied, often using structural equation modeling. These studies have found that ride-sharing with strangers or high occupancy decreases the willingness to use SAVs, although individuals are more open to sharing their ride for commuting purposes [124,127,133]. Lavieri and Bhat [22] investigated individuals' willingness to share trips with strangers in SAVs. Their results indicated that individuals were generally uncomfortable with sharing rides with strangers. However, the study also found that people were more open to sharing rides for their commute trips than for leisure trips. Specifically, the results showed that, on average, people were willing to pay around 50 cents more to avoid having an additional passenger on a commute trip, but this amount increased to approximately 90 cents for a leisure trip, suggesting a significantly lower tolerance for ride-sharing in non-work settings. Similarly, riding with family and friends decreases the willingness to use SAVs, albeit not as negatively as riding with strangers [114,130,145]. Contrary to expectations, Guo et al. [138] found in their stated-choice experiment that passengers traveling with companions actually exhibited a higher likelihood of opting for automated buses over conventional ones. The authors speculated that this preference could stem from solo travelers feeling a greater sense of familiarity and ease with conventional bus services compared to the novelty and potential uncertainties associated with automated buses when riding alone.

Technology Acceptance

Technology interest emerges as one of the most significant predictors of SAV adoption. Out of the 24 studies that examined this factor, 22 found that technology-interested respondents are more open to using SAVs, while only three studies did not find any impact [24,144,148]. For example, Carteni's [53] study involving 3140 respondents in Naples, Italy, demonstrated that individuals with a higher interest in technology were more inclined to choose SAVs, estimating a positive willingness to pay for driverless vehicles (+1.21 Euro per trip) among those who commonly utilize on-board automation features. Current shortcomings in autonomous driving technology, such as limitations in complex traffic situations and adverse weather conditions [149], could influence how and when people choose to use SAVs for their trips. Milakis et al. [149] suggest that as these technical challenges are gradually resolved, user acceptance and travel behavior patterns may evolve.

A positive attitude towards SAVs strongly predicts willingness to use such services. This relationship has been demonstrated in 33 studies that found a positive significance, while only seven studies found no significant effect [44,45,105,126,133,147]. Kang et al. [62] found that individuals with favorable perceptions of shared mobility services were more likely to use SAVs in Austin, Texas. A positive attitude towards public transport has also been shown to have a strong positive impact on the choice to use SAVs, as highlighted in all five studies that investigated this variable [55,61,111]. In stark contrast, individuals who enjoy driving rather than simply seeing it as a means of mobility are strongly opposed to SAVs, as demonstrated in all five studies that examined this factor [101,103,150]. Ashkrof et al. [150] found that individuals who derived pleasure from driving were less likely to adopt SAVs in the Netherlands, as they perceived these services as a threat to their driving enjoyment.

Personal preferences regarding reliability and waiting tolerance have been investigated in 13 studies. The results show that car users have a lower tolerance for waiting and expect higher reliability than public transport users [117,146,148]. Zhou et al. [86] explored how time-sensitivity and convenience affect users' choices in SAV trip chains in Beijing, China. The authors examined users' decisions to either pay and keep the same SAV or call a new SAV after short stops. The study found that time-sensitive and convenience-oriented users are more likely to choose to pay and keep the same SAV, valuing a seamless travel experience and avoiding multiple wait times, despite the extra cost.

The determinants of SAV acceptance operate through multiple, interconnected mechanisms. While safety and privacy concerns present adoption barriers, positive technology attitudes and supportive social environments facilitate acceptance. These findings suggest that successful SAV implementation requires addressing both technical capabilities and user perceptions across different demographic segments.

The factors affecting SAV adoption require systematic examination to advance sustainable autonomous mobility. While socio-demographic characteristics (age, income, education) provide baseline understanding, behavioral variables including travel patterns, trip purposes, and built environment parameters, combined with attitudinal factors such as perceived reliability and technology acceptance, demonstrate stronger associations with adoption likelihood. These findings indicate that policy interventions should focus on promoting shared mobility services, establishing technical performance standards, and developing evidence-based public engagement strategies. Addressing equity considerations and data privacy protocols remains fundamental for establishing SAVs as a sustainable and inclusive transportation alternative.

3.4. Use of Travel Time and Value of Time

SAVs are projected to transform in-vehicle VOT by eliminating driving responsibilities, enabling occupants to engage in alternative activities during travel. While Harb et al. [151] suggest significant benefits from this multitasking capability, some researchers express reservations about its universal appeal.

Singleton [152] identified only moderate increases in travel utility in AV scenarios. This skepticism aligns with Sivak and Schoettle's [73] findings, which highlight the potentially modest impact of AVs on travel behavior, challenging assumptions of widespread appeal for productive use of travel time.

Empirical research into the types of activities passengers might undertake in SAVs reveals a range of preferences that diverge from the productivity narrative. A survey by Schoettle and Sivak [153] across the U.S., U.K., and Australia found that only 5% of respondents would use the extra time for productive tasks, while 41% would continue watching the road, and 30% would engage in passive activities like reading, sleeping, or texting. Similarly, Bansal and Kockelman [4] reported that the majority of surveyed Texans anticipated engaging in social interaction or simply looking out the window, with a mere 17.4% considering work-related activities.

While engaging in tasks while traveling has a notable yet modest impact on mode choice, the potential for reduced VOT in the context of AV adoption has garnered significant attention. Numerous studies have explored the impact of multitasking capabilities on travel preferences towards SAVs [52,54,62,90,99,100,118,123,128]. Comparative analysis highlights the variability in VOT based on factors such as vehicle interior design [130], income level [127,136], and educational background [23], as detailed in Appendix F.

For instance, Gao et al. [131] found that the perceived value of time in a driverless SAV was 15% higher compared to driving a personal car, attributing this discrepancy to the novelty and unfamiliarity of autonomous technology. Kolarova and Cherchi's [23] research further emphasizes how psychological factors, such as trust in AV technology and positive travel experiences, affect travel time valuation, directly influencing mode choices for such vehicles. Moreover, Correia et al. [130] noted a difference in willingness to pay for travel time reductions between AV travelers who could work (EUR 5.50 per hour) versus those engaged in leisure activities (EUR 8.17 per hour), underscoring the contextual nature of VOT and its dependence on the availability and type of in-vehicle activities. Lavieri and Bhat's [22] research suggests that potential productive time use may mitigate barriers to SAV adoption, particularly among high-income individuals. Similarly, Paddeu's [24] experiment shows that brief SAV exposure can positively influence mode choice preferences.

These varying perspectives on travel time use and valuation have direct sustainability implications: the ability to use travel time productively in SAVs will likely increase their attractiveness as a single-occupancy mode, potentially leading to more vehicle miles traveled and working against sustainable mobility goals.

4. Future Research Directions

Table 4 synthesizes the current evidence and identifies key research gaps across three main aspects of SAV travel behavior: total travel demand, mode choice, and travel time use. Building on this synthesis, the following sections discuss specific research needs in detail.

Table 4. Synthesis of evidence and research needs for SAV travel behavior impacts.

Travel Behavior Aspect	Current Evidence	Research Gaps and Future Research
Total Travel Demand	• VMT increases vary (2–125%) depending on scenario • Key factors: empty repositioning, induced demand, residential relocation • Mitigation through ride-sharing shows promise (up to 19% reduction)	• Need for real-world data and pilot studies • Assessment of long-term effects on travel patterns • Evaluation of effectiveness of mitigation strategies • Research on environmental impacts across contexts
Mode Choice	• Younger, educated, higher-income more likely to adopt • Public transport users show greater interest • Vehicle ownership negatively affects adoption • Travel cost and time are key determinants	• Understanding mode substitution through real-world studies • Impact on public transit integration • Cross-cultural and rural-urban comparative studies • Assessment of equity impacts and behavioral factors
Travel Time Use	• Limited interest in productive activities (5%) • Majority prefer passive activities • VOT varies strongly by country and trip purpose (USD 11.77–30.58/h) • Income level influences acceptance	• Real-world usage pattern studies • Vehicle design impact research • Cross-cultural and longitudinal studies • Investigation of actual vs. projected behavior

4.1. Mode Substitution Dynamics and Travel Behavior

Future research should examine substitution patterns between SAVs and other transport modes by using integrated approaches that combine stated preference surveys with granular traffic simulations (e.g., MATSim, POLARIS). Studies should identify contextual thresholds (e.g., trip distance, cost, service availability) that determine whether SAVs replace private cars or complement public transit, as this has critical implications for achieving sustainable mobility goals. Priority areas include designing multimodal incentives (e.g., subsidized first/last-mile SAV connections) and assessing active travel trade-offs through cycling/pedestrian trajectory analysis in cities with high walking/cycling rates, as these modes are essential for low-carbon urban transport [55,120].

4.2. Geographical, Cultural, and Social Considerations

Research must expand beyond current geographical limitations by using standardized survey instruments (e.g., Unified Theory of Acceptance and Use of Technology Models) to conduct cross-cultural comparisons between tech-centric megacities and informal transit-dependent communities, ensuring equitable and sustainable mobility solutions across different contexts. Studies should develop rural-specific SAV frameworks that prioritize healthcare access and school commutes, while maintaining environmental considerations. Longitudinal studies leveraging partnerships with ride-hailing platforms are needed to track how perceptions and behaviors evolve across diverse geographic and cultural contexts, particularly regarding sustainable travel choices [154–157].

4.3. Overcoming the Intention–Behavior Gap Through Data Collection

To bridge the intention-behavior gap, researchers should analyze usage patterns from operational SAV pilots (e.g., Waymo’s Phoenix deployments) to compare hypothetical versus actual adoption rates [24,123]. Studies should evaluate various interventions, including dynamic pricing schemes, SAV-transit bundling programs, and parking policy reforms, all of which could significantly impact transportation sustainability. This includes examining the impact of “parking cash-out” programs and integration with existing transit systems through subscription packages similar to Helsinki’s Whim app, which promote more sustainable mobility patterns [158].

5. Conclusions

This systematic review of 107 articles presents the first comprehensive classification of SAV impacts on travel behavior, systematically categorizing 59 adoption factors and examining how SAVs could contribute to sustainable mobility. While our review included both English and Chinese language databases, the findings highlight the need for more comprehensive research on sustainable implementation across diverse contexts, particularly in emerging markets, where SAV pilots are rapidly expanding.

The analysis reveals that SAVs could either support or hinder sustainability goals: while they could increase vehicle miles traveled through empty repositioning trips and induced demand, they also offer opportunities for emissions reduction through electrification and improved system efficiency. Users’ strong preferences for private space and varying willingness-to-pay suggest the need for carefully designed incentives to promote shared rides and sustainable travel choices.

The findings indicate that effective SAV implementation requires systematic policy frameworks to ensure alignment with sustainability goals. Transportation authorities should implement demand management policies through congestion pricing mechanisms and shared-ride incentive structures. These measures must be integrated with public transportation investments to establish efficient low-carbon multimodal networks.

This study faced certain limitations. The scope restriction to peer-reviewed publications may have excluded relevant industry and government findings. The focus on three specific behavioral dimensions necessarily limited coverage of other important aspects. Additionally, rapid technological advancement suggests the need for continuous updates to these findings. Future research should address equity considerations and environmental impacts more comprehensively.

Land-use policies require modification to support sustainable mobility patterns, particularly regarding parking provision standards and transit-oriented development. The potential for optimized routing, reduced traffic congestion, and electric SAV fleets could contribute significantly to greenhouse gas emissions reduction and improved air quality, provided appropriate policy frameworks are in place.

Urban planners and policymakers should develop coordinated transportation-land use strategies that prioritize sustainability through dynamic pricing mechanisms reflecting environmental costs. Such strategies must ensure SAVs complement rather than compete with public transit and active travel modes while promoting equitable access across demographic groups.

Through evidence-based policy development and systematic implementation protocols, municipalities can leverage SAV technology to advance transportation sustainability while ensuring social equity and system efficiency.

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

Appendix A. Studies Included in the Systematic Literature Review

No.	References	City	Country	Sample Details	Robo-Taxi	Pooled Robo-Taxi	AV-Shuttle (PAX)	AV-Bus (PAX)	SAV (n.s.)
1	Aasvik et al., 2024 [95]	Oslo	Norway						•
2	Abe et al., 2020 [143]	-	Japan	2000					
3	Abe, 2021 [106]	Tokyo	Japan	1800					•
4	Alhajyaseen et al., 2021 [98]	-	Qatar	315	•				
5	Andrei et al., 2022 [100]	-	Romania	309	•				
6	Asgari et al., 2018 [117]	-	USA	878					•
7	Ashkrof et al., 2019 [150]	-	The Netherlands	663	•				
8	Asmussen et al., 2020 [148]	Austin, Texas	USA	1127					•
9	Bakioglu et al., 2022 [60]	Istanbul	Turkey	323	•	•			
10	Bansal and Daziano, 2018 [129]	New York City	USA	298	•	•			
11	Bansal et al., 2016 [47]	Austin, Texas	USA	510					•
12	Barbour et al., 2019 [109]	-	USA	782					•
13	Booth et al., 2019 [45]	Perth	Australia	1621					•
14	Cai et al., 2019 [92]	-	Singapore	927	•	•			
15	Carrese et al., 2019 [68]	Rome	Italy	201					•
16	Carteni, 2020 [53]	Naples	Italy	3140	•				
17	Cordera et al., 2022 [113]	Cantabria	Spain	296	•				
18	Correia et al., 2019 [130]	-	The Netherlands	252	•				
19	Ding et al., 2022 [50]	-	China	1132					•
20	Etminani-Ghasrodashti et al., 2023 [134]	Arlington, Texas	USA						•
21	Etzioni et al., 2020 [90]	-	Cyprus, UK, Slovenia, Montenegro, Hungary, Iceland	1669	•	•			
22	Etzioni et al., 2021 [136]	-	Israel	713	•	•			

No.	References	City	Country	Sample Details	Robo-Taxi	Pooled Robo-Taxi	AV-Shuttle (PAX)	AV-Bus (PAX)	SAV (n.s.)
23	Farmer et al., 2024 [144]	Chungju	Republic of Korea						•
24	Frei et al., 2017 [118]	Chicago	USA	103	•				
25	Fu et al., 2022 [91]	University of Alabama	USA	424					•
26	Gao et al., 2019 [131]	-	USA	502	•				
27	Gkartzonikas et al., 2022 [99]	Chicago	USA	400	•	•			
28	Guo et al., 2021 [131]	Stockholm	Sweden	568				•	
29	Gurumurthy and Kockelman, 2020 [48]	-	USA	2588	•	•			
30	Haboucha et al., 2017 [111]	-	Israel	721	•				
31	Hao and Yamamoto, 2017 [19]	Nagoya	Japan	4294					•
32	Hao et al., 2019 [114]	Nagoya	Japan	136					•
33	Huo et al., 2021 [121]	-	China	964	•				
34	Irannezhad and Mahadevan, 2022 [61]	-	Australia	777	•	•			
35	Jabbari et al., 2022 [93]	-	USA	757	•				
36	Kang et al., 2021 [62]	Austin, Texas	USA	953	•	•			
37	Kashani et al., 2023 [145]	-	Iran			•			
38	Kim2019 [85]	Georgia	USA	2890	•				
39	Kolarova and Cherchi, 2021 [23]	-	Germany	484					•
40	Kolarova et al., 2018 [54]	-	Germany	485	•	•			
41	Kolarova, 2019 [127]	-	Germany	511	•				
42	König and Grippenkov, 2020 [88]	-	Germany	150	•	•			
43	Kontar et al., 2021 [120]	Madison, Wisconsin	USA	805	•				
44	Krueger et al., 2016 [12]	-	Australia	435	•	•			
45	Krueger et al., 2019 [97]	Sydney	Australia	512	•				
46	Lavieri and Bhat, 2019 [22]	Dallas-Fort Worth Arlington, Texas	USA	1607	•	•			
47	Li et al., 2023 [51]	Shanghai	China	627				• (8–12)	
48	Liao et al., 2023 [142]	Chengdu	China						•
49	Maeng and Cho, 2022 [139]	-	Republic of Korea	1000					•
50	Nair et al., 2018 [49]	Puget Sound region	USA	4786	•				

No.	References	City	Country	Sample Details	Robo-Taxi	Pooled Robo-Taxi	AV-Shuttle (PAX)	AV-Bus (PAX)	SAV (n.s.)
51	Nazari et al., 2018 [87]	Puget Sound region	USA	4481	•				
52	Nickkar et al., 2023 [137]	-	USA	216	•	•			
53	Paddeu et al., 2021 [24]	Bristol	UK	123	•	•		• (15)	
54	Pakusch et al., 2018 [11]	-	Germany	302	•				
55	Patel et al., 2023 [146]	Arlington, Texas	USA						•
56	Piatkowski, 2021 [96]	Lincoln, Nebraska.	USA	551			•		
57	Saeed et al., 2020 [103]	-	USA	1922	•	•			
58	Sheldon and Dua, 2024 [132]	-	USA	750	•				
59	Si et al., 2024 [147]	-	China						•
60	Steck et al., 2018 [128]	-	Germany	485	•	•			
61	Stoiber et al., 2019 [124]	-	Switzerland	709	•	•	• (4)		
62	Susilawati and Lim, 2021 [94]	Kuala Lumpur	Malaysia	161					•
63	Sweet, 2021 [104]	Toronto and Hamilton, Southern Ontario	Canada	1684	•		•		
64	Sweet, 2021 [104]	Kopenhagen	Denmark	249			• (12)		
65	Thaithatkul et al., 2024 [89]	Bangkok	Thailand		•	•			
66	Tian et al., 2021 [17]	Dalian	China	708	•				
67	Triantafillidi et al., 2023 [125]	Athens	Greece						•
68	Wang and Zhao, 2019 [141]	-	Singapore	1142					•
69	Wang et al., 2021 [116]	Greater Toronto Area	Canada	190	•				
70	Wang et al., 2021 [116]	Lahore and Dalian	Pakistan and China	910	•				
71	Webb et al., 2019 [101]	Brisbane, Queensland	Australia	447	•				
72	Weiss et al., 2019 [133]	Greater Toronto Area	Canada	217	•				
73	Weschke et al., 2021 [123]	Braunschweig and Berlin	Germany	98				•	
74	Wicki et al., 2019 [108]	Schaffhausen	Switzerland	773				• (11)	
75	Winter et al., 2019 [135]	-	The Netherlands	282				•	

No.	References	City	Country	Sample Details	Robo-Taxi	Pooled Robo-Taxi	AV-Shuttle (PAX)	AV-Bus (PAX)	SAV (n.s.)
76	Winter et al., 2020 [55]	-	The Netherlands	796	•				
77	Yan et al., 2024 [44]	-	China						•
78	Yao et al., 2021 [105]	-	China	459	•				
79	Yao et al., 2022 [126]	-	China	311	•				
80	Yap et al., 2016 [112]	-	The Netherlands	1053					•
81	Yin and Cherchi, 2024 [52]	-	China	450	•				
82	Yu et al., 2023 [122]	Nanjing	China						•
83	Zhong et al., 2020 [102]	-	USA	1881					•
84	Zhou et al., 2020 [46]	Beijing	China	566					•
85	Zhou et al., 2023 [86]	-	Australia	1433	•	•			

Appendix B. Changes in Travel Demand

Reference	City	Country	Change of Travel Demand	Reason
Alam et al., 2018 [63]	Halifax	Canada	15–20% of trips served by SAVs with a corresponding 1.73–14% increase in VKT	Relocation of a shared vehicle to the next client leads to empty vehicle miles
Brown et al., 2014 [74]	-	USA	50% increase in VMT among individuals aged 16–85 years	New demand from underserved populations including youth, disabled, and elderly
Carrese et al., 2019 [68]	Rome	Italy	VKT could decrease by 19% or increase by 13% due to SAV	Due to suburban relocation
Chen et al., 2016 [75]	Austin, Texas	USA	7–9.4% increase in VMT due to SAV charging and traveler pickup	Empty vehicle miles due to charging and traveler pick-up
Childress et al., 2015 [69]	Puget Sound region	USA	VMT could decrease by 35% or increase by 19.6% with automated vehicles	Improved traffic flow, reduced travel times, and decreased parking costs
Fagnant et al., 2015 [5]	Austin, Texas	USA	2–9% increase in VMT	Empty vehicle miles
Fagnant et al., 2014 [21]	Austin, Texas	USA	Up to 11% increase in VMT	Relocation results in empty vehicle miles
Gelauff et al., 2019 [67]	-	The Netherlands	5–25% increase in VKT	Due to suburban relocation
Harb et al., 2018 [76]	San Francisco Bay Area	USA	VMT increases ranging from 4–341%	New demand from specific groups (elderly, drunk) leads to more trips
Harper et al., 2016 [77]	-	USA	2–14% increase in VMT among those aged 19 years and above	New demand from underserved populations aged 19 years and above
Hörl et al., 2017 [78]	-	Switzerland	28.01% and 30.57% of VKT are empty in Taxi and Taxi Pool with 1000 SAVs	Empty VKT in Taxi and Taxi Pool within a fleet of 1000 SAVs
Levin et al., 2017 [65]	City center Austin, Texas	USA	Up to 125% increase in VMT, dependent on fleet size	Empty vehicle miles due to repositioning dependent on fleet size
Loeb et al., 2019 [72]	Austin, Texas	USA	6.7–19.54% increase in empty VMT per SAV	Empty vehicle miles resulting from SAV relocation and charging

Reference	City	Country	Change of Travel Demand	Reason
Loeb et al., 2018 [71]	Austin, Texas 6-county region	USA	9.6–31.5% increase in vacant VMT with SAV	SAEV generates more vacant VMT due to relocation and charging
Ma et al., 2017 [70]	New York City	USA	2–14% increase in daily travel VMT	Empty vehicle miles due to relocation of sharing vehicles, compensated by reduced AV fleet size and optimized AV trip chains
Oh et al., 2020 [79]	Singapore	Singapore	11–42% increase in VKT in different adoption scenarios, with a decrease of 8.8–20.2% in private car VKT	Empty vehicle miles under different pricing scenarios, with decreases in private car VKT
Pudane et al., 2018 [66]	-	The Netherlands	Increases in VMT	Reduced stress and fatigue, increased comfort, and ability to engage in non-driving activities
Schoettle et al., 2015 [73]	-	USA	75% increase in annual VMT	Reductions in household vehicle ownership
Wadud et al., 2016 [80]	-	USA	60% increase in overall VMT and 2–10% additional increase from new travelers	Reduction of travel cost and new demand from additional user groups (e.g., older people)
Zhang et al., 2017 [64]	Atlanta, Georgia	USA	5–14% increase in VMT	Empty vehicle miles due to relocation and parking
Zhang et al., 2018 [81]	Atlanta Metropolitan Area	USA	3.3% increase in VMT	Relocation of a shared vehicle to the next client leads to empty vehicle miles
Zhang et al., 2015 [82]	Atlanta, Georgia	USA	Up to 62.6% increase in daily VMT	Empty vehicle miles from cruising to avoid parking costs

Appendix C. User-Centric Factors of SAV Adoption

Categories		User-Centric Factors																						
Sub-Categories		Sociodemographic										Current Travel Habits and Mobility Needs												
No.	References/Factors	Age (Young)	Gender (Male)	Education (High)	Income (High)	Household (Children)	Employment (Yes)	Disability/Impairment	Level of Physical Activity	Driver's License (Yes)	Vehicle Ownership (Yes)	Transport Mode (Private Vehicle)	Transport Mode (Public Transport)	Transport Mode (Active Transport)	PT Card Owner	Car Crash History	Familiarity Ride-Sharing	Familiarity AV/SAV	Trip Purpose (Commute)	Trip Purpose (Leisure)	Commute Time	First Class Train Travel	Need to Carry Items	Yearly Mileage/Usage Freq. (High)
1	Aasvik et al., 2024 [95]	•	•	•	•							•						•						
2	Abe et al., 2020 [143]	•	•		•							•	•	•				•	•	•				
3	Abe, 2021 [106]	•	•		•	•	•	•		•		•	•	•	•					•	•			
4	Alhajyaseen et al., 2021 [98]	•		•	•		•				•	•	•											
5	Andrei et al., 2022 [100]	•	•	•	•	•	•			•	•													
6	Asgari et al., 2018 [117]	•	•									•	•					•						•
7	Ashkrof et al., 2019 [150]	•	•	•	•		•					•	•							•	•			

Categories		User-Centric Factors																						
Sub-Categories		Sociodemographic								Current Travel Habits and Mobility Needs														
No.	References/Factors	Age (Young)	Gender (Male)	Education (High)	Income (High)	Household (Children)	Employment (Yes)	Disability/Impairment	Level of Physical Activity	Driver's License (Yes)	Vehicle Ownership (Yes)	Transport Mode (Private Vehicle)	Transport Mode (Public Transport)	Transport Mode (Active Transport)	PT Card Owner	Car Crash History	Familiarity Ride-Sharing	Familiarity AV/SAV	Trip Purpose (Commute)	Trip Purpose (Leisure)	Commute Time	First Class Train Travel	Need to Carry Items	Yearly Mileage/Usage Freq. (High)
8	Asmussen et al., 2020 [148]	•	•	•	•						•													
9	Bakioglu et al., 2022 [60]	•	•														•		•					
10	Bansal and Daziano, 2018 [129]																							
11	Bansal et al., 2016 [47]	•	•	•	•	•	•			•							•	•	•	•	•			•
12	Barbour et al., 2019 [109]	•	•	•	•	•	•			•	•	•					•			•		•		
13	Booth et al., 2019 [45]	•	•						•				•	•				•						•
14	Cai et al., 2019 [92]	•	•	•	•							•	•					•						
15	Carrese et al., 2019 [68]	•	•	•			•																	
16	Carteni, 2020 [53]	•	•	•			•				•		•							•	•			•
17	Cordera et al., 2022 [113]	•	•		•			•			•	•								•	•			
18	Correia et al., 2019 [130]	•	•	•	•		•			•	•	•	•					•	•	•				
19	Ding et al., 2022 [50]	•	•	•	•				•															
20	Etminani-Ghasrodashti et al., 2023 [134]	•	•	•	•																			
21	Etzioni et al., 2020 [90]	•	•	•	•	•	•				•	•								•	•			
22	Etzioni et al., 2021 [136]	•	•	•	•	•				•	•	•												
23	Farmer et al., 2024 [144]																	•						
24	Frei et al., 2017 [118]	•	•	•	•	•						•	•	•	•							•		•
25	Fu et al., 2022 [91]	•	•	•	•		•			•	•							•						•
26	Gao et al., 2019 [131]	•	•	•	•		•				•													
27	Gkartzonikas et al., 2022 [99]	•	•	•	•							•	•					•	•	•				•
28	Guo et al., 2021 [131]	•	•	•	•						•							•	•	•				
29	Gurumurthy and Kockelman, 2020 [48]	•		•	•	•	•	•		•	•									•	•			
30	Haboucha et al., 2017 [111]	•	•	•	•	•	•					•	•								•		•	•
31	Hao and Yamamoto, 2017 [19]	•	•				•				•	•								•	•			•
32	Hao et al., 2019 [114]	•				•	•					•												•
33	Huo et al., 2021 [121]		•	•	•					•		•					•	•						
34	Irannezhad and Mahadevan, 2022 [61]	•	•	•	•		•				•		•							•	•			
35	Jabbari et al., 2022 [93]	•	•	•	•		•				•		•							•	•			

Categories		User-Centric Factors																						
Sub-Categories		Sociodemographic								Current Travel Habits and Mobility Needs														
No.	References/Factors	Age (Young)	Gender (Male)	Education (High)	Income (High)	Household (Children)	Employment (Yes)	Disability/Impairment	Level of Physical Activity	Driver's License (Yes)	Vehicle Ownership (Yes)	Transport Mode (Private Vehicle)	Transport Mode (Public Transport)	Transport Mode (Active Transport)	PT Card Owner	Car Crash History	Familiarity Ride-Sharing	Familiarity AV/SAV	Trip Purpose (Commute)	Trip Purpose (Leisure)	Commute Time	First Class Train Travel	Need to Carry Items	Yearly Mileage/Usage Freq. (High)
36	Kang et al., 2021 [62]	•	•	•	•		•											•	•	•				
37	Kashani et al., 2023 [145]		•																					
38	Kim2019 [85]	•	•	•	•	•			•		•	•	•	•										
39	Kolarova and Cherchi, 2021 [23]	•	•	•	•					•	•	•	•	•	•	•		•						
40	Kolarova et al., 2018 [54]	•	•		•					•						•					•			
40	Kolarova2019 [127]				•					•		•	•	•	•					•	•			
42	König and Grippenkov, 2020 [88]	•	•	•	•		•																	
43	Kontar et al., 2021 [120]	•	•		•						•	•	•	•	•			•						•
44	Krueger et al., 2016 [12]	•	•		•	•	•				•	•	•					•	•	•				
45	Krueger et al., 2019 [97]	•	•	•	•	•				•	•	•						•						
46	Lavieri and Bhat, 2019 [22]	•	•	•	•	•	•				•	•	•					•	•	•				
47	Li et al., 2023 [51]	•		•	•	•				•	•		•									•		
48	Liao et al., 2023 [142]																							
49	Maeng and Cho, 2022 [139]	•	•	•	•																			
50	Nair et al., 2018 [49]	•	•	•	•	•	•					•	•											
51	Nazari et al., 2018 [87]	•	•			•	•			•	•	•						•	•	•	•			•
52	Nickkar et al., 2023 [137]			•								•												
53	Paddeu et al., 2021 [24]	•	•							•			•				•	•						
54	Pakusch et al., 2018 [11]	•	•	•	•						•	•	•											
55	Patel et al., 2023 [146]																•							
56	Piatkowski, 2021 [96]	•										•	•	•										
57	Saeed et al., 2020 [103]	•	•	•		•						•						•				•		
58	Sheldon and Dua, 2024 [132]	•	•		•						•							•	•	•				
59	Si et al., 2024 [147]																							
60	Steck et al., 2018 [128]	•	•		•					•		•	•		•			•	•					
61	Stoiber et al., 2019 [124]										•				•									
62	Susilawati and Lim, 2021 [94]	•	•	•	•		•				•	•	•					•	•	•				
63	Sweet, 2021 [104]	•	•	•	•	•	•		•		•	•	•	•	•			•	•	•				
64	Sweet, 2021 [104]	•	•								•	•	•	•						•				

Categories		User-Centric Factors																						
Sub-Categories		Sociodemographic								Current Travel Habits and Mobility Needs														
No.	References/Factors	Age (Young)	Gender (Male)	Education (High)	Income (High)	Household (Children)	Employment (Yes)	Disability/Impairment	Level of Physical Activity	Driver's License (Yes)	Vehicle Ownership (Yes)	Transport Mode (Private Vehicle)	Transport Mode (Public Transport)	Transport Mode (Active Transport)	PT Card Owner	Car Crash History	Familiarity Ride-Sharing	Familiarity AV/SAV	Trip Purpose (Commute)	Trip Purpose (Leisure)	Commute Time	First Class Train Travel	Need to Carry Items	Yearly Mileage/Usage Freq. (High)
65	Thaithatkul et al., 2024 [89]	•	•		•					•	•	•	•				•	•						
66	Tian et al., 2021 [17]	•	•	•	•	•	•				•													
67	Triantafillidi et al., 2023 [125]	•	•	•	•																			
68	Wang and Zhao, 2019 [141]	•	•	•	•		•																	
69	Wang et al., 2021 [116]	•	•	•	•	•	•	•	•	•	•									•				•
70	Wang et al., 2021 [116]	•	•	•	•		•			•	•									•	•			•
71	Webb et al., 2019 [101]	•	•		•	•	•				•	•	•					•	•			•		
72	Weiss et al., 2019 [133]	•	•																					
73	Weschke et al., 2021 [123]	•	•	•	•					•			•	•	•		•					•		
74	Wicki et al., 2019 [108]	•	•	•				•	•								•	•						
75	Winter et al., 2019 [135]	•	•	•	•		•						•											
76	Winter et al., 2020 [55]	•	•	•	•				•	•	•	•	•	•				•	•					
77	Yan et al., 2024 [44]																•	•						
78	Yao et al., 2021 [105]	•	•	•	•	•	•			•								•	•	•	•			•
79	Yao et al., 2022 [126]	•	•	•	•	•	•			•	•	•							•	•				
80	Yap et al., 2016 [112]	•	•		•		•			•	•	•	•	•	•				•	•		•		•
81	Yin and Cherchi, 2024 [52]	•	•	•	•		•											•			•		•	•
82	Yu et al., 2023 [122]		•	•	•					•	•													
83	Zhong et al., 2020 [102]	•	•	•	•	•	•																	
84	Zhou et al., 2020 [46]	•	•	•	•		•				•	•	•	•				•	•	•				•
85	Zhou et al., 2023 [86]	•	•	•	•					•		•	•					•	•					

Appendix D. Contextual Factors of SAV Adoption

Categories		Contextual Factors																							
Sub-Categories		Operational Travel Factors										SAV-Specific Features							Built Environment						
No.	References/Factors	Travel Distance (Long Distance)	Travel Time (Higher)	Travel Cost	Accessibility/Service Reliability (Trip Detour and Delay)	Travel Speed	Access/Egress Time	Waiting Time	Congestion Time	In-Vehicle-Time	Parking Time	Parking Cost	Weather (Bad/Cold)	Vehicle Interior	Chauffeur /Monitoring	Seating	Trip delay Insurance	Preferred Lane	Liability Holder	Multitasking	Willingness-to-Pay for Automation	VOT	City size (Metropolis)	Neighborhood Density	Center vs. Rural
1	Aasvik et al., 2024 [95]																								
2	Abe et al., 2020 [143]		•	•				•		•						•									
3	Abe, 2021 [106]	•	•	•	•			•		•		•												•	•
4	Alhajyaseen et al., 2021 [98]		•	•													•								
5	Andrei et al., 2022 [100]		•	•																			•		
6	Asgari et al., 2018 [117]	•	•	•	•								•	•						•		•			
7	Ashkrof et al., 2019 [150]	•	•	•				•		•	•														
8	Asmussen et al., 2020 [148]				•																				
9	Bakioglu et al., 2022 [60]				•										•				•						
10	Bansal and Daziano, 2018 [129]		•	•				•													•				
11	Bansal et al., 2016 [47]	•		•																•	•		•	•	
12	Barbour et al., 2019 [109]	•	•	•		•					•													•	
13	Booth et al., 2019 [45]																						•		
14	Cai et al., 2019 [92]		•	•	•			•							•										
15	Carrese et al., 2019 [68]		•						•	•								•		•			•	•	
16	Carteni, 2020 [53]		•	•											•	•					•				
17	Cordera et al., 2022 [113]	•	•	•	•			•							•										
18	Correia et al., 2019 [130]		•	•				•							•	•				•		•			
19	Ding et al., 2022 [50]																								
20	Etminani-Ghasrodashti et al., 2023 [134]		•	•	•		•	•		•	•	•	•					•							
21	Etzioni et al., 2020 [90]		•	•											•								•		
22	Etzioni et al., 2021 [136]	•	•	•	•			•	•	•						•				•					
23	Farmer et al., 2024 [144]																								
24	Frei et al., 2017 [118]		•	•	•			•	•		•		•	•						•		•		•	•
25	Fu et al., 2022 [91]				•																				
26	Gao et al., 2019 [131]		•	•				•												•		•			
27	Gkartzonikas et al., 2022 [99]		•	•																			•		
28	Guo et al., 2021 [131]	•			•		•	•					•					•							

Categories		Contextual Factors																								
Sub-Categories		Operational Travel Factors												SAV-Specific Features							Built Environment					
No.	References/Factors	Travel Distance (Long Distance)	Travel Time (Higher)	Travel Cost	Accessibility/Service	Reliability (Trip Detour and Delay)	Travel Speed	Access/Egress Time	Waiting Time	Congestion Time	In-Vehicle-Time	Parking Time	Parking Cost	Weather (Bad/Cold)	Vehicle Interior	Chauffeur /Monitoring	Seating	Trip delay Insurance	Preferred Lane	Liability Holder	Multitasking	Willingness-to-Pay for Automation	VOT	City size (Metropolis)	Neighborhood Density	Center vs. Rural
58	Sheldon and Dua, 2024 [132]		•	•		•											•									•
59	Si et al., 2024 [147]																									•
60	Steck et al., 2018 [128]		•	•						•		•												•		•
61	Stoiber et al., 2019 [124]		•	•	•					•			•			•										
62	Susilawati and Lim, 2021 [94]		•	•	•			•	•																	
63	Sweet, 2021 [104]		•	•																				•	•	•
64	Sweet, 2021 [104]		•	•	•		•	•	•					•												
65	Thaithatkul et al., 2024 [89]													•										•		
66	Tian et al., 2021 [17]			•	•			•	•												•					
67	Triantafillidi et al., 2023 [125]		•	•	•	•	•		•		•	•		•	•											
68	Wang and Zhao, 2019 [141]		•	•					•																	
69	Wang et al., 2021 [116]			•	•								•										•			
70	Wang et al., 2021 [116]		•	•	•			•	•																	
71	Webb et al., 2019 [101]		•	•						•																•
72	Weiss et al., 2019 [133]		•	•		•							•													
73	Weschke et al., 2021 [123]		•	•	•			•	•															•		
74	Wicki et al., 2019 [108]		•	•					•					•	•								•	•		
75	Winter et al., 2019 [135]	•	•	•					•						•	•								•		
76	Winter et al., 2020 [55]		•	•	•				•		•	•	•			•										
77	Yan et al., 2024 [44]																									
78	Yao et al., 2021 [105]	•	•	•	•				•		•		•		•											
79	Yao et al., 2022 [126]		•	•					•																	
80	Yap et al., 2016 [112]		•	•				•	•		•											•	•	•		
81	Yin and Cherchi, 2024 [52]	•	•	•		•			•		•					•								•		
82	Yu et al., 2023 [122]																									
83	Zhong et al., 2020 [102]		•	•							•													•		•
84	Zhou et al., 2020 [46]				•				•																	•
85	Zhou et al., 2023 [86]		•	•					•										•					•		

Appendix E. Psycho-Attitudinal Factors

Categories		Psycho-Attitudinal Influences										
Sub-Categories		Attitude										
No.	References/Factors	Ride-Sharing (Strangers)	Ride-Sharing (Family/Friends)	Safety Con-cerns/Trust	Time Sensitivity	Attitude towards PT	Attitude towards SAV	Technology Interest	Enjoyment Driving	Environmental Attitude	Privacy Concern	Social Influence
1	Aasvik et al., 2024 [95]		•	•		•	•			•		
2	Abe et al., 2020 [143]			•			•	•				
3	Abe, 2021 [106]	•	•									
4	Alhajyaseen et al., 2021 [98]											
5	Andrei et al., 2022 [100]											
6	Asgari et al., 2018 [117]	•		•	•					•		
7	Ashkrof et al., 2019 [150]			•			•	•	•	•		
8	Asmussen et al., 2020 [148]			•	•		•	•				
9	Bakioglu et al., 2022 [60]	•		•								
10	Bansal and Daziano, 2018 [129]									•		
11	Bansal et al., 2016 [47]		•	•	•		•	•		•	•	•
12	Barbour et al., 2019 [109]			•							•	
13	Booth et al., 2019 [45]						•	•				
14	Cai et al., 2019 [92]	•			•		•				•	
15	Carrese et al., 2019 [68]	•					•					
16	Carteni, 2020 [53]			•			•	•			•	
17	Cordera et al., 2022 [113]											
18	Correia et al., 2019 [130]	•	•	•	•		•					
19	Ding et al., 2022 [50]						•	•				•
20	Etminani-Ghasrodashti et al., 2023 [134]	•		•	•	•	•	•	•			
21	Etzioni et al., 2020 [90]						•					
22	Etzioni et al., 2021 [136]	•			•	•	•					
23	Farmer et al., 2024 [144]	•				•	•					
24	Frei et al., 2017 [118]				•							
25	Fu et al., 2022 [91]	•		•			•	•			•	
26	Gao et al., 2019 [131]											
27	Gkartzonikas et al., 2022 [99]	•		•			•	•			•	•
28	Guo et al., 2021 [131]	•	•		•		•					
29	Gurumurthy and Kockelman, 2020 [48]	•					•				•	
30	Haboucha et al., 2017 [111]			•		•	•	•	•	•		
31	Hao and Yamamoto, 2017 [19]											
32	Hao et al., 2019 [114]		•				•					
33	Huo et al., 2021 [121]						•	•				

Categories		Psycho-Attitudinal Influences										
Sub-Categories		Attitude										
No.	References/Factors	Ride-Sharing (Strangers)	Ride-Sharing (Family/Friends)	Safety Con-cerns/Trust	Time Sensitivity	Attitude towards PT	Attitude towards SAV	Technology Interest	Enjoyment Driving	Environmental Attitude	Privacy Concern	Social Influence
34	Irannezhad and Mahadevan, 2022 [61]			•		•		•		•		
35	Jabbari et al., 2022 [93]			•								
36	Kang et al., 2021 [62]	•					•	•		•		
37	Kashani et al., 2023 [145]	•		•	•	•	•	•	•			
38	Kim2019 [85]				•		•	•		•		•
39	Kolarova and Cherchi, 2021 [23]	•		•								
40	Kolarova et al., 2018 [54]	•										
40	Kolarova2019 [127]	•										
42	König and Grippenkoven, 2020 [88]	•										
43	Kontar et al., 2021 [120]											
44	Krueger et al., 2016 [12]	•										
45	Krueger et al., 2019 [97]											
46	Lavieri and Bhat, 2019 [22]	•		•			•	•			•	
47	Li et al., 2023 [51]	•		•	•		•					•
48	Liao et al., 2023 [142]	•			•	•			•			
49	Maeng and Cho, 2022 [139]											
50	Nair et al., 2018 [49]											
51	Nazari et al., 2018 [87]	•		•				•		•		
52	Nickkar et al., 2023 [137]	•									•	
53	Paddeu et al., 2021 [24]			•			•	•				
54	Pakusch et al., 2018 [11]			•								
55	Patel et al., 2023 [146]	•	•	•	•	•	•	•	•			
56	Piatkowski, 2021 [96]	•					•					
57	Saeed et al., 2020 [103]	•					•		•			
58	Sheldon and Dua, 2024 [132]	•		•			•					
59	Si et al., 2024 [147]	•		•			•	•	•			
60	Steck et al., 2018 [128]	•										
61	Stoiber et al., 2019 [124]	•										
62	Susilawati and Lim, 2021 [94]						•	•				
63	Sweet, 2021 [104]	•										
64	Sweet, 2021 [104]											
65	Thaithatkul et al., 2024 [89]		•									
66	Tian et al., 2021 [17]											
67	Triantafillidi et al., 2023 [125]	•	•		•		•					
68	Wang and Zhao, 2019 [141]	•		•			•					

Categories		Psycho-Attitudinal Influences										
Sub-Categories		Attitude										
No.	References/Factors	Ride-Sharing (Strangers)	Ride-Sharing (Family/Friends)	Safety Con-cerns/Trust	Time Sensitivity	Attitude towards PT	Attitude towards SAV	Technology Interest	Enjoyment Driving	Environmental Attitude	Privacy Concern	Social Influence
69	Wang et al., 2021 [116]											
70	Wang et al., 2021 [116]											
71	Webb et al., 2019 [101]								•	•		
72	Weiss et al., 2019 [133]	•					•					
73	Weschke et al., 2021 [123]	•										
74	Wicki et al., 2019 [108]	•		•				•				
75	Winter et al., 2019 [135]			•				•				
76	Winter et al., 2020 [55]					•						
77	Yan et al., 2024 [44]			•	•	•	•	•		•		
78	Yao et al., 2021 [105]			•			•					
79	Yao et al., 2022 [126]	•					•	•				
80	Yap et al., 2016 [112]	•		•	•		•		•	•		
81	Yin and Cherchi, 2024 [52]							•				
82	Yu et al., 2023 [122]							•	•			
83	Zhong et al., 2020 [102]											
84	Zhou et al., 2020 [46]	•			•							
85	Zhou et al., 2023 [86]							•		•		

Appendix F. Usage of Travel Time and Value of Time

	City	Country	Usage of Travel Time and Value of Time	Comparison
Andrei et al., 2022 [100]	-	Romania	VOT is 34.4% lower than cars.	SAV vs. Car
Asgari et al., 2018 [117]	-	USA	Median travel time savings of 15.9 min per trip for SAVs.	SAV vs. Car
Correia et al., 2019 [130]	-	The Netherlands	VOT for AV-office travelers is 26% lower (EUR 5.50/h); for AV-leisure, it is 9.4% higher (EUR 8.17/h) than conventional cars.	SAV-office/SAV-leisure vs. Car
Etzioni et al., 2020 [90]	-	Slovenia, Cyprus, UK, Hungary, Montenegro	Variations in VOT among seven EU countries could relate to cultural differences, sample size, or economic disparities.	VOT across EU Countries vs. GDP Per Capita
Etzioni et al., 2020 (Iceland) [90]	-	Iceland	Iceland's VOT for SAVs is notably higher than for cars, reflecting possible wealth and user type effects.	SAV vs. Car in Iceland
Frei et al., 2017 [118]	Chicago	USA	SAV VOT is 29% higher than cars, 15% higher than public transport.	SAV vs. Car and Public Transport
Gao et al., 2019 [131]	-	USA	Multitasking reduces VOT by approximately 50% in SAVs, though VOT remains 15% higher than that for personal cars.	SAV vs. Car (Mentioning Multitasking)

	City	Country	Usage of Travel Time and Value of Time	Comparison
Gkartzonikas et al., 2022 [99]	Chicago	USA	VTTS is lower for SAVs than for single-passenger AVs.	Robo-taxi vs. Pooled
Kang et al., 2021 [62]	Austin, Texas	USA	VOT is USD 27.80/hr for commute, USD 19.40/h for shopping, USD 10.70/h for leisure; willingness to share costs is USD 0.62, USD 1.70, and USD 1.32, respectively.	Different Trip Types
Kolarova et al., 2018 [54]	-	Germany	SAV VOT is 30% lower for low income, 13% for high income compared to cars.	SAV vs. Car across Income Levels
Kolarova et al., 2019 [127]	-	Germany	In-vehicle time differences not found across trip purposes or income classes; SAV VOT EUR 6.2 (low), EUR 11 (high).	SAV vs. AV and Car (across Trip Types and Income Classes)
Kolarova et al., 2021 [23]	-	Germany	SAV VTTS is 18% lower for public transport, 28% for personal AVs; age, education, and ADAS experience influence VTTS.	Psychological Factors in AV vs. PAV and PT
Krueger et al., 2016 [12]	-	Australia	Robo-taxi travel time around 25% lower than pooled.	Robo-taxi vs. Pooled
Lavieri et al., 2019 [22]	Dallas-Fort Worth, Arlington, Texas	USA	Willing to pay 14% more to reduce commute time vs. leisure in private AVs, 84% more to avoid additional passenger in leisure trips.	Private AV vs. Shared AV (Commute vs. Leisure)
Paddeu et al., 2021 [24]	Bristol	UK	Post-experiment VOT for own car increased by 15.3%, for AV taxi by 29.2%; shared AV taxi decreased by 0.07%.	VOT Pre- and Post-Experiment across Various SAV Modes
Steck et al., 2018 [128]	-	Germany	VTTS for SAVs higher than for AVs but 10% lower than for driving oneself.	SAV vs. AV and Car
Sweet et al., 2021 [104]	Toronto and Hamilton, Ontario	Canada	Driverless cars are seen as a penalty by commuters compared to public transport.	SAV vs. Public Transport
Weschke et al., 2021 [123]	Braunschweig and Berlin	Germany	VOT after exposure changed to EUR 5.25/h in Braunschweig and EUR 3.68/h in Berlin.	VOT Pre and Post Experiment in Germany
Wicki et al., 2019 [108]	Schaffhausen	Switzerland	VTTS for travel time is CHF 10.2 to 10.8/h, and for waiting time CHF 15.6 to 16.8/h.	AV-Bus vs. Regular Bus
Winter et al., 2019 [135]	-	The Netherlands	Preference for self-driving buses over regular buses for short trips due to higher VOT.	AV-Bus vs. Regular Bus for Short Trips
Yap et al., 2016 [112]	-	The Netherlands	SAV is 28% higher VOT than cars; egress VOT is three times public transport, 17% higher than bikes.	SAV vs. First-Mile Alternatives and Car
Yin et al., 2024 [52]	-	China	Chinese respondents willing to pay on average EUR 3.61 to save one hour of travel time.	AV Features in China

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