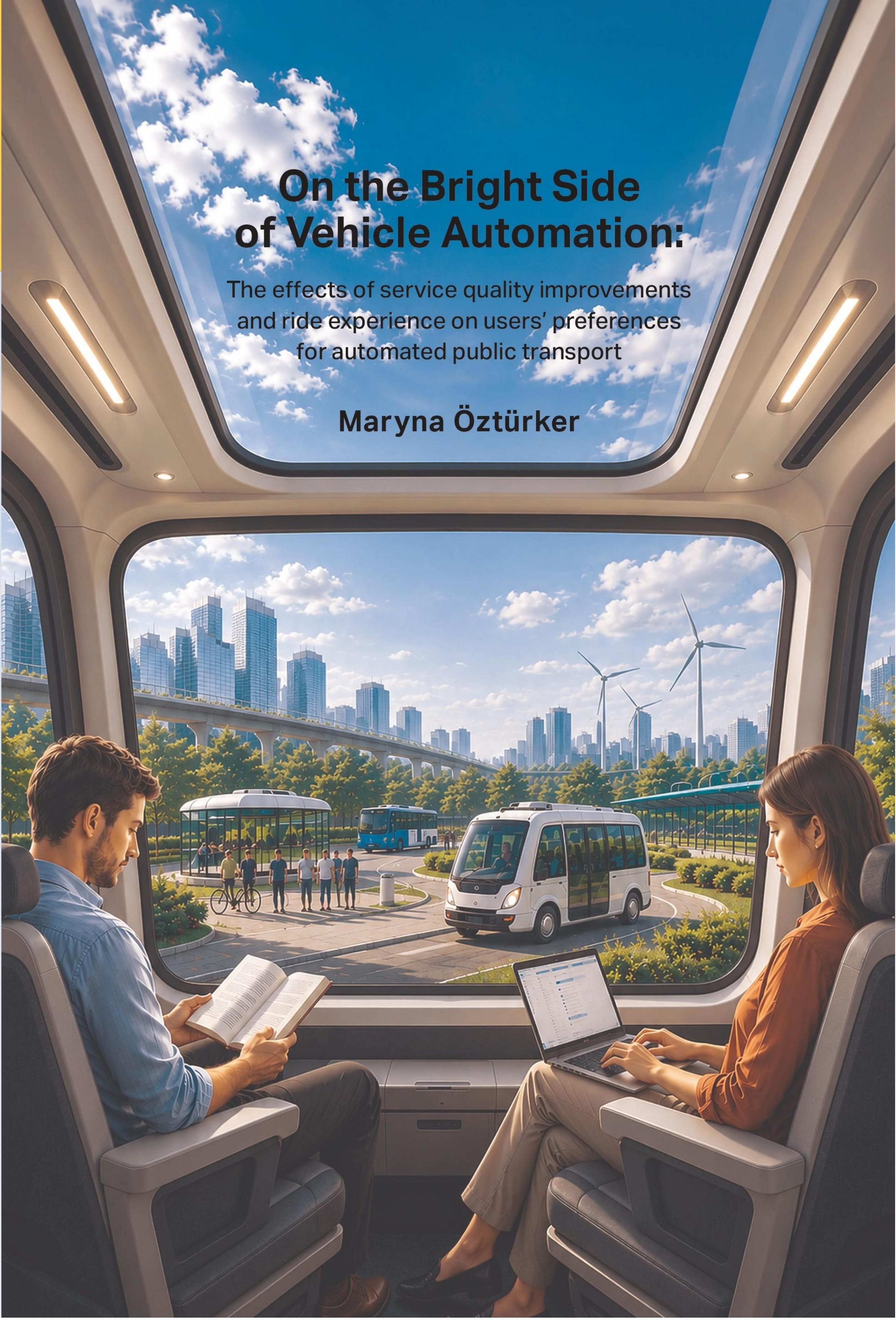
On the Bright Side of Vehicle Automation:

The effects of service quality improvements and ride experience on users' preferences for automated public transport

Maryna Öztürker



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"The only constant of transport history *is change"*

Inspired by Yuval Noah Harari

Acknowledgements

Relocating to the Netherlands marked both a new beginning and an uncertain chapter in my life. Determined to continue working as a researcher, I reached out to Bart, who believed in my ambitions and opened the door for me to pursue my PhD at TU Delft. I am deeply thankful to him for giving me this opportunity to follow a dream that once felt distant. I am also sincerely grateful to Gonçalo, who stepped in when my first daily supervisor could no longer continue due to illness. His guidance shaped not only the direction of this dissertation but also supported me through some of the most difficult moments of my life. I especially appreciate his role in strengthening the choice-modelling component of this research, an area in which he invested considerable time to train and support me.

Three major events marked my PhD journey – one joyful and two profoundly challenging. The happiest moment was becoming a mother, a life-changing experience that gave this journey an entirely new meaning. The difficult moments came with the COVID-19 pandemic and later the war in my home country, Ukraine. During the pandemic, the original design of this research, requiring participants to physically experience automated transport, became nearly impossible, and I felt overwhelmed as the project's foundations were shaken. Yet together we navigated this crisis and found a solution that preserved the essential themes of the research, namely service quality and ride experience. When the war began, my world changed once again. I am deeply grateful for the patience, empathy, and moral support offered to me during those devastating months as I tried to regain balance.

My heartfelt appreciation extends to the entire Transport & Planning department. Being part of this community made the everyday joys and challenges of PhD life feel shared rather than solitary. To the room 4.14 team – Reanne, Bahman, Jeroen, Pablo, Yihong, Koen, Sara, Nirmal, Iria, Renzo, Kuldeep, Yiyun, Zamzam, Rina, and Jirka, thank you for creating an environment filled with both support and laughter. I also treasure the moments spent with Sina and Nirvana, especially our coffee chats that often provided the reset I needed.

Beyond the university walls, I benefited greatly from collaborations with external partners, something I greatly admire about the Dutch academic ecosystem. I am grateful to Arthur Scheltes and Marie-Jose Olde Kalter at Goudappel for supporting our nationwide survey; to Alwin Bakker, Joop Veenis, and Ahmed Hashish from The Future Mobility Networks for their partnership during the automated minibus pilot in Helmond; and to Sascha and Sina for our fruitful collaboration with the Wizard-of-Oz vehicle experiment. My special thanks go to Edwin and Peter for their technical support, as well as to the Municipality of Delft and café Labs for their facilitation. I truly hope that one day similar collaborations between academia, government, and industry will flourish in Ukraine as well.

I gratefully acknowledge the financial support that made several parts of this research possible. The nationwide survey was funded by Goudappel BV. The research on the ride experience of passengers during the automated minibus pilot in Helmond (part of the FABULOS project) was supported financially by the TU Delft Transport Institute. The Wizard-of-Oz experiment received financial support from the hEAT Lab and the TU Delft Transport Institute. I am sincerely thankful for these contributions, without which the empirical foundations of this dissertation could not have been realised.

I also owe deep gratitude to my family. Their love, patience, and unwavering belief in me carried me through moments of doubt, exhaustion, and uncertainty. Their support made it possible to continue, even when life became heavier than research alone.

This PhD has taught me far more than research methodologies or academic writing. It has reshaped my way of thinking. I often describe the PhD experience as becoming a one-person orchestra, simultaneously a composer, a conductor, and a musician. It requires critical thinking when digesting information, courage in making decisions along uncharted paths, and the resilience to continue even when progress seems invisible. A PhD teaches patience, self-mastery, the courage to stay curious, and the ability to turn uncertainty into momentum. It transforms the way you approach problems, people, and the world, shaping not only what you know, but who you become.

Looking forward, I hold a personal hope for the future of mobility in our society. I hope that more people will consciously choose to let go of the comfort and habit of private vehicle ownership in favour of a more sustainable, collective, and ultimately more comfortable future enabled by automated public transport. For me, this is choosing to stay on the bright side of automation.

Maryna Öztürker

November 2025

Summary

Transport systems are undergoing a profound transformation driven by technological innovation and urgent sustainability challenges. The long-standing paradigm of automobility, built on widespread ownership and use of fossil-fuelled private cars, has produced major environmental, social, and spatial externalities, from greenhouse gas emissions and air pollution to congestion and inequitable access. The emerging combination of automation, electrification, and shared mobility, often described as the "Three Revolutions," offers new opportunities to address these issues if guided by well-designed public policy and governance.

Within this context, Automated minibuses (AmBs) and shared automated vehicles (SAVs) have attracted growing attention as promising modes capable of complementing existing public transport. Their potential "bright side" lies in improving service quality through enhanced flexibility, availability, and comfort, while their "dark side" involves risks of induced demand, modal shift from high-capacity transit, and digital or social exclusion. Realising the benefits of vehicle automation, therefore, depends not only on technical feasibility and policy design but also on users' willingness to adopt these new services. Understanding how people perceive service quality improvements and how their attitudes and preferences evolve after a real ride experience is essential for integrating AmBs and SAVs into sustainable public transport systems.

The overarching objective of this thesis is to explore the effects of service quality improvements and ride experience on users' preferences for automated public transport, specifically AmBs and SAVs. The research follows a two-stage approach. The pre-empirical stage comprises a structured literature review that identifies how vehicle automation may enhance or challenge public transport service quality. The empirical stage involves three stated-preference (SP) studies supported by field trials that provide potential users with a real ride experience. These studies analyse how users evaluate AmBs and SAVs before and after experiential exposure, offering behavioural evidence on preference formation and adoption potential.

The first study (Chapter 2) establishes a conceptual foundation by examining how vehicle automation affects public transport service quality. Using the European Standard EN 13816:2002 as the analytical framework, complemented by Maslow's hierarchy of needs and the Kano model, the chapter reviews 23 recent literature review papers to map the opportunities and risks of vehicle automation across eight service dimensions. The results highlight substantial potential for improvement in availability, accessibility, comfort, and environmental impact, alongside challenges related to safety, customer care, and digital exclusion. The synthesis organises fragmented evidence into a coherent structure, providing a scientific and

policy-relevant basis for understanding the “bright” and “dark” sides of automated public transport.

The second study (Chapter 3) investigates travellers’ preferences for AmB service types in the Netherlands, focusing on differences across current travel-mode segments. A nationwide SP survey asked respondents to choose between regular (fixed-route, fixed-schedule) and flexible (on-demand, door-to-door) AmB services compared with their usual mode, namely car, public transport, or active modes (cycling or walking). The analysis revealed clear segmentation. Public transport users expressed the highest preference for flexible services, valuing door-to-door convenience but remaining sensitive to price. Car users showed greater acceptance of regular services, appreciating their predictability and lower perceived costs. Active-mode users displayed no strong preference, implying limited substitution effects. Across all groups, perceived safety, trust, and enjoyment significantly shaped preferences. These findings emphasise that there is no one-size-fits-all design: effective AmB deployment requires differentiation by user segment and careful alignment with travellers’ existing habits.

The third study (Chapter 4) explores how ride experience alters user preferences for AmBs. Conducted in Helmond, the Netherlands, this two-wave pre- and post-ride SP experiment measured changes in attitudes and preferences after a short pilot ride. Results show that even a single ride meaningfully reshapes perceptions. AmBs providing flexible service became more attractive, perceived as combining the advantages of car convenience and bus affordability, while AmB’s regular services gained appeal among participants who found the ride enjoyable or valued onboard supervision. Following the ride, participants exhibited greater sensitivity to waiting and walking times and placed less emphasis on travel cost. The experiment demonstrates that direct experiential exposure substantially modifies how users value service attributes and that pilot trials play a crucial role in building preferences for AmBs.

The fourth study (Chapter 5) examines SAVs and how the potential to use travel time for work or leisure activities influences preferences and the value of travel time (VoTT). Using a Wizard-of-Oz simulator-on-wheels experiment in Delft, participants completed two rides while engaging in non-driving-related tasks. Pre- and post-ride SP surveys captured how experience and activity engagement affected perceived utility. The results show that when travellers preferred to use travel time for work, the disutility of travel time decreased and the VoTT for SAVs dropped relative to cars and public transport. Participants who concentrated fully on their tasks during SAV rides subsequently evaluated car travel time more negatively, recognising the burden of driving. The travel costs for SAVs were consistently perceived as less negative than for private cars and PT, mainly due to expectations of lower fixed expenses. Trust, safety perceptions, and attitudes toward automation further moderated preferences. Together, these findings illustrate that experiential exposure and productive travel time potential fundamentally reshape perceptions of automated mobility.

Taken together, the results demonstrate that service design, user segmentation, and experiential exposure are decisive for the adoption and successful integration of automated public transport. AmBs and SAVs can enhance perceived service quality and attract new user groups, but only if implemented in ways that address diverse needs, trust levels, and expectations. The research underscores that ride experience is not merely an informational tool but a behavioural catalyst that reshapes how individuals evaluate flexibility, comfort, and the productive use of travel time.

Beyond its empirical contributions, the thesis provides a structured understanding of how automated modes may influence public transport service quality and passenger perceptions. It offers actionable guidance for policymakers, planners, and operators seeking to deploy automated mobility responsibly. For AmBs, the findings suggest prioritising flexible feeders for public transport users while designing regular services to appeal to car commuters and ensuring affordable pricing. For SAVs, the results emphasise interior and service designs that facilitate multitasking, gradual deployment to build trust, and continued use of pilot trials as learning environments for both operators and users.

In societal terms, the thesis addresses a central challenge of contemporary mobility: how to make public transport more attractive, flexible, and sustainable in the face of environmental and urbanisation pressures. By linking user perceptions, ride experience, and service design, it shows that the path toward sustainable automated mobility depends as much on social acceptance as on technological progress. The collective insights presented here support the development of inclusive, evidence-based strategies for integrating automated modes into public transport systems that are not only efficient but also trusted, equitable, and user-centred.

Samenvatting

Transportsystemen ondergaan een ingrijpende transformatie, gedreven door technologische innovatie en urgente duurzaamheidsuitdagingen. Het langdurige paradigma van de automobility, gebaseerd op grootschalig bezit en gebruik van fossiel aangedreven privéauto's, heeft geleid tot aanzienlijke milieu-, sociale en ruimtelijke externaliteiten, variërend van broeikasgasemissies en luchtvervuiling tot congestie en ongelijke toegang. De opkomende combinatie van automatisering, elektrificatie en gedeelde mobiliteit, vaak omschreven als de "drie revoluties", biedt nieuwe mogelijkheden om deze problemen aan te pakken, mits ondersteund door doordacht beleid en adequaat bestuur.

Binnen deze context trekken autonome minibussen (AmBs) en autonome deelauto's (ADAs) steeds meer aandacht als veelbelovende vervoersvormen die het bestaande openbaar vervoer kunnen aanvullen. Hun potentiële "lichte kant" ligt in het verbeteren van de dienstverlening door middel van meer flexibiliteit, beschikbaarheid en comfort, terwijl hun "donkere kant" risico's inhoudt zoals extra verkeersvraag, overstap van hoogcapaciteitsvervoer naar kleinere voertuigen, en digitale of sociale uitsluiting. Het realiseren van de voordelen van voertuigautomatisering hangt daarom niet alleen af van technische haalbaarheid en beleidsontwerp, maar ook van de bereidheid van gebruikers om deze nieuwe diensten te omarmen. Inzicht in hoe mensen verbeteringen in servicekwaliteit waarnemen en hoe hun attitudes en voorkeuren zich ontwikkelen na een daadwerkelijke ritervaring, is essentieel voor de integratie van AmBs en ADAs in duurzame openbaarvervoerssystemen.

Het overkoepelende doel van dit proefschrift is het onderzoeken van de effecten van verbeteringen in servicekwaliteit en ritervaring op de voorkeuren van gebruikers voor geautomatiseerd openbaar vervoer, in het bijzonder AmBs en ADAs. Het onderzoek volgt een tweefasenbenadering. De eerste, pre-empirische fase bestaat uit een gestructureerde literatuurstudie waarin wordt onderzocht hoe voertuigautomatisering de kwaliteit van openbaar vervoer kan versterken of juist ondermijnen. De tweede, empirische fase omvat drie stated-preference (SP)-experimenten, dat wil zeggen keuze-experimenten op basis van verklaarde voorkeuren, ondersteund door veldproeven waarbij potentiële gebruikers een echte ritervaring opdoen. Deze studies analyseren hoe gebruikers AmBs en ADAs beoordelen vóór en na hun ervaring, en leveren gedragsmatig bewijs over de vorming van voorkeuren en adoptiepotentieel.

De eerste studie (Hoofdstuk 2) legt een conceptuele basis door te onderzoeken hoe voertuigautomatisering de kwaliteit van openbaar vervoer beïnvloedt. Met de Europese norm EN 13816:2002 als analytisch kader, aangevuld met de behoeftepiramide van Maslow en het Kano-model, worden 23 recente overzichtsstudies geanalyseerd om de kansen en risico's van automatisering in kaart te brengen binnen acht dienstverleningsdimensies. De resultaten tonen

aanzienlijke verbeteringsmogelijkheden op het gebied van beschikbaarheid, toegankelijkheid, comfort en milieueffecten, naast uitdagingen op het vlak van veiligheid, klantgerichtheid en digitale uitsluiting. De synthese ordent gefragmenteerd bewijs tot een samenhangend geheel en biedt zo een wetenschappelijke en beleidsrelevante basis voor het begrijpen van de “lichte” en “donkere” kanten van geautomatiseerd openbaar vervoer.

De tweede studie (Hoofdstuk 3) onderzoekt de voorkeuren van reizigers voor verschillende typen AmB-diensten in Nederland, met aandacht voor verschillen tussen vervoerssegmenten. Een landelijke SP-enquête vroeg respondenten te kiezen tussen reguliere (vaste route, vaste dienstregeling) en flexibele (on-demand, deur-tot-deur) AmB-diensten, vergeleken met hun gebruikelijke vervoermiddel: auto, openbaar vervoer (OV) of actieve modi (fietsen of lopen). De analyse liet duidelijke segmentatie zien. OV-gebruikers gaven de voorkeur aan flexibele diensten, waardeerden het deur-tot-deur gemak, maar bleven prijsgevoelig. Autogebruikers accepteerden eerder reguliere diensten, vanwege hun voorspelbaarheid en lagere waargenomen kosten. Gebruikers van actieve modi toonden geen sterke voorkeur, wat wijst op beperkte substitutie-effecten. Over alle groepen heen bleken waargenomen veiligheid, vertrouwen en plezier significante bepalende factoren voor voorkeuren. Deze bevindingen benadrukken dat er geen universeel ontwerp bestaat: effectieve invoering van AmBs vereist differentiatie naar gebruikerssegment en een zorgvuldige afstemming op bestaande reisgewoonten.

De derde studie (Hoofdstuk 4) onderzoekt hoe ritervaring de voorkeuren van gebruikers voor AmBs beïnvloedt. In Helmond werd een tweefasen SP-experiment uitgevoerd, vóór en na een korte testrit. De resultaten tonen aan dat zelfs één rit de percepties merkbaar verandert. Flexibele AmB-diensten werden aantrekkelijker, aangezien ze werden gezien als een combinatie van het gemak van de auto en de betaalbaarheid van de bus. Reguliere diensten wonnen aan waardering bij deelnemers die de rit aangenaam vonden of waarde hechtten aan toezicht aan boord. Na de rit bleken deelnemers gevoeliger voor wachttijd en loopafstand, en hechtten zij minder belang aan reiskosten. Het experiment toont aan dat directe ervaring de waardering van servicekenmerken wezenlijk beïnvloedt, en dat proefritten cruciaal zijn om voorkeuren voor AmBs op te bouwen.

De vierde studie (Hoofdstuk 5) richt zich op ADAs en onderzoekt hoe de mogelijkheid om reistijd te benutten voor werk- of vrijetijdsactiviteiten de voorkeuren en de waarde van reistijd (VRT) beïnvloedt. In een Wizard-of-Oz-experiment in Delft maakten deelnemers twee ritten in een simulatorvoertuig terwijl zij niet-rijgerelateerde taken uitvoerden. Pre- en postrit SP-enquêtes legden vast hoe ervaring en activiteit de waargenomen nut beïnvloedden. De resultaten tonen dat wanneer reizigers reistijd benutten voor werk, de negatieve beleving van reistijd afneemt en de VRT voor ADAs lager wordt ten opzichte van auto’s en openbaar vervoer. Deelnemers die zich volledig op hun taken concentreerden, beoordeelden autorijden daarna negatiever, aangezien zij de belasting van zelf rijden sterker ervoeren. De reiskosten van ADAs werden consequent als minder negatief ervaren dan die van privéauto’s en OV, voornamelijk door verwachtingen van lagere vaste kosten. Vertrouwen, veiligheidspercepties en attitudes ten opzichte van automatisering bleken verdere moderatoren van voorkeuren. Samen tonen deze bevindingen dat ervaring en de mogelijkheid tot productieve reistijd de perceptie van geautomatiseerde mobiliteit fundamenteel hervormen.

Gezamenlijk tonen de resultaten aan dat dienstontwerp, gebruikerssegmentatie en ervaringsopbouw doorslaggevend zijn voor de adoptie en succesvolle integratie van geautomatiseerd openbaar vervoer. AmBs en ADAs kunnen de waargenomen servicekwaliteit verhogen en nieuwe gebruikersgroepen aantrekken, maar alleen wanneer zij worden ingevoerd op manieren die rekening houden met uiteenlopende behoeften, vertrouwensniveaus en verwachtingen. Het onderzoek benadrukt dat ritervaring niet enkel een informatie-instrument is, maar een gedragsmatige katalysator die bepaalt hoe individuen flexibiliteit, comfort en productief gebruik van reistijd waarderen.

Naast de empirische bijdragen biedt dit proefschrift een gestructureerd inzicht in hoe geautomatiseerde vervoersvormen de kwaliteit van openbaar vervoer en de percepties van reizigers kunnen beïnvloeden. Het levert concrete handvatten voor beleidsmakers, planners en exploitanten die geautomatiseerde mobiliteit op verantwoorde wijze willen implementeren. Voor AmBs wijzen de resultaten op het prioriteren van flexibele voortransportdiensten voor OV-gebruikers, het ontwerpen van reguliere diensten voor autocommuters, en het waarborgen van betaalbare tarieven. Voor ADAs benadrukken de bevindingen het belang van voertuiginterieur en serviceontwerp die multitasking mogelijk maken, een stapsgewijze invoering om vertrouwen op te bouwen, en het voortzetten van proefprojecten als leeromgevingen voor zowel exploitanten als gebruikers.

Op maatschappelijk niveau adresseert het proefschrift een centrale uitdaging van hedendaagse mobiliteit: hoe openbaar vervoer aantrekkelijker, flexibeler en duurzamer te maken in het licht van milieu- en verstedelijkingsdruk. Door gebruikerspercepties, ritervaring en dienstontwerp te verbinden, toont het aan dat de weg naar duurzame geautomatiseerde mobiliteit evenzeer afhangt van sociale acceptatie als van technologische vooruitgang. De hier gepresenteerde inzichten ondersteunen de ontwikkeling van inclusieve, op bewijs gebaseerde strategieën voor de integratie van geautomatiseerde vervoersvormen in openbaarvervoerssystemen die niet alleen efficiënt, maar ook betrouwbaar, rechtvaardig en gebruiksgericht zijn.

Автореферат

Транспортні системи зазнають глибокої трансформації, зумовленої технологічними інноваціями та нагальними викликами сталого розвитку. Давня парадигма автомобільності, побудована на масовому володінні та використанні приватних автомобілів із двигунами внутрішнього згоряння, спричинила значні екологічні, соціальні та просторові зовнішні ефекти — від викидів парникових газів і забруднення повітря до заторів і нерівного доступу до пересування. Нова комбінація автоматизації, електрифікації та спільної мобільності, яку часто називають “трьома революціями”, відкриває можливості для розв’язання цих проблем за умови належного державного регулювання та ефективного управління.

У цьому контексті автономні мікробуси та автономні автомобілі спільного використання викликають зростаючу зацікавленість як перспективні види транспорту, здатні доповнити існуючу систему громадського транспорту. Їхній потенційний “світлий бік” полягає у підвищенні якості послуг завдяки більшій гнучкості, доступності та комфорту, тоді як “темний бік” включає ризики додаткового попиту, відтоку пасажирів із масового транспорту та цифрового чи соціального виключення. Тому реалізація переваг автоматизації транспортних засобів залежить не лише від технічної завершеності та державної політики, але й від готовності користувачів приймати нові послуги. Розуміння того, як люди сприймають покращення якості обслуговування і як змінюються їхні ставлення та уподобання після реального досвіду поїздки, є ключовим для інтеграції автономних мікробусів і спільних автономних автомобілів у сталі системи громадського транспорту.

Загальна мета цього дослідження полягає у вивченні впливу покращень якості послуг та досвіду поїздки на вибір користувачів щодо автоматизованого громадського транспорту, зокрема автономних мікробусів і спільних автономних автомобілів. Дослідження має двоетапну структуру. На попередньому, теоретико-аналітичному етапі здійснено структурований огляд літератури, який визначає, як автоматизація транспортних засобів може покращувати або, навпаки, ускладнювати якість громадського транспорту. Емпіричний етап включає три експерименти з вибором транспортних засобів, підкріплені польовими випробуваннями, що надали потенційним користувачам можливість реальної поїздки. Ці дослідження аналізують, як користувачі оцінюють автономні мікробуси і спільні автономні автомобілі до та після отриманого досвіду, надаючи поведінкові докази формування переваг та потенціалу їх прийняття.

Перше дослідження (Розділ 2) формує концептуальну основу, досліджуючи, як автоматизація транспортних засобів впливає на якість громадського транспорту.

Використовуючи європейський стандарт EN 13816:2002 як аналітичну основу, доповнену ієрархією потреб Маслоу та моделлю Кано, у роботі проаналізовано 23 нещодавніх оглядових дослідження для картування можливостей і ризиків автоматизації за вісьмома вимірами якості послуг. Результати вказують на значний потенціал покращення доступності, зручності, комфорту та екологічного впливу, водночас виокремлюючи виклики, пов'язані з безпекою, обслуговуванням клієнтів і цифровим виключенням. Узагальнення структурує розрізнені докази у цілісну систему, створюючи наукове та політичне підґрунтя для розуміння "світлих" і "темних" сторін автоматизованого громадського транспорту.

Друге дослідження (Розділ 3) аналізує уподобання пасажирів щодо видів сервісу автономних мікробусів у Нідерландах, а також відмінності між користувачами різних видів транспорту. Загальнонаціональне опитування запропонувало респондентам обирати між звичайними (фіксований маршрут, розклад) та гнучкими (за запитом, "від дверей до дверей") видами сервісу автономних мікробусів порівняно з їхнім звичним видом пересування — автомобілем, громадським транспортом або активними видами (велосипед, піша хода). Аналіз виявив чітку сегментацію. Користувачі громадського транспорту найвище оцінили гнучкий вид сервісу, цінуючи зручність "від дверей до дверей", але залишаючись чутливими до ціни. Водії автомобілів віддавали перевагу звичайному виду сервісу, зважаючи на їхню передбачуваність і нижчі витрати. Користувачі активних видів пересування не виявили сильної переваги, що свідчить про обмежені ефекти заміщення. Загалом на вибір істотно впливали відчуття безпеки, довіри та задоволення від поїздки. Ці висновки підкреслюють, що універсального рішення не існує: ефективне впровадження автономних мікробусів вимагає диференціації за сегментами користувачів і ретельного узгодження з їхніми звичками.

Третє дослідження (Розділ 4) аналізує, як досвід поїздки змінює переваги користувачів щодо автономних мікробусів. У Гелмонді (Нідерланди) проведено двоетапний експеримент "до" і "після" короткої пробної поїздки. Результати показують, що навіть одна поїздка суттєво змінює сприйняття. Гнучкий сервіс автономних мікробусів став привабливішим, оскільки поєднував зручність автомобіля і доступність автобуса, тоді як звичайний вид сервісу здобув прихильність тих учасників, які отримали задоволення від поїздки або цінували наявність нагляду в салоні. Після поїздки учасники виявили більшу чутливість до часу очікування та пішого доступу, а значення вартості поїздки зменшилось. Експеримент продемонстрував, що безпосередній досвід істотно змінює оцінку атрибутів сервісу, а пілотні поїздки відіграють вирішальну роль у формуванні вибору користувачів.

Четверте дослідження (Розділ 5) присвячене спільним автономним автомобілям і вивчає, як можливість використовувати час у дорозі для роботи або відпочинку впливає на вибір користувачів і вартість часу подорожі. У експерименті типу "чарівник країни Оз" у Делфті учасники здійснили дві поїздки, виконуючи завдання, не пов'язані з водінням. Опитування до та після поїздки фіксували, як досвід і вид діяльності впливали на сприйняту корисність. Результати показують, що коли пасажири використовують час у дорозі для роботи, негативне сприйняття часу подорожі зменшується, а вартість часу подорожі для спільних автономних автомобілів стає нижчою порівняно з автомобілями та громадським транспортом. Учасники, які повністю зосередилися на завданнях під час поїздки, згодом оцінювали керування автомобілем більш негативно, усвідомлюючи навантаження від процесу водіння. Вартість поїздки на спільних автономних автомобілях сприймалася менш негативно, ніж на приватному автомобілі чи у громадському транспорті, головним чином через очікування нижчих постійних витрат. Довіра, відчуття безпеки та ставлення до автоматизації транспортних засобів додатково модифікували вибір. Сукупно ці результати свідчать, що досвід і можливість продуктивного використання часу подорожі радикально змінюють сприйняття автоматизованої мобільності.

Підсумовуючи, результати демонструють, що проєктування сервісу, сегментація користувачів і набуття досвіду є вирішальними для прийняття та успішної інтеграції автоматизованого громадського транспорту. Автономні мікробуси та спільні автономні автомобілі можуть підвищити сприйняття якості послуг і залучити нові групи користувачів, але лише за умови впровадження, орієнтованого на різноманітні потреби, рівні довіри та очікування. Дослідження підкреслює, що досвід поїздки — це не просто інформаційний інструмент, а поведінковий каталізатор, який формує те, як люди оцінюють гнучкість, комфорт і продуктивне використання часу подорожі.

Крім емпіричних результатів, дисертація пропонує структуроване розуміння того, як автономні транспортні засоби можуть впливати на якість громадського транспорту та сприйняття пасажирів. Вона містить практичні рекомендації для політиків, планувальників і операторів, які прагнуть відповідально впроваджувати автоматизовану мобільність. Для автономних мікробусів результати свідчать про доцільність пріоритетного розвитку гнучких сервісів для користувачів громадського транспорту, розроблення звичайного сервісу для автомобілістів черезб забезпечення доступних тарифів. Для спільних автономних автомобілів наголошено на важливості дизайну салону та сервісу, що дозволяють багатозадачність, поступового впровадження для підвищення довіри та продовження пілотних випробувань як навчальних середовищ для операторів і користувачів.

Загалом дисертація звертається до центрального виклику сучасної мобільності — як зробити громадський транспорт привабливішим, гнучкішим і сталим в умовах екологічного та урбанізаційного тиску. Поєднуючи сприйняття користувачів, досвід поїздки та проєктування послуг, робота демонструє, що шлях до сталої автоматизованої мобільності залежить не менше від соціального прийняття, ніж від технологічного прогресу. Представлені результати підтримують розроблення інклюзивних, науково обґрунтованих стратегій інтеграції автономних транспортних засобів у системи громадського транспорту, які є не лише ефективними, але й надійними, справедливими та орієнтованими на користувача.

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Chapter 1

Introduction

1.1 Research motivation

Transport history is marked by continual innovation, evolving from horse-drawn carriages to motorised vehicles and expanding into railways, mass transit, and global aviation. These developments have consistently responded to changing societal needs while harnessing technological opportunities (König & Neumayr, 2017; Axsen & Sovacool, 2019). Today, transport systems appear to be approaching a significant structural transformation. For over a century, mobility has been shaped by the paradigm of automobility, characterised by the widespread ownership and use of petroleum-fuelled private vehicles (Urry, 2004; Axsen & Sovacool, 2019). Although private cars have long symbolised freedom and convenience, their continued dominance has also produced a wide range of negative externalities: rising greenhouse gas emissions, air and noise pollution, traffic injuries and fatalities, congestion, urban sprawl, and deepening spatial inequality (Urry, 2004; Axsen & Sovacool, 2019).

The transport sector currently accounts for approximately 21% of global energy-related greenhouse gas emissions, with road transport contributing three-quarters of it (Statista, 2025a; 2025b). According to the World Health Organisation (WHO, 2024), air pollution is responsible for an estimated 6.7 million premature deaths each year, with the vast majority of the global population exposed to unsafe air quality. Road traffic injuries also remain a leading cause of death globally, especially among young people (WHO, 2023).

Simultaneously, accelerating urbanisation, tightening resource constraints, and global sustainability targets have placed growing pressure on transport systems to become more efficient, inclusive, and environmentally sustainable (Faisal et al., 2019; Garus et al., 2022). In dense urban areas, especially, limited space and resources make continued automobility dominance physically and environmentally unsustainable (Atasoy et al., 2025). While public transport (PT) remains the most viable large-scale alternative to private car use, its effectiveness is often undermined by fixed schedules, inflexible routes, and limited first-/last-mile connectivity, particularly in suburban and peri-urban areas (Lu et al., 2024; Carrese et al., 2023). These limitations have prompted growing interest in new technologies and service models aimed at expanding the reach, flexibility, and responsiveness of PT systems.

In this context, the emergence of automated vehicle (AV) technology is frequently described as one of the most promising and potentially transformative innovations in transport. In some cases, vehicle automation is described as a "creative destruction," meaning automated transport could complement or even replace traditional transport services with new, more efficient alternatives (König & Neumayr, 2017). Especially at higher levels of automation (SAE Level 4 and 5), AV technology promises safer, cleaner, and more responsive transport systems (Shladover, 2018; Kroesen et al., 2023).

However, whether automation contributes to more sustainable and equitable transport or instead exacerbates current challenges depends largely on how it is implemented and integrated into existing systems. It might enable a "bright side": a future of more inclusive, sustainable, and user-oriented mobility. Yet it also harbours a potential "dark side," risking the amplification of problems long associated with automobility, such as increased vehicle kilometres travelled, reduced PT ridership, and new forms of social or spatial exclusion (Sovacool & Axsen, 2018; Milakis & Müller, 2021).

The potential "bright side" emerges most clearly when automation is integrated with two other transformative trends: electrification and shared mobility. Together, these form the so-called "Three Revolutions" (Sperling, 2018), which, if steered wisely, can yield substantial public benefits. Each trend contributes a partial solution to long-standing automobility challenges: electrification reduces greenhouse gas emissions and local pollutants; sharing addresses inefficiencies of single-occupancy private vehicles and expands access to mobility; and automation introduces new potential for safer, more flexible, and cost-effective services (Axsen & Sovacool, 2019; Sanguinetti et al., 2021).

Shared Automated Vehicles (SAVs) and Automated Minibuses (AmBs) are two novel transport modes that reflect the intersection of these three trends. SAVs are autonomous electric vehicles shared by multiple passengers, typically accommodating 1 to 6 riders via on-demand car- or ride-sharing platforms (Golbabaei et al., 2021; Karolemeas et al., 2024). AmBs are small, low-speed, driverless electric shuttles designed for short-distance trips and first-/last-mile connections, with a typical capacity of 8 to 15 passengers (Chaalal et al., 2023; Heikoop et al., 2020; Zubin et al., 2021).

The operational "bright side" of SAVs and AmBs lies in their potential to improve the service quality of conventional PT, including enhancements in availability (particularly in low-demand or underserved areas), improvements in cost-efficiency, and increased accessibility for diverse user groups, among other factors (Almaskati et al., 2024; Greifenstein, 2024). These two new transport modes can be deployed as flexible, demand-responsive feeder services to main transit lines, potentially addressing the persistent first- and last-mile challenge affecting PT systems (Carrese et al., 2023; Narayanan et al., 2020). Their smaller size allows operation in narrow streets and compact urban environments, further enhancing accessibility (Chaalal et al., 2023; Millonig & Fröhlich, 2018). Empirical evidence from pilot projects, ranging from the EasyMile EZ10 trials in France and Singapore to Waymo's driverless services in San Francisco, demonstrates not only technical viability but also growing public familiarity with such services (Gurumurthy & Kockelman, 2018; La Delfa et al., preprint).

On the "dark side" of vehicle automation, the integration of SAVs and AmBs into existing PT systems is far from straightforward. While these transport modes offer operational advantages, they also present risks if deployed in isolation or without strategic coordination. The prospect of induced travel demand and a modal shift from high-capacity public transit to lower-occupancy automated PT poses serious challenges to sustainable urban transport planning (Almaskati et al., 2024; Carrese et al., 2023). As such, the potential for SAVs and

AmBs to enhance PT is contingent on their ability to complement rather than compete with established services, underscoring the critical role of governance and public policy in shaping the trajectory of automated mobility (Golbabaei et al., 2021; Almaskati et al., 2024).

Forward-looking governance frameworks should actively steer AV development toward shared-use models and ensure their alignment with sustainability targets. This might include supporting SAV and AmB deployment in contexts where they offer clear societal benefit, such as rural areas with limited transport options, and curbing their use in ways that would undermine PT in high-density corridors (Almaskati et al., 2024; Bala et al., 2023). Incentivising shared over private AV use, mandating data transparency, ensuring equity of access, and integrating automated PT services into broader mobility-as-a-service (MaaS) platforms are among the policy levers that potentially could be used by governments (Shaheen et al., 2020; Chaalal et al., 2023).

Assuming that the transformative potential of automation can be realised by enabling the “bright side” and minimising the “dark side” through proactive policy choices and thoughtful PT system design, one pivotal factor remains: the willingness of users to adopt these new automated PT services. While user acceptance of automated PT services has been widely studied in recent years, much of this work has focused on general attitudes such as trust, safety, and intention to use (Bala et al., 2023; Lécureux et al., 2023; Nordhoff et al., 2019), often in abstract or hypothetical contexts. In contrast, the societal uptake of SAVs and AmBs as components of PT systems depends not only on technological performance or regulatory frameworks, but also on how specific service quality improvements are perceived and evaluated by users.

The actual ride experience becomes especially important, as most potential users are unfamiliar with novel services such as SAVs and AmBs. In the absence of firsthand experience, perceptions are often based on assumptions, mental images, or media portrayals. Direct exposure, such as that offered through the pilot projects mentioned earlier, provides a concrete foundation for users to evaluate these emerging modes of transport. This ride experience enables them to form more informed and realistic preferences. Consequently, users’ preferences grounded in actual ride experiences yield more reliable insights into the likely adoption and use of SAVs and AmBs.

Despite the growing body of research on automated mobility, important gaps remain in understanding how these technologies may be adopted within the context of PT systems. Existing knowledge on automated transport is often fragmented across different service quality dimensions (e.g., Almaskati et al., 2024) and tends to emphasise potential system-level benefits and risks, rather than how users evaluate these changes in practice. While prior research has identified opportunities for improvements in flexibility, accessibility, comfort, and other service attributes (Carrese et al., 2023; Narayanan et al., 2020), less attention has been paid to how these improvements are perceived by users and how such perceptions evolve through actual ride experience.

Against this backdrop, the present study investigates how perceived service quality improvements and actual ride experiences influence user preferences for automated PT, specifically SAVs and AmBs. Gaining insight into these factors is critical for understanding the conditions under which automated mobility can earn public trust and respond to diverse mobility needs. By examining how users evaluate these emerging services, this research offers practical guidance for transport planners and policymakers striving to design and implement automated transport in ways that are not only technically efficient but also socially accepted and user-oriented.

1.2 Main research objective and questions

The main research objective of this thesis is:

“to explore the effects of service quality improvements and ride experience on users' preferences for automated public transport, such as shared automated vehicles and automated minibuses”.

To achieve this objective, the thesis is structured around two interrelated themes. The first theme concerns service quality (SQ) improvements, focusing on how vehicle automation can enhance or challenge key attributes of public transport such as flexibility, accessibility, comfort, and reliability. The second theme focuses on ride experience, recognising that direct exposure to automated public transport services plays a crucial role in shaping users’ perceptions and preferences, moving them from hypothetical expectations toward more informed and realistic evaluations. Together, these themes provide a comprehensive perspective on how automation may improve public transport in principle and how such improvements are perceived and internalised by travellers in practice.

The research first turns to SQ, identifying which aspects of public transport could be strengthened through automation, particularly where SAVs and AmBs may offer advantages over conventional modes and where knowledge gaps remain. The question guiding this part of the research can be formulated as follows:

Research Question 1

In which aspects could the service quality of public transport be improved through the introduction of automated public transport modes such as shared automated vehicles and automated minibuses?

With regards to SQ improvements, the thesis focuses on two aspects: the type of provided service and the use of travel time. In terms of service type, AmBs, given their similarity to conventional bus services, have the potential to enhance flexibility by offering fixed-route, scheduled services; on-demand, flexible services; or a combination of both, depending on passenger demand and operational context. SAVs, on the other hand, typically operate like taxis and inherently provide a high degree of flexibility by default.

In what respects to the use of travel time, this is particularly relevant for SAVs. Owing to their private or semi-private nature, SAVs provide a more suitable environment for productive or restful use of travel time compared to conventional PT modes and AmBs, where space is shared and the setting may be less suitable for concentration or relaxation. As a result, SAVs offer greater opportunities for travellers to make effective use of their time while in transit.

Accordingly, this thesis examines service type primarily in relation to AmBs and travel time use primarily in relation to SAVs, as each aspect aligns most closely with the unique characteristics and potential benefits of these respective automated transport modes.

The ride experience (a person having or not having an experience inside a vehicle with no driver) is the second major thematic focus of this thesis, alongside SQ improvements. These two dimensions, SQ and ride experience, form a conceptual framework for analysis, represented in Figure 1.1 as a two-dimensional space. The horizontal axis captures SQ improvements, while the vertical axis reflects the ride experience.

In this framework, SQ improvements for AmBs are represented through the transition from *Standard* to *Enhanced* service types, that is, from *regular* fixed-route and fixed-timetable operation to *flexible* on-demand, flexible-route service. For SAVs, SQ improvements are conceptualised through the evolving potential for productive travel time use, ranging from *Standard* conditions that resemble those of current PT to *Enhanced* environments that actively support the use of travel time for working or resting.

Along the vertical axis, the ride experience dimension distinguishes between perceptions formed without any real ride experience (*No Ride Experience*), relying instead on mental images, media portrayals, or assumptions, and those shaped after actual exposure to automated PT modes (*Ride Experience*), whether through riding in a SAV or an AmB. This distinction recognises the role of direct experience in shaping users' preferences and allows for a more nuanced understanding of how individuals respond to new transport modes.

The logical sequence of research questions within the exploratory framework (Figure 1.1) is outlined below, beginning with AmBs and followed by SAVs.

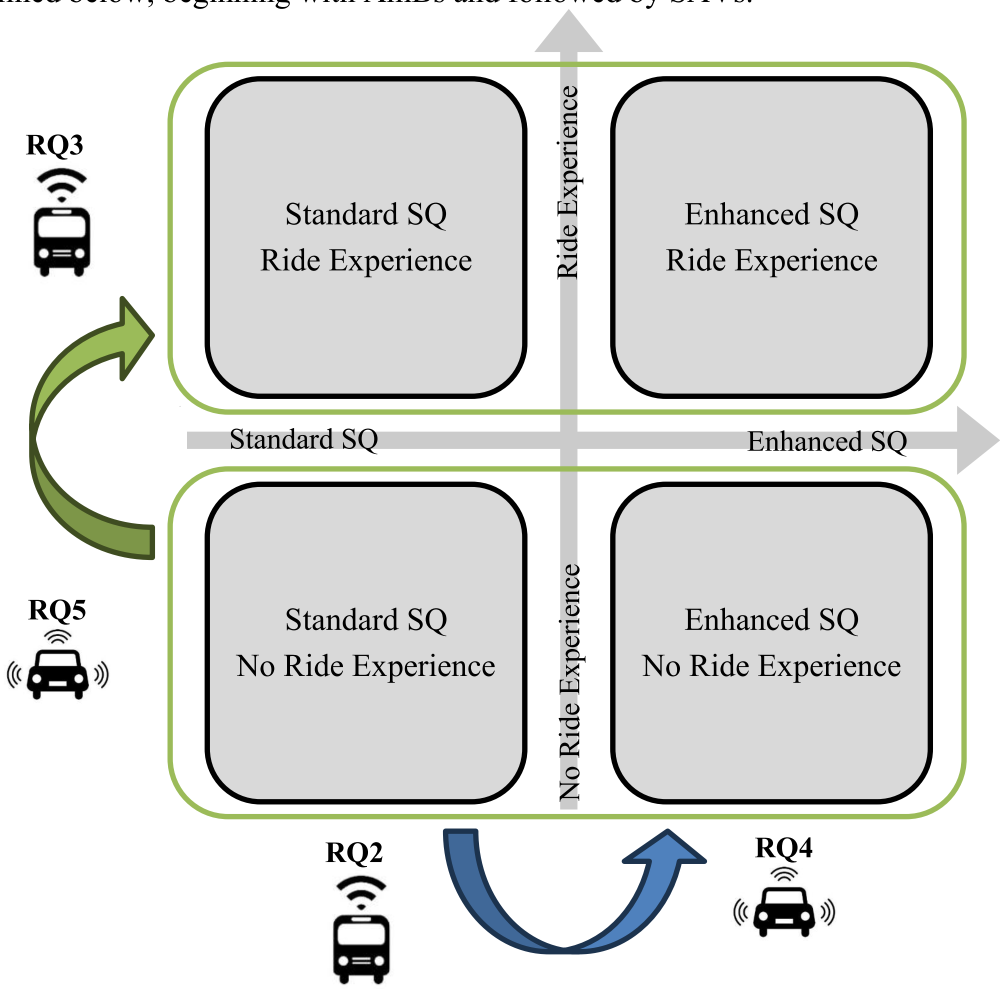


Figure 1.1. Two-dimensional exploration space

Research questions linked to the Automated minibuses (RQ2 and RQ3)

We start by examining how the type of service influences users' preferences for AmBs in the absence of actual ride experience. This approach allows us to establish baseline preferences toward regular and flexible services. In addition, we aim to distinguish these preferences across user groups based on their current travel mode, whether they are car users, PT users, or active mode users such as cyclists or pedestrians. This corresponds to addressing RQ2:

Research Question 2

Which type of service, regular or flexible, offered by automated minibuses is preferred, and how do these preferences vary across user groups based on their current travel mode?

In the next step, we explore the impact of having ride experience in AmBs on users' preferences for the type of service. This impact is reflected in the shift from preferences based on mental images to those formed after a real ride experience. RQ3 can now be formulated as:

Research Question 3
How does ride experience affect users' preferences for the type of service provided by automated minibuses?

Research questions linked to Shared automated vehicles (RQ4 and RQ5)
We explore whether the potential to use travel time influences users' preferences for SAVs, focusing on the added value of the private or semi-private travel environment these vehicles can offer. As with AmBs, we first establish baseline preferences formed without actual ride experience. We then investigate how these preferences may change after an actual ride, capturing the shift from expectations based on mental images to evaluations grounded in direct experience.

Research Question 4
How does the possibility of using travel time influence users' preferences for shared automated vehicles?

Research Question 5
How does ride experience shape users' preferences for shared automated vehicles, particularly in relation to the potential use of travel time?

This sequential structure provides a coherent framework for examining how SQ improvements – specifically, type of service and use of travel time – as well as former ride experience shape users' preferences for AmBs and SAVs. In the following chapter, we present the research approach used to operationalise these questions and gather the empirical data.

1.3 Research approach

This thesis employs a two-stage research approach to investigate how SQ improvements and ride experience influence preferences for automated PT, specifically SAVs and AmBs. The approach consists of:

1. *Pre-empirical stage*, which involves a literature review to identify relevant aspects of SQ that may be improved through automation.
2. *Empirical stage*, in which stated preference (SP) surveys are used to collect data on user preferences, and discrete choice modelling is applied to analyse the data and quantify behavioural responses.

1.3.1. Pre-empirical stage

The research begins with a structured literature review aimed at identifying which aspects of PT service quality may be enhanced through the introduction of automated transport modes, specifically SAVs and AmBs. This phase supports Research Question 1 (Chapter 2) by synthesising current knowledge on service attributes relevant to these emerging modes and identifying gaps in the existing evidence base. To provide a systematic and policy-relevant assessment, the review adopts the European standard EN 13816:2002 as a framework for evaluating SQ (European Committee for Standardisation [CEN], 2002). This standard classifies

PT service quality into eight core dimensions: availability, accessibility, information, time, customer care, comfort, security, and environmental impact.

In adopting this framework, the thesis does not assume that automated PT requires an entirely separate set of SQ dimensions from conventional PT. Rather, it starts from the premise that all PT services must satisfy a common baseline of expected quality. The relevance of SAVs and AmBs lies in how automation, shared use, driverless operation, and potentially flexible service provision may change the way these established dimensions are operationalised, prioritised, and experienced by users. For example, dimensions such as availability and accessibility may be affected by demand-responsive routing and first-/last-mile deployment, while information, customer care, and security may gain new relevance in services where interaction with a human driver or onboard staff is reduced or absent. Therefore, the analysis considers the potential contributions of SAVs and AmBs to each EN 13816 dimension, focusing mainly on the "bright side" (opportunities for improvement) while also addressing the "dark side" (possible drawbacks or trade-offs) introduced by automation.

Given the substantial body of research accumulated over the past decade on automated mobility, this review focuses on literature review studies published in the last five years that consolidate findings from earlier work. A systematic search was conducted in the Scopus and Web of Science databases using queries that combined various terms for SAVs and AmBs (e.g., self-driving shuttles, driverless vehicles, robotaxis) with review-oriented keywords (e.g., state-of-the-art, systematic review, literature review). The search targeted studies published in English up to January 2025 and included journal articles, conference proceedings, and book chapters. Titles, abstracts, and keywords were screened for relevance. In addition, backward and forward snowballing techniques were applied to capture additional relevant studies not identified through database searches. The final selection comprised 23 review papers, forming the evidence base for the analysis presented in Chapter 2.

1.3.2. Empirical stage

To empirically assess user preferences, three SP experiments are conducted (RQ2–5, Chapters 3–5). SP surveys are a well-established method in transport research, used to explore hypothetical yet realistic situations involving new or unfamiliar transport options (Louviere et al., 2000; Hensher, 1994). They are particularly suitable in this research context, as automated transport modes such as SAVs and AmBs are not yet widely available in real-world settings, limiting the feasibility of revealed preference data. Respondents are presented with repeated choice sets involving either SAVs or AmBs, and conventional modes such as private cars, public transport, and active modes (cycling and walking) in the application case of first-/last-mile connection to transit lines. These alternatives are described through varying levels of service attributes, enabling the identification of trade-offs in user decision-making (de Dios Ortúzar & Willumsen, 2011). While SP experiments allow the systematic variation of service attributes, it is recognised that they may be subject to hypothetical bias and may not fully reflect actual behaviour. To mitigate this limitation, this thesis complements SP surveys with experiential components, including pilot trials and a Wizard-of-Oz experimental setup, enabling participants to form preferences based on direct ride experience rather than solely on assumptions.

To enhance the behavioural realism of the models, the surveys also include attitudinal indicators and socio-economic characteristics, which are used to explain differences in preferences across individuals. This allows for segmentation by current travel behaviour and psychological predispositions toward automation and innovation (Train, 2009).

In Chapters 4 and 5 (RQ3-5), participants are exposed to ride experience through pilot trials (AmBs) or controlled simulations using the Wizard-of-Oz (WoZ) experimental setup

(SAVs). These experiments use a pre-post survey design, where participants complete key parts of the survey, including SP tasks and attitudinal measures, both before and after the ride. This design allows for the identification of changes in preferences caused by direct exposure to the new mode and helps to distinguish between hypothetical expectations and grounded evaluations (Jensen et al., 2013; González et al., 2016).

To analyse the data collected through SP surveys, the thesis applies discrete choice modelling, which assumes that individuals select the alternative that maximises their utility in a given choice situation (Train, 2009; Hensher et al., 2005). The systematic part of the utility function includes instrumental variables (e.g. travel time, cost, waiting time), socio-economic variables, and latent constructs representing attitudes. To operationalise this, the thesis applies hybrid choice models in a sequential estimation framework, balancing interpretability and complexity. To account for repeated observations from the same individuals, panel effects are included.

Moreover, scale parameters are introduced to adjust for differences in the error variance between respondent groups or experimental waves. In Chapter 3 (RQ2), scale parameters allow comparisons of preferences across traveller segments (car, PT, active modes) via an artificial nested logit structure (Swait & Bernardino, 2000). In Chapters 4 and 5 (RQ3, 5), scale parameters capture preference changes between the pre- and post-ride survey waves, isolating the effect of ride experience (Jensen et al., 2013; González et al., 2016).

All models are estimated using the Biogeme software package (Bierlaire, 2023), which supports complex specifications involving panel data and latent variables.

1.4 Scientific contributions

This thesis contributes to the evolving body of knowledge on the adoption of automated PT by offering an integrated behavioural perspective on how users perceive and experience two emerging modes: AmBs and SAVs, as reflected in their preferences for them. The scientific contributions of each chapter are as follows:

Identifying the key improvement areas in service quality of PT through the introduction of automated PT modes such as AmBs and SAVs (RQ 1, Chapter 2)

This chapter contributes to the scientific understanding of how automated PT modes (AmBs and SAVs) may impact the quality of PT services through an up-to-date and structured synthesis of recent literature. Applying the EN 13816:2002 standard as a conceptual framework, it identifies key service quality dimensions likely to be influenced by automation, highlights potential improvements, and assesses possible drawbacks. By organising fragmented knowledge into a coherent, policy-relevant framework, the chapter clarifies the current state of evidence, identifies research gaps, and provides a scientific and strategic foundation for understanding the role of automation in shaping future PT systems.

Establishing users' baseline preferences for AmB service types across travel mode segments in the absence of ride experience (RQ2, Chapter 3)

The following chapter contributes to the empirical knowledge of initial user preferences for AmBs, prior to any direct ride experience. It distinguishes between user segments based on their current travel modes (private conventional car, PT, active modes) and shows how preferences for service types (regular vs. flexible) differ across these groups. By doing so, the chapter provides insight into pre-adoption perceptions of emerging PT services and highlights the importance of considering behavioural heterogeneity when forecasting potential demand for AmBs.

This contribution has led to the following journal article:

Öztürker, M., Homem de Almeida Correia, G., Scheltes, A., Olde Kalter, M. J., & van Arem, B. (2022). Exploring users' preferences for automated minibuses and their service type: A stated choice experiment in the Netherlands. *Journal of Advanced Transportation, 2022*, 4614848. https://doi.org/10.1155/2022/4614848

Revealing the impact of ride experience on users' preferences for AmB service types (RQ3, Chapter 4)

This chapter demonstrates how ride experience influences users' preferences for automated PT. Using a panel-based pre-post design, it shows that even brief exposure to AmBs can significantly shift attitudes and choice behaviour. This is highly relevant, as most potential users currently lack direct experience with automated modes, making their preferences uncertain or assumption-based. By grounding SP data in actual ride experience, the study provides more reliable and realistic insights into the likely adoption and use of AmBs.

This contribution has led to the following conference paper:

Öztürker, M., de Almeida Correia, G. H., & van Arem, B. (2024). Ride experience in automated minibuses: measuring users' transport mode preferences before and after a test ride. *Transportation Research Procedia*, *78*, 335-344. https://doi.org/10.1016/j.trpro.2024.02.043

Understanding users' preferences for travel time use in SAVs through experiential exposure to work and leisure activities in a Wizard-of-Oz experimental setup (RQ 4 and 5, Chapter 5)

This chapter contributes to scientific knowledge by demonstrating how engagement in work and leisure activities in SAVs influences mode preferences and the perceived value of travel time (VoTT). It captures the dynamic nature of preferences before and after experiential exposure and quantifies how specific types of activities and levels of engagement shape perceived utility.

From a methodological perspective, the chapter first shows that immersive experiments (Wizard-of-Oz) are an effective approach for studying how participants experience and respond to new mobility services. Second, it demonstrates how physiological data, such as facial video recordings, used as a proxy for engagement levels during activities, can be integrated into discrete choice models to enhance behavioural analysis.

This contribution has led to the following journal article:

Öztürker, M., Nordhoff, S., Hoogendoorn-Lanser, S., van Arem, B., & Homem de Almeida Correia, G. (2026). Use of travel time in a shared automated vehicle for work and leisure: Results from a field experiment with a Wizard-of-Oz simulator-on-wheels vehicle. *Transportation Research Part C: Emerging Technologies*, *188*, 105646. https://doi.org/10.1016/j.trc.2026.105646

1.5 Societal relevance

Urban transport systems are under increasing pressure to respond to a range of urgent societal challenges, including reducing greenhouse gas emissions, improving air quality, addressing traffic safety, and managing space and resource constraints in growing cities. At the same time, traditional PT services often struggle to meet evolving mobility needs, especially in areas with low density or limited connectivity. Fixed routes, inflexible schedules, insufficient service coverage, and a growing shortage of qualified drivers further constrain public transport's capacity to provide reliable and attractive services, particularly when compared to the flexibility and privacy of private car use.

This thesis responds to these challenges by investigating the potential of automated PT modes, such as AmBs and SAVs, to improve service quality and attract a broader range of users. By focusing on two key aspects of service improvement, flexibility in service type and the ability to use travel time productively or restfully, it addresses the critical question of how automated mobility can make PT more responsive, comfortable, and appealing.

To realise their societal potential, these technologies must not only function technically but also align with user expectations. This research contributes to that alignment by uncovering how preferences for AmBs and SAVs differ across user groups and change after real-life exposure to the services. The findings show that assumptions alone are not sufficient to predict acceptance; ride experience plays a crucial role in shaping attitudes and mode choices.

By grounding stated preference data in actual ride experiences, the thesis produces more realistic insights into the likely adoption and use of automated public transport. This knowledge supports the design of targeted deployment strategies that move beyond one-size-fits-all approaches. For instance, current car users may require different incentives and service features than public transport users or active travellers. Understanding these differences is essential for developing scalable, inclusive, and sustainable automation policies.

The thesis also emphasises the importance of iterative pilot trials with structured evaluation methods, enabling policymakers and transport operators to monitor behavioural responses and adjust services accordingly. Experience-based pilots are not only technical tests but also behavioural learning environments that can help build public trust and improve service design.

Finally, the study underscores the relevance of travel time use perception for the design and pricing of automated services. By demonstrating how productive or relaxing travel time can influence preferences and the value of time, it supports more user-centred strategies, such as work-friendly vehicle layouts or differentiated pricing based on use cases. These strategies can further support a shift away from private car use, reducing environmental and spatial burdens on urban systems.

To summarise, this thesis addresses a core societal problem: how to make PT more attractive, flexible, and sustainable in the face of environmental, health, and urbanisation pressures. By combining behavioural research with real-world experimentation, it provides practical and evidence-based guidance for the responsible integration of automated mobility into future transport systems.

1.6 Thesis outline

This thesis is organised into six chapters (Figure 1.2), beginning with the development of a conceptual framework, continuing through the literature review and the empirical core of the study, and concluding with the main findings and their practical implications.

Chapter 1 introduces the research motivation, presents the main focus of the thesis on automated PT (AmBs and SAVs), SQ improvements, and ride experience, and states the overarching research objective. It also outlines the conceptual framework that guides the empirical research and highlights the contributions of the thesis.

Chapter 2 (RQ1) presents a structured literature review aimed at identifying which aspects of SQ can be improved through automation. Based on this review, two specific service features are selected for further empirical exploration: service type in relation to AmBs and use of travel time in relation to SAVs.

Chapter 3 (RQ2) focuses on user preferences for the type of service provided by AmBs without prior ride experience. It analyses how these preferences vary across different user groups based on their current travel behaviour, providing a baseline understanding of perceptions of AmBs' services.

Chapter 4 (RQ3) extends the previous chapter by incorporating actual ride experience in AmBs. It examines how direct exposure to the service influences users' preferences for the type of service provided by AmBs.

Chapter 5 (RQ 4 and RQ 5) shifts the focus to SAVs, exploring how the potential to use travel time productively or restfully influences user preferences. As in Chapter 4, it also assesses how these preferences change after participants experience SAVs and try to use their travel time during a ride in an experimental setting.

Chapter 6 concludes the thesis by synthesising the main findings across all empirical studies. It reflects on the theoretical and methodological contributions of the research and discusses implications for transport planning, service design, and future research.

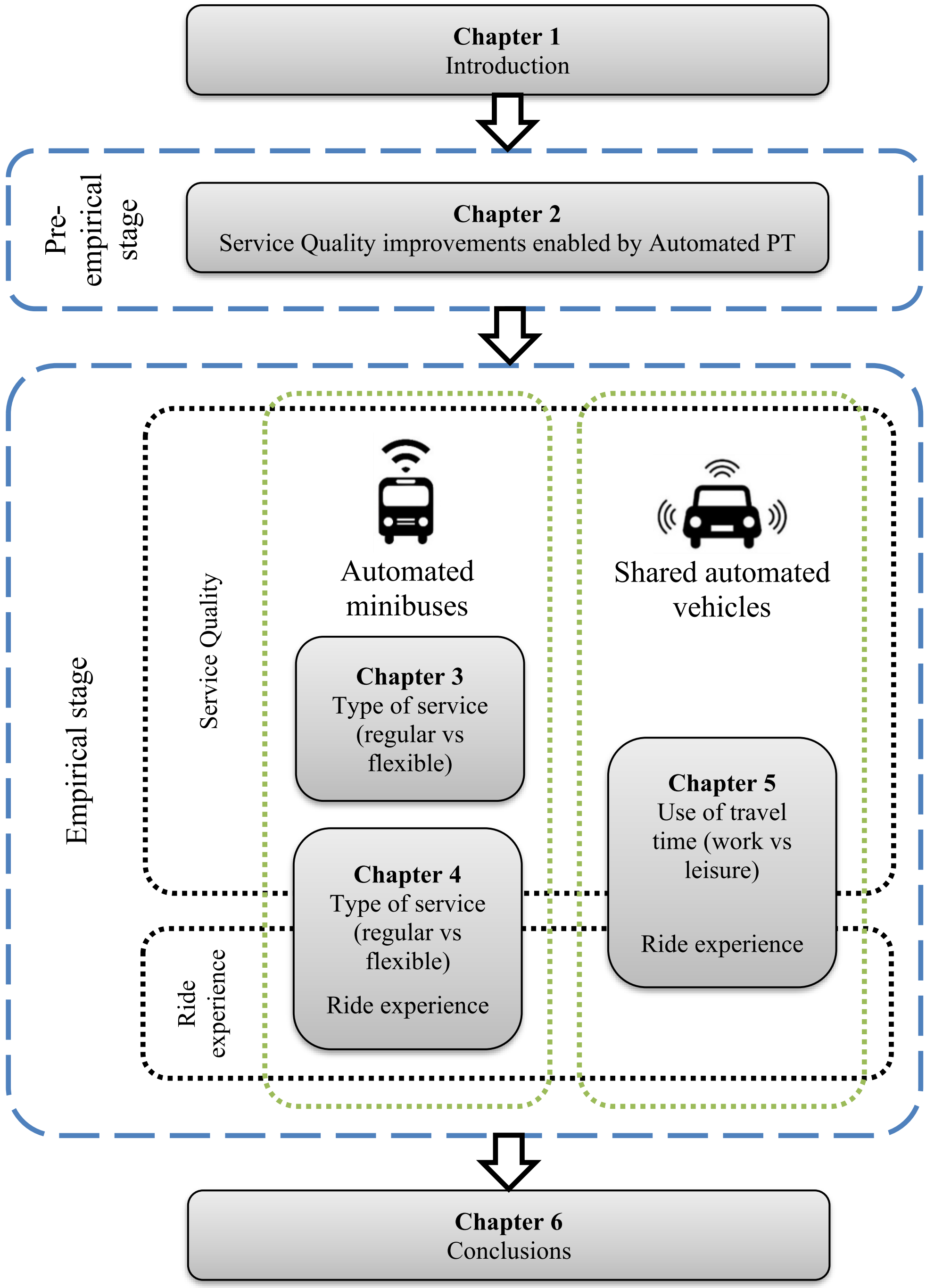


Figure 1.2. Thesis outline

Chapter 2

Service Quality Improvements of Public Transport Enabled by Vehicle Automation

Building on the conceptual framework introduced in Chapter 1, this chapter investigates how vehicle automation may influence the quality of public transport services. Specifically, it investigates which dimensions of service quality could benefit from the introduction of automated public transport modes such as shared automated vehicles (SAVs) and automated minibuses (AmBs), and where potential challenges or trade-offs may arise.

The main goal is to establish a structured understanding of how automation can shape user-perceived service quality, providing the conceptual foundation for the empirical analyses presented in later chapters. To this end, a user-centred analytical framework is developed that combines three complementary perspectives: the European Standard for Public Passenger Transport Service Quality (EN 13816), Maslow's hierarchy of needs, and the Kano model of customer satisfaction. This integrated framework supports a comprehensive and systematic evaluation of automation's "bright" and "dark" sides.

The analysis draws on a structured literature review synthesising 23 recent review papers on automated mobility, focusing on findings relevant to SAVs and AmBs. The chapter is structured as follows: Section 2.1 introduces the scope and rationale of the study; Section 2.2 outlines the analytical framework and search strategy; Section 2.3 presents the results; Section 2.4 discusses research gaps and future directions; and Section 2.5 concludes by summarising the key findings and outlining their implications for the empirical analyses in the following chapters.

2.1 Introduction

Public transport (PT) is a cornerstone of sustainable urban mobility, with the potential to reduce emissions, ease congestion, and improve equitable access to opportunities. Service quality underpins PT performance, shaping how users experience transit services and directly influencing decisions to adopt, continue, or abandon them. High-quality services that are reliable, accessible, safe, and comfortable not only attract riders but also help achieve broader societal goals related to sustainability, equity, and urban efficiency. Conversely, deficits in service quality, such as long waiting times, poor coverage, limited accessibility, or inadequate comfort, are well-documented barriers to widespread adoption, particularly when users have access to private vehicles (Allen et al., 2019; Lu et al., 2024). Although cities and governments have invested heavily in expanding and upgrading PT systems, ridership growth remains elusive in many contexts. For example, the European Union invests over €100 billion annually in transport infrastructure, with a significant portion dedicated to rail and urban transit. In the Netherlands, the national government committed €4 billion in the mid-2020s for PT infrastructure improvements, with an additional €3.5 billion allocated over the current decade for system upgrades such as corridor expansions and station developments (European Court of Auditors, 2023; RailJournal, 2022; Intertraffic, 2025). However, car dependency persists, with approximately 69% of the Dutch population still relying on cars (CBS, 2023c). These substantial investments demonstrate a strong policy commitment to improving the service quality of PT systems, yet they have not always translated into improved user satisfaction or sustained increases in ridership.

Public transport systems face a range of persistent challenges, from labour shortages and low service frequencies to limited network coverage, safety concerns, and accessibility barriers. Among these various obstacles to greater PT adoption, the first- and last-mile (FLM) problem remains especially significant in shaping access and user choices, particularly where service coverage is sparse or walking and cycling connections are poor. When stations or stops are difficult to reach, travellers often resort to driving, either to access PT or to complete their entire journey by car (Chidambara & Gupta, 2018; Meng et al., 2016, in Lu et al., 2024). A variety of solutions have been implemented to address FLM challenges, including park-and-ride facilities, bike-sharing systems, feeder buses, and, more recently, on-demand shuttles and shared micro-mobility options such as e-scooters and e-bikes. While these interventions have helped reduce access barriers in some settings, they also present limitations: park-and-ride requires substantial space and investment, generates local congestion, and excludes those without private vehicles; bike-sharing and micro-mobility may be inaccessible to less mobile users or unavailable in low-density areas; and on-demand services often face scalability and funding constraints (Habib et al., 2013; Olaru et al., 2014, in Lu et al., 2024). These persistent shortcomings highlight the need for more adaptive and inclusive solutions.

Emerging automated transport modes, such as shared automated vehicles (SAVs) and automated minibuses (AmBs), have gained attention as promising innovations with the potential to reconfigure how PT systems address these long-standing challenges. These modes offer flexible routing, can respond to real-time demand, and may provide viable service in low-density or underserved areas where conventional PT struggles to operate efficiently. Their automated nature also holds the potential to reduce operational costs, lower emissions, and improve overall convenience and reliability (Abe, 2021; Yap et al., 2016). In future mobility visions such as the "Hyperconnected Systems" scenario, SAVs and AmBs are envisioned as key components of integrated, sustainable transport ecosystems supported by proactive governance and technological interoperability (Atasoy et al., 2025). However, their implementation also raises critical concerns, including cybersecurity, social acceptance, accessibility for digitally excluded or less mobile users, and effective integration with existing PT networks (Greifenstein, 2024; Bala et al., 2023; Chaalal et al., 2023; Carrese et al., 2023). These emerging modes thus offer both new opportunities and new risks for the perceived service quality of PT systems.

To assess how SAVs and AmBs might enhance or compromise PT service quality, this study adopts the European standard EN 13816:2002 (European Committee for Standardisation [CEN], 2002), which defines eight key dimensions of service quality. These dimensions, namely, availability, accessibility, information, time, customer care, comfort, security, and environmental impact, offer a structured basis for assessing how emerging modes meet user expectations.

While EN 13816 defines *what* aspects of service should be measured, understanding *how* users evaluate these aspects requires a conceptual lens. This study integrates two psychological models, namely Maslow's hierarchy of needs and the Kano model, both of which have been adapted to the PT context to explore how users prioritise different service attributes (Aleen et al., 2019; Chee et al., 2020). Together, these models help explain why technical enhancements alone may not be sufficient to improve perceived service quality or increase ridership. By integrating the normative depth of psychological theory with the structured scope of EN 13816, this study enables a systematic and user-centred evaluation of where automated PT, specifically SAVs and AmBs, may enhance or undermine the passenger perception of PT service quality.

A growing body of review studies has explored different aspects of automated PT. Research centred on user perceptions and behaviour, including Bala et al. (2023), Heikoop et al. (2020), Nordhoff et al. (2019), Pigeon et al. (2021), and Greifenstein (2024), has provided valuable insights into acceptance, willingness to use, and intention to adopt automated services. Similarly, studies like Lécureux et al. (2023) and La Delfa et al. (preprint) advance understanding of behavioural responses and travel preferences, including the use of travel time.

A second group of studies has emphasised operational integration and system performance, analysing how automation can complement or compete with conventional transport. Reviews such as Carrese et al. (2023), Chaalal et al. (2023), and Lee and Gim (2024) examined integration strategies, accessibility, and equity implications, whereas Azad et al. (2019) and Iclodean et al. (2020) addressed safety, regulatory frameworks, and technological readiness.

Finally, several strategic and modelling-based reviews, including Narayanan et al. (2020), Karolemeas et al. (2024), Garus et al. (2022), and Almaskati et al. (2024), offer broader syntheses of traffic, land-use, and environmental impacts, often through simulation or demand-modelling perspectives. While these works deepen understanding of systemic implications, they rarely consider how automation may influence perceived service quality from the passenger's point of view.

Collectively, these studies reveal that research on automated PT remains fragmented, focusing mainly on user acceptance, preferences, and design aspects without systematically linking these insights to established service quality frameworks such as EN 13816. Although the literature has advanced understanding of user attitudes toward vehicle automation, it offers limited evidence on how these perceptions translate into evaluations of key service quality dimensions, such as accessibility, time, comfort, security, and customer care.

To address this gap, the present research begins with a structured literature review aimed at identifying which aspects of PT service quality may be enhanced or challenged by the introduction of automated PT modes, specifically SAVs and AmBs. The review is conducted from a user perspective, acknowledging that service quality ultimately hinges on passenger perception and experience. It applies the European standard EN 13816 as an analytical framework for evaluating service quality, while psychological models such as Maslow's hierarchy of needs and the Kano model provide insight into how users prioritise different service attributes.

On the one hand, automated modes may improve access, reduce waiting times, increase flexibility, or enhance comfort and perceived safety. On the other hand, they may diminish service quality by removing human support, introducing digital exclusion, or reducing social safety, particularly for certain user groups. While the analysis focuses primarily on the "bright side" of automation, it does not overlook the potential "dark side". Understanding both is essential to capturing the full range of user perceptions of automated PT.

Through this user-oriented and structured approach, the chapter seeks to identify which aspects of service quality users may perceive as improved when SAVs and AmBs are introduced and to determine where knowledge gaps remain. In doing so, it contributes to a more comprehensive understanding of how automation can support or undermine the perceived service quality of PT systems.

The chapter is structured as follows: Section 2.2 outlines the analytical framework and search strategy; Section 2.3 presents the results; Section 2.4 discusses research gaps and future directions; and Section 2.5 concludes by summarising the key findings and outlining their implications for the empirical analyses in the following chapters.

2.2 User-centred service quality in automated public transport: analytical framework and search strategy

This section outlines the analytical framework and methods used to assess how SAVs and AmBs may influence PT service quality from a user perspective. It is structured in three parts: first, it introduces the EN 13816 framework; second, it incorporates Maslow's and Kano's psychological models; and third, it describes the structured literature review used to populate the framework with empirical insights.

2.2.1. Defining the service quality of public transport

Assessing service quality in PT involves a multidimensional set of criteria that reflect both system performance and user experience. The European standards EN 13816:2002 and EN 15140:2006 offer a formalised framework for evaluating these dimensions (European Committee for Standardisation [CEN], 2002, 2006). This chapter uses the EN 13816 standard as its primary reference, which identifies eight key dimensions: availability, accessibility, information, time, customer care, comfort, security, and environmental impact. These categories provide a structured basis for assessing how well PT systems respond to the expectations and needs of passengers.

Although AmBs and SAVs represent novel forms of automated PT, this thesis does not treat them as requiring a separate set of service quality dimensions from conventional PT. They are still expected to meet the baseline quality requirements of any PT service. However, automation may change how these established dimensions are operationalised, perceived, and prioritised. Flexible and demand-responsive operation may alter the meaning of availability and accessibility; the absence of an onboard driver may increase the relevance of information, remote assistance, supervision, trust, and perceived security; and the more private or semi-private setting of SAVs may affect comfort and the use of travel time. Therefore, EN 13816 is used as a baseline structure for service quality, while the analysis examines how AmBs and SAVs may reshape the opportunities, risks, and trade-offs associated with each dimension.

Each dimension captures a distinct aspect of service quality. Availability concerns the extent and coverage of the PT network, including operational hours and frequency. Accessibility refers to the ease of reaching and using services, including physical design, fare structures, and modal integration. Information focuses on the accuracy and clarity of travel guidance. Time captures travel duration, punctuality and schedule reliability, while customer care reflects staff conduct and responsiveness to disruptions or special needs. Comfort includes physical conditions such as cleanliness, crowding, and noise levels. Security comprises both objective safety and subjective perceptions of personal risk. Lastly, environmental impact refers to how PT contributes to or mitigates pollution and congestion.

Together, these eight dimensions provide a comprehensive framework to evaluate how SAVs and AmBs might influence service quality from the perspective of passengers.

2.2.2. Integrating user-centred models: Maslow and Kano

While the EN 13816 standard defines what aspects of service should be measured, it does not specify how users weigh or interpret these elements. To address this gap, the current analysis is supported by two psychological models that provide a conceptual lens for understanding user priorities: Maslow's hierarchy of needs and the Kano model of user satisfaction.

Allen et al. (2019) proposed a three-level structure of user needs in the PT context (Figure 2.1), adapted from Maslow's hierarchy and aligned with the Kano three-factor model:

1. Functional needs (Basic factor in Kano): These are foundational requirements for using public transport and include attributes such as availability, accessibility, travel time, and information. Their absence leads to dissatisfaction, but their presence is typically taken for granted and does not elevate satisfaction further. As long as functional needs are unmet, they dominate user concern. Once satisfied, their relevance diminishes, allowing higher-order needs to become salient.
2. Security needs (Performance factor): These include aspects such as personal safety and perceived risk. Unlike functional needs, satisfaction with security attributes increases proportionally with service quality, and dissatisfaction arises when these expectations are not met. These attributes thus exert a linear influence on user satisfaction and become important once basic functional requirements are fulfilled.
3. Hedonic needs (Excitement factor): These needs relate to the emotional and experiential qualities of PT, including comfort, customer care, and environmental impact. While users do not expect these features by default, their presence can significantly enhance satisfaction. Conversely, their absence does not lead to dissatisfaction, making them asymmetrical influencers in the service experience.

The EN 13816 quality dimensions can be distributed across these levels as follows:

Maslow / Kano User Needs Levels	**EN 13816 Service Quality Dimensions**
Functional / Basic	Availability, Accessibility, Time, Information
Security / Performance	Security
Hedonic / Excitement	Comfort, Customer care, Environmental impact

This layered integration of EN 13816 with Maslow's and Kano's frameworks enables a more nuanced understanding of how users perceive and prioritise PT service quality. It highlights that while meeting basic functional needs is essential, it is rarely sufficient to enhance overall satisfaction or encourage sustained ridership. Instead, user experience depends on a combination of reliable operations, perceived safety, and emotionally resonant features such as comfort or environmental performance. This perspective is particularly valuable when assessing the potential of emerging service modes like SAVs and AmBs, which may improve hedonic attributes like comfort and environmental impact but also risk undermining perceived safety or customer care if not carefully implemented. By aligning technical service attributes with psychological models of need and satisfaction, this approach offers a more user-centred lens for evaluating how service innovations may shape perceptions, satisfaction, and ultimately the uptake of automated PT.

2.2.3. Literature search strategy

To populate the analytical framework with empirical insights, a structured literature review was conducted, guided by predefined research questions focused on how SAVs and AmBs may influence perceived PT service quality. Given the rapidly expanding body of research on automated mobility, this targeted and user-centred approach was chosen to synthesise key findings and identify knowledge gaps relevant to passenger experience.

The search was carried out across the Scopus and Web of Science databases using a combination of keywords related to automated PT modes (e.g., "shared automated vehicles", "self-driving shuttles", "robotaxis", "driverless minibuses") and review-oriented terms (e.g., "systematic review", "state-of-the-art", "literature review"). The search strategy was refined iteratively to capture variations in terminology and ensure thematic relevance. The scope was limited to peer-reviewed publications in English, available up to January 2025.

Inclusion and exclusion criteria were applied systematically during the screening process. Studies were retained if they offered insights into user experience, service design, or societal outcomes related to automated PT. Reviews focused solely on engineering, vehicle mechanics, or technocentric evaluations were excluded to maintain alignment with the study's behavioural and service-oriented perspective. Modal overlap was considered; for example, studies that addressed general forms of shared automated mobility were included if they offered transferable findings relevant to PT-like services. Although some studies included agent-based simulations or modelling approaches, only those that addressed user experience, behavioural dynamics, or perceived service quality were retained for analysis.

Eligible sources included peer-reviewed journal articles, conference proceedings, and book chapters. Titles, abstracts, and keywords were initially screened for relevance, followed by full-text review of selected articles. Backward and forward snowballing techniques were also employed to identify additional studies not captured in the initial database searches.

The final sample consisted of 23 review papers (Appendix A, Table A.1). These studies were then analysed using the EN 13816 quality framework, interpreted through the combined lens of Maslow's hierarchy of needs and the Kano model of user satisfaction. This process enabled the identification of how SAVs and AmBs may enhance or compromise different aspects of perceived service quality, providing a structured foundation for subsequent analysis.

2.3 Results

This analysis evaluates the impacts of AmBs and SAVs on PT service quality, following the dimensions outlined in EN 13816:2002 and their hierarchical importance based on Maslow's and Kano's models. For each dimension, we consider both the potential improvements these technologies may offer and the possible drawbacks they might introduce. The assessment distinguishes between effects that apply to both AmBs and SAVs and those specific to one mode. While the EN 13816 dimensions are treated as common baseline indicators for PT service quality, the analysis examines how their operational and experiential relevance may shift under automated, shared, driverless, or demand-responsive service conditions. This structure allows for a nuanced understanding of how each mode could enhance or complicate different aspects of PT service quality.

2.3.1. Functional / Basic needs

Availabililty

Availability refers to the extent to which PT services are offered across time, space, and transport modes. It encompasses the geographic reach of the network, operational hours, service frequency, and the suitability of available modes for different user needs.

AmBs and SAVs offer considerable potential to improve the availability of PT. Beyond their operational flexibility, these services can increase availability because vehicle deployment is no longer constrained by driver scheduling, labour shortages, or the cost of staffing low-demand routes. One of their most widely recognised advantages is the ability to extend service coverage to areas traditionally underserved by conventional fixed-route transit, such as rural regions, low-density suburbs, campuses, and business or healthcare complexes (Almlöf, 2022; Carrese et al., 2023; Millonig & Fröhlich, 2018; Chaalal et al., 2023; Zubin et al., 2021). Their smaller vehicle size and greater manoeuvrability support operations in narrow streets or low-demand zones that are inaccessible or economically inefficient for full-sized buses (Almlöf, 2022; Millonig & Fröhlich, 2018). In addition, simulations and pilot studies show that SAVs enhance spatial accessibility by bridging first- and last-mile gaps and functioning as feeders to high-capacity transit corridors (Carrese et al., 2023; La Delfa et al., preprint; Narayanan et al., 2020).

Automation also enables significant improvements in temporal availability. The absence of driver-related constraints allows for continuous or extended-hour operations, particularly valuable for shift workers or late-night travellers (Azad et al., 2019; Millonig & Fröhlich, 2018; Narayanan et al., 2020). On-demand scheduling capabilities, particularly prominent in SAV systems, allow services to be dynamically deployed according to temporal variations in demand, offering greater flexibility than fixed-route systems (Chaalal et al., 2023; Carrese et al., 2023; Zubin et al., 2021). AmBs, while often operating along predefined or semi-flexible routes, can still benefit from automation to increase frequency and maintain more consistent service during off-peak hours (Xu & Zheng, 2024; Zhao et al., 2022).

The flexibility of these modes further supports modal adaptability. SAVs in particular are suitable for a wide range of use cases, including long-distance commuting, multimodal trips, and contexts requiring door-to-door service (Golbabaei et al., 2021; Iclodean et al., 2020; La Delfa et al., preprint). Their ability to adjust operations based on trip types, living contexts, and land-use conditions makes them suitable for highly personalised transport needs (Iclodean et al., 2020; Zubin et al., 2021). Ridesharing, when implemented effectively, can enhance spatial and temporal availability by increasing occupancy rates and reducing the need for empty vehicle repositioning (Carrese et al., 2023).

However, realising this potential depends on addressing several critical challenges. A common concern is that initial deployments of AmBs and SAVs tend to occur in high-income, central urban areas, where technological infrastructure and political support are strongest, thereby risking the reinforcement of existing geographic and social inequities (Bala et al., 2023; Narayanan et al., 2020; Zubin et al., 2021). Moreover, if SAVs are introduced competitively rather than complementarily to existing transit, they may divert passengers from high-capacity modes, reduce network efficiency, and undermine service availability in the broader system (Narayanan et al., 2020; La Delfa et al., preprint).

Operational constraints also remain. AmBs, while more agile than traditional buses, still face limitations due to vehicle size, capacity, and infrastructure requirements, making them less suitable for high-demand corridors (Almlöf, 2022; Millonig & Fröhlich, 2018). Similarly, SAV availability is dependent on adequate fleet sizing and responsive system management. In contexts where fleets are under-resourced or poorly optimised, users may experience long wait times and inconsistent service, particularly during peak demand periods (Karolemeas et al., 2024; Zhao et al., 2022; Xu & Zheng, 2024). Studies also show that user acceptance of SAVs is sensitive to availability factors such as waiting time, travel time, and frequency, with low levels of service acting as a significant barrier to continued use (Pigeon et al., 2021; Nordhoff et al., 2019).

Taken together, the reviewed studies suggest that different AmB service types are viable in different operating contexts. Fixed-route or semi-fixed AmBs tend to perform best on dedicated lanes or in low-complexity traffic environments, where they can provide reliable and frequent feeder services to high-capacity corridors, whereas fully on-demand AmBs are more suitable in low-density urban or rural areas, where they can flexibly connect dispersed origins and destinations (e.g., Wen et al., 2018; Roche-Cerasi, 2019, as cited in Greifenstein, 2024). This supports a context-specific deployment strategy: on-demand AmBs can enhance spatial and temporal availability in areas with limited conventional transit, while dedicated-lane operations in busy corridors can improve reliability and travel time predictability. Across the literature, AmBs are therefore predominantly framed as complementary first- and last-mile feeders integrated with existing PT, rather than as substitutes for high-capacity bus or rail services (Greifenstein, 2024).

In sum, both AmBs and SAVs offer meaningful opportunities to enhance the availability of public transport, particularly by increasing geographic coverage, extending operational hours, and introducing flexible and user-responsive service models. Their potential is especially promising in low-density, peripheral, or otherwise hard-to-serve areas. However, these benefits will only be realised through careful planning, intentional integration with existing systems, and proactive measures to ensure equitable deployment. Without such safeguards, their introduction could exacerbate spatial disparities or reduce the overall efficiency and availability of public transport.

Accessibility

Accessibility refers to the ease with which users can access and utilise PT systems. This includes both physical access, such as the proximity and design of boarding and alighting points, and functional access, which encompasses integration with other transport modes, ease of transfers, and the inclusivity of ticketing and fare systems (Millonig & Fröhlich, 2018; Milakis & van Wee, 2020).

In terms of potential improvements, both AmBs and SAVs can enhance accessibility by offering flexible connections to and from major transit lines, especially in areas with long walking distances to stops, or in challenging terrain (La Delfa et al., preprint; Greifenstein, 2024). These services are particularly promising for improving first- and last-mile connectivity, allowing passengers to access main corridors more easily and with reduced physical strain, benefits that are particularly important for older adults, people with disabilities, and those with heavy luggage or strollers (Chaalal et al., 2023; Pigeon et al., 2021).

AmBs, operating on regular or semi-flexible routes, can provide structured and predictable access, which is valued by users who rely on routine, such as elderly individuals or those with cognitive impairments (Almlöf, 2022). In contrast, SAVs offer greater flexibility and responsiveness, empowering users in dispersed or rapidly changing environments (Ribeiro Pimenta et al., 2023). However, user acceptance is highly sensitive to access and egress time;

even a two-minute walk to an SAV stop can significantly reduce adoption (La Delfa et al., preprint).

When well-integrated with broader transport networks, both modes can enhance multimodal travel, improving functional accessibility by facilitating smoother transitions between modes such as walking, cycling, and traditional PT (Azad et al., 2019; Golbabaei et al., 2021). Coordinated pick-up and drop-off points at PT hubs can further support this integration (Garus et al., 2022; Zubin et al., 2021).

A critical element of functional accessibility is the ticketing system. AmBs and SAVs have the potential to support modern, app-based or contactless fare systems, which can simplify access, enable fare integration across providers, and allow personalised pricing models, including distance-based fares or targeted discounts for low-income users, students, and seniors (Bellet & Banet, 2023; Shaheen & Bouzaghrane, 2019). However, these benefits are not automatic. Where digital access is required for booking and payment, digital exclusion becomes a major barrier, especially for older adults, people with disabilities, or low-income individuals lacking smartphones, data plans, or banking access (Milakis & van Wee, 2020). To ensure equitable access, alternative booking and payment channels (e.g., physical kiosks, call centres, or in-person support) must accompany digital systems.

Vehicle design is equally critical. To meet physical accessibility standards, AVs must include low floors, ramps, sufficient space for wheelchairs or strollers, and provide multisensory information (visual, auditory, tactile) (Millonig & Fröhlich, 2018; Pigeon et al., 2021). Without these features, AVs risk excluding people with physical or sensory impairments. While some jurisdictions (e.g., Seattle) have mandated ADA-compliant SAVs, many fleets lack such features or provide them at a premium cost (Almaskati et al., 2024; Milakis et al., 2017). Furthermore, the removal of drivers from AVs eliminates a valuable source of human assistance, which is especially missed by users who need help boarding or feel unsafe in unattended vehicles (Almlöf, 2022; Zubin et al., 2021).

There is also a concern that SAVs may prioritise deployment in high-demand or high-income areas, sidelining communities where transport needs are significant but less profitable (Narayanan et al., 2020; Golbabaei et al., 2021). Without public sector coordination and integration with the PT system, these services could deepen spatial and social inequalities, especially if conventional PT routes are reduced or defunded in response (Milakis & van Wee, 2020; Bala et al., 2023).

In short, AmBs and SAVs hold substantial promise for improving both the physical and functional accessibility of PT systems, especially for people with limited mobility, those living in underserved or sprawling areas, and users with multimodal travel needs. However, realising this potential requires deliberate attention to inclusive vehicle design, accessible digital and non-digital service channels, and governance mechanisms that ensure these technologies serve the public good, not just market efficiency (Millonig & Fröhlich, 2018; Milakis & van Wee, 2020; La Delfa et al., preprint).

Time

Time refers to all aspects of temporal efficiency in PT, encompassing not just the total duration of a trip but also reliability, regularity, and synchronisation of services. Key indicators include travel time, schedule adherence, waiting time, access and egress time, transfer duration, and the availability of direct connections. These time-related factors are central to the attractiveness and competitiveness of automated PT, particularly in comparison to private vehicles.

The integration of AmBs and SAVs offers various opportunities to improve time-related aspects of service quality. Due to their automation and real-time coordination capabilities, both vehicle types can potentially reduce waiting and travel times by optimising dispatching and routing in response to current traffic conditions (Azad et al., 2019; Chaalal et al., 2023). Automated control systems also remove human-related variability, such as inconsistent driving speeds or delayed departures, thereby improving schedule regularity and reliability.

AmBs, when operating on fixed or semi-fixed routes, can deliver predictable travel times and more consistent service, especially if supported by transit signal priority or dedicated lanes (Azad et al., 2019; Xu & Zheng, 2024). SAVs, on the other hand, offer more flexible, on-demand routing and are especially effective in low-density or off-peak contexts. Their ability to serve first- and last-mile connections can significantly enhance journey efficiency for passengers whose origins or destinations are poorly served by conventional transit (La Delfa et al., preprint).

However, several challenges complicate these benefits. One key limitation is the low operational speed of many current AmB systems, restricted by legal or safety requirements to around 15–25 km/h. This reduced speed has been perceived by users as inefficient compared to other modes (Heikoop et al., 2020; Pigeon et al., 2021). In addition, real-world trials show that the very cautious driving style of current shuttles, characterised by frequent abrupt braking and prolonged yielding to other road users, can lead to longer and less predictable journey times and is sometimes experienced as uncomfortable or frustrating (Nordhoff et al., 2018; Straub & Schaefer, 2019, as cited in Heikoop et al., 2020). While slower speeds may enhance safety and user comfort, they can also undermine perceived travel efficiency, an important determinant of user acceptance (Zhao et al., 2022).

In the case of SAVs, shared ride-pooling can introduce delays if detours are needed to pick up or drop off other passengers. Studies show that longer travel or waiting times caused by these detours reduce willingness to use shared services (Greifenstein, 2024; La Delfa et al., preprint). Some users show very low tolerance for delays, with roughly 80% unwilling to wait more than six minutes for a ride (Christie et al., 2016, as cited in Zhao et al., 2022), and perceived waiting time being weighted more heavily than in-vehicle time (Othman, 2022; La Delfa et al., preprint).

Fleet availability and demand management are also critical. During peak periods, insufficient vehicle supply may lead to longer waiting times and lower ride reliability (Karolemeas et al., 2024). Efficient fleet size and scheduling strategies are therefore essential to deliver promised time savings. Simulation studies suggest that average waiting times can be reduced by 20–80% with well-optimised SAV systems (Karolemeas et al., 2024), although performance may decline in mixed-traffic environments unless managed carefully (Xu & Zheng, 2024).

A further challenge lies in coordinating transfers and multimodal integration. Without seamless booking systems and real-time updates, users may experience inefficient or unpredictable transfers between AVs and other PT modes, undermining overall journey reliability (Zhao & Malikopoulos, 2020; La Delfa et al., preprint). Research also shows that access and egress time are important to users and can heavily influence system acceptance, especially among older populations or those with limited mobility (La Delfa et al., preprint).

Finally, user perceptions of time-related service quality evolve with experience. As shown in longitudinal studies, users may reassess their expectations and become less tolerant of delays or slow service as automated systems become normalised (Zhao et al., 2022). Therefore, maintaining high and consistent levels of service speed, frequency, and coordination over time is essential.

In summary, AmBs and SAVs hold considerable potential to improve the temporal dimension of public transport by enhancing reliability, reducing waiting times, and offering flexible, responsive services. However, realising these benefits at scale depends on effective traffic prioritisation, dynamic fleet management, seamless network integration, and better alignment between system performance and user time sensitivity.

Information

Information dimension of service quality refers to the availability, clarity, and timeliness of data that support passengers in planning, executing, and adapting their journeys. This includes static information (such as route maps, schedules, and fare structures) as well as dynamic, real-time updates on vehicle arrivals, delays, service disruptions, and alternative travel options. In the context of AmBs and SAVs, information provision is central to the user experience, given that these services rely heavily on digital platforms and real-time communication infrastructure.

On the “bright” side of automation, AmBs and SAVs are inherently supported by digital ecosystems, enabling enhanced delivery of dynamic information. AmBs, for example, can provide real-time updates on routes and schedules, helping to reduce waiting times and improve passenger confidence in planning (Chaalal et al., 2023). These updates can be delivered through mobile apps, in-vehicle displays, or MaaS (Mobility-as-a-Service) platforms, facilitating seamless trip coordination across multiple transport modes (Axsen & Sovacool, 2019).

Digital platforms can also support information personalisation. For instance, users may receive notifications about delays, changes to their booked ride, or features tailored to accessibility preferences. Several studies suggest that the perceived sufficiency of information has a notable impact on initial adoption: Zhao et al. (2022) found that passengers were motivated to try automated buses when the provided information met their expectations. Similarly, Greifenstein (2024) reports that service attributes such as information quality were positively associated with the intention to use SAVs in approximately one-third of the reviewed studies (Greifenstein, 2024).

On-board systems also play a key role. Pigeon et al. (2021) emphasise the importance of clear and visible information inside vehicles, including real-time updates on position, route progress, and vehicle intentions (e.g., braking or turning). Multiple screen layouts may be necessary to accommodate bidirectional seating arrangements, while design considerations must ensure that visibility does not compromise external views. Additionally, studies have recommended incorporating icons, text, and even augmented reality to convey vehicle status effectively (Fröhlich et al., 2019, as cited in Pigeon et al., 2021).

On the “dark” side, there are several critical limitations to current information systems in automated PT. Digital access and literacy represent key barriers to inclusivity. Millonig and Fröhlich (2018) warn that passengers who are unfamiliar with complex networks or digital routing apps, such as older adults or residents of rural areas, may struggle to use automated PT services. Poor usability may cause them to abandon the service entirely. Additionally, the dependence on smartphones and internet connectivity risks excluding people without regular access or those with low digital literacy.

Automated PT systems also raise concerns about information equity. Data-driven models like MaaS often require the collection of personal data to operate effectively, including trip history for fare calculations. Millonig and Fröhlich (2018) point out that users who are unwilling to share this data may face exclusion from services, especially if there are no non-digital alternatives.

A further structural challenge, although not directly addressed in the reviewed studies, is the fragmentation of information in systems operated by multiple providers. If private automated PT services do not integrate their data with public authorities or MaaS platforms, passengers may be unable to plan multimodal trips coherently or receive reliable updates across different service providers. Without interoperability and standardised communication protocols, the broader PT ecosystem may become opaque and confusing.

In addition, the absence of drivers eliminates a traditional source of guidance and reassurance. Heikoop et al. (2020), citing Nordhoff et al. (2018), suggest that user confidence in automated PT systems may depend on the presence of on-board displays showing real-time system status or supervision from a remote control room. These technological substitutes for human interaction must be carefully designed to ensure they meet passengers' informational needs.

Finally, accessibility in information formats is critical. Pigeon et al. (2021) highlight the need for information to be conveyed through multiple channels, visual, auditory, and tactile, to accommodate users with sensory impairments. While some solutions have been proposed, such as audio alerts or transparent display screens, there is still little consensus on best practices for format, content, and user interaction.

In summary, while automation offers considerable potential to enhance the quality and personalisation of public transport information, its benefits remain unevenly distributed due to challenges related to digital access, inclusivity, and system integration.

Future research should investigate how user expectations evolve over time with continued exposure to automated transport systems, particularly in relation to information sufficiency and trust. There is a pressing need to develop strategies that promote digital inclusion, such as designing user interfaces that accommodate low digital literacy and integrating non-digital alternatives. Research should also explore how technological substitutes, like real-time displays or remote supervision, can effectively compensate for the absence of drivers and maintain user reassurance. In addition, studies are needed to assess the impacts of data-sharing policies and interoperability on passengers' ability to plan multimodal trips, especially within fragmented service networks. Finally, further work is required to establish inclusive standards for multisensory information formats and to understand how users respond to inconsistent or overwhelming information flows in automated public transport environments.

2.3.2. Security / Performance needs

Security

Security refers to both the actual and perceived protection of passengers throughout their public transport journey. According to EN 13816:2002, this includes the prevention of accidents, as well as measures that ensure passengers feel safe from crime, harassment, or technical failure. It encompasses both objective indicators, such as crash rates, system malfunctions, and cyberattacks, and subjective perceptions, like feeling secure while waiting at stops or travelling alone, particularly during off-peak hours (Azad et al., 2019; Millonig & Fröhlich, 2018).

AmBs and SAVs offer substantial opportunities to improve objective traffic safety. By eliminating human driving errors, responsible for over 90% of crashes, they promise to reduce accident rates significantly (Faisal et al., 2019; Narayanan et al., 2020; Sohrabi et al., 2021). Automation enables precise rule-following and removes risks linked to fatigue, distraction, or intoxication. These improvements are especially evident in simulations and pilot trials showing lower conflict rates and smoother operations (Othman, 2022; Xu & Zheng, 2024). However, in the context of public transport, where crash rates are already low, the marginal benefit in terms of accident reduction may be limited (Almlöf, 2022).

AmBs and SAVs can also be equipped with advanced monitoring systems, such as cameras, remote sensors, GPS tracking, and emergency communication tools, that enable real-time supervision and rapid response to incidents (Diba et al., 2025; Zubin et al., 2021). Such features are particularly valuable in the absence of drivers, as they allow for centralised oversight and intervention. However, while these technologies may deter crime or antisocial behaviour, they also raise concerns around surveillance and data privacy (König & Neumayr, 2017; Faisal et al., 2019; Narayanan et al., 2020).

Despite these advances, transitioning to fully autonomous, unstaffed services poses challenges for user security. The lack of onboard personnel can undermine feelings of safety, especially in confined vehicles or low-supervision contexts. Passengers, particularly women, older adults, and those travelling at night, may feel uncomfortable or vulnerable when sharing space with strangers, and the absence of staff removes a key deterrent against harassment or incivility (Azad et al., 2019; Bala et al., 2023; Pigeon et al., 2021). Studies consistently show that the presence of a steward, even passively, significantly improves perceived safety and increases willingness to ride (Heikoop et al., 2020; La Delfa et al., preprint). Where physical presence is not feasible, alternatives such as virtual assistants or control room monitoring may help, but their effectiveness is mixed (Zubin et al., 2021; Greifenstein, 2024).

Moreover, public trust in automation remains fragile. Even if autonomous systems prove statistically safer than human drivers, high-profile failures and lack of transparency can heighten public anxiety and resistance (Nordhoff et al., 2019; Bellet & Banet, 2023). Perceived safety, not just actual performance, is a decisive factor in the adoption of automated public transport (Lécureux et al., 2023; Chaalal et al., 2023). Clear communication, visible safety features (e.g., emergency stop buttons, in-vehicle displays), and well-tested protocols are essential for confidence-building.

From a broader system perspective, regulatory clarity is also crucial. Uncertainty around liability in the event of crashes can discourage users and create hesitancy about technology adoption (La Delfa et al., preprint; Milakis et al., 2017). Infrastructure must be adapted to support safety, particularly at pick-up and drop-off points. These areas should be well-lit, accessible, and under surveillance to reduce the risk of crime while waiting, especially in low-density areas or off-peak times (Millonig & Fröhlich, 2018; Diba et al., 2025).

Finally, cybersecurity is an increasingly prominent dimension of transport security. AVs' reliance on data transmission and connectivity exposes them to hacking, spoofing, and data misuse (Narayanan et al., 2020; Sohrabi et al., 2021; Faisal et al., 2019). Without robust safeguards, these vulnerabilities could lead to both physical harm and privacy violations, eroding public trust and undermining system integrity.

In summary, while AmBs and SAVs offer significant potential to enhance both actual and perceived safety through automation, monitoring, and rule-based control, these benefits will only be realised if accompanied by human-centred design, inclusive safety protocols, secure infrastructure, and strong governance frameworks. Attention must be paid not only to crash reduction but also to crime prevention, equitable access, and user trust—particularly for vulnerable groups and in transitional deployment phases.

2.3.3. Hedonic / Excitement needs

Comfort

Comfort encompasses the physical and sensory conditions experienced by passengers during their journey, including seating and standing availability, ride smoothness, ambient temperature, cleanliness, and noise or vibration levels. It also includes elements designed to make the journey as pleasant and convenient as possible. The introduction of AmBs and SAVs has the potential to improve comfort in several areas but also presents new challenges, particularly regarding capacity, consistency, and user expectations.

On the positive side, both AmBs and SAVs are often modern, purpose-built vehicles equipped with up-to-date interior features, such as ergonomic seating, climate control, low-floor entry, and real-time digital displays. Automation can also lead to smoother driving behaviour, as autonomous systems tend to apply gentler acceleration and braking, contributing to ride stability and reduced motion discomfort (Almlöf, 2022; Bala et al., 2023; Heikoop et al., 2020; Pigeon et al., 2021). This smoother ride is linked in several studies to reduced travel stress and increased relaxation, which can enhance well-being and enable multitasking during the journey (Kroesen et al., 2023; Almlöf, 2022; Othman, 2022; Sanguinetti et al., 2021).

Additionally, since these vehicles are frequently part of pilot programs or newly implemented services, they often operate with cleaner interiors and newer materials compared to older conventional fleets (Sanguinetti et al., 2021; Pigeon et al., 2021; Millonig & Fröhlich, 2018). Hygiene features such as non-porous surfaces, contactless controls, and cleaning protocols have become increasingly important for perceived comfort, especially in shared settings (Sanguinetti et al., 2021).

SAVs, in particular, can offer a more personalised and quieter experience when not pooled with multiple passengers. For those travelling alone or in small groups, the environment may feel less crowded and more private than traditional buses or trains (Sanguinetti et al., 2021; Millonig & Fröhlich, 2018; La Delfa et al., preprint; Xu & Zheng, 2024). This is especially appealing for riders concerned about noise, overcrowding, or social discomfort, and has been supported by studies highlighting the influence of seating orientation, spatial barriers, and territorial markers on perceived comfort in shared automated vehicles (Sanguinetti et al., 2021; Bala et al., 2023; Millonig & Fröhlich, 2018).

AmBs, while shared, are usually smaller in size than conventional buses, which may allow for better control of passenger load and more focused maintenance routines. If deployed in low-demand areas or off-peak periods, they can offer a calm and relatively spacious ride (Bala et al., 2023; Zhao et al., 2022; Greifenstein, 2024). Empirical studies show that comfort, more than initial novelty, is what sustains continued use of automated services over time (Bala et al., 2023; Zhao et al., 2022).

Modern vehicle interiors may also feature amenities such as Wi-Fi, charging ports, entertainment systems, adjustable lighting, and infotainment screens, all of which contribute to a more pleasant and convenient journey experience (Sanguinetti et al., 2021; Pigeon et al., 2021; Millonig & Fröhlich, 2018). These amenities increase passengers' perceived control and satisfaction, particularly when travel time can be used productively or recreationally (Kroesen et al., 2023; Othman, 2022; Sanguinetti et al., 2021). At the same time, the literature points to considerable variability in how passengers expect to use travel time in SAVs. Some, especially regular commuters, express a strong interest in working, studying, or relaxing during the ride, whereas others doubt they will engage in such activities unless the vehicle offers sufficient privacy, space, and a calm environment (Greifenstein, 2024). In several studies, a share of respondents indicated a willingness to pay more for exclusive or less crowded SAV services, suggesting that privacy and personal comfort are prerequisites for productive or enjoyable in-vehicle time, rather than guaranteed outcomes of automation (Greifenstein, 2024; Nazari et al., 2018). This implies that the hedonic benefits of SAV travel, such as being able to reclaim travel time, are contingent on meeting minimum thresholds for comfort and perceived security in shared settings.

However, comfort-related drawbacks must also be considered. The limited size and seating capacity of both AmBs and SAVs can reduce comfort when demand exceeds expectations, particularly during peak hours or special events. In such situations, passengers may face overcrowding or a lack of seating, especially if services are not frequent enough to absorb fluctuating demand (Xu & Zheng, 2024; La Delfa et al., preprint). Research shows that shared use with strangers, especially for long periods, can amplify discomfort unless adequate space and personal boundaries are maintained (Sanguinetti et al., 2021; Millonig & Fröhlich, 2018).

Another potential issue is the absence of staff, which may affect passengers' comfort in dealing with unexpected situations, disturbances caused by other passengers, or questions about the service. In traditional systems, the presence of a driver or conductor can serve as a deterrent to anti-social behaviour and a source of reassurance for passengers; automated systems lack this human oversight. This concern ties into both social comfort and the broader perception of service quality (Bala et al., 2023; Millonig & Fröhlich, 2018).

Cleanliness and interior maintenance can also become problematic if not well managed. While automated systems often include remote monitoring and scheduled cleaning, the lack of on-board staff may reduce real-time oversight, leading to slower responses to spills, littering, or vandalism (Sanguinetti et al., 2021; Pigeon et al., 2021). Moreover, without a clear feedback loop, passengers may be unsure how to report cleanliness issues quickly and effectively, undermining their comfort and satisfaction.

Lastly, for SAVs in pooled-use formats, the dynamic routing and frequent stops associated with ride-sharing may negatively impact the sense of comfort, particularly for those seeking a quiet, uninterrupted trip (Sanguinetti et al., 2021; Xu & Zheng, 2024). In such cases, the design of seating layouts, personal space management, and social interaction cues become even more critical to maintaining an acceptable level of comfort.

In conclusion, while AmBs and SAVs can enhance comfort through modern vehicle design, smoother rides, and potentially quieter or more private environments (Almlöf, 2022; Bala et al., 2023; Sanguinetti et al., 2021), their ability to maintain high comfort levels depends on fleet sizing, service frequency, interior maintenance, and user-sensitive design (Greifenstein, 2024; Zhao et al., 2022; La Delfa et al., preprint; Pigeon et al., 2021; Millonig & Fröhlich, 2018). Thoughtful planning and real-time support systems are crucial to ensure that automated services provide a consistently comfortable experience for all passengers.

Customer care

Customer care refers to the extent to which PT services respond to the individual needs of passengers, particularly through assistance mechanisms, human interaction, and responsiveness to questions, complaints, or disruptions. This dimension traditionally relies on direct contact with staff who can provide support and reassurance. In the context of AmBs and SAVs, the absence of on-board personnel prompts a shift toward digital and remote customer service systems, presenting both potential improvements and challenges.

On the "bright" side, AmBs and SAVs can enhance customer care by offering scalable, standardised support through integrated digital platforms. These systems may allow passengers to request help, receive personalised guidance, and access multilingual assistance through AI-powered or chat-based interfaces. For digitally fluent users with routine needs, such solutions can offer fast, consistent responses and eliminate variations often encountered in human-based interactions. Additionally, studies have identified "facilitating conditions", such as organisational support, available infrastructure, and system responsiveness, as modestly influential in shaping behavioural intention to use SAVs (Yuen et al., 2020; Paddeu et al., 2020, as cited in Greifenstein, 2024). These conditions may include digital help channels, escalation procedures, or backend responsiveness that collectively contribute to a more reliable customer experience.

However, on the "dark" side, significant limitations remain. The lack of on-board staff removes a crucial layer of in-situ support, particularly important for passengers who may require assistance, such as older adults, people with disabilities, or those unfamiliar with the technology. In traditional transport systems, drivers or conductors are often the first point of contact during unexpected events such as delays, technical malfunctions, or personal distress. Without this human presence, AmBs and SAVs risk leaving passengers without immediate help in such situations. Millonig and Fröhlich (2018) underscore that drivers serve important social functions beyond transportation; they offer guidance, help manage conflicts, and contribute to a sense of safety. In AV systems, these social roles remain unresolved, and their absence could significantly reduce the sense of emotional security for some user groups.

In support of this concern, Heikoop et al. (2020) found that the presence of a steward or attendant on board was perceived by users as beneficial for ensuring comfort and safety, not just for passengers, but also in facilitating interaction with surrounding traffic. The social reassurance provided by a staff member was valued alongside their role in information dissemination (Boersma et al., 2018; Distler et al., 2018; Rehrl & Zankl, 2018, all as cited in Heikoop et al., 2020). Such human contact also contributes to perceptions of accountability and system reliability, especially during incidents or service disruptions.

Other studies echo these findings, showing that users, especially women and older passengers, may feel emotionally vulnerable in the absence of human presence. Axsen & Sovacool (2019) report that fully automated vehicles could exacerbate feelings of isolation, anxiety, and distrust, particularly in situations where inappropriate behaviour or conflict occurs on board. In such contexts, the lack of a human figure of authority can intensify discomfort and reduce perceived personal safety.

Moreover, while digital customer care systems can support passengers remotely, the literature provides little evidence that they are equally effective in fostering trust or emotional reassurance. Automated feedback systems, voice control interfaces, and live chat features may functionally resolve issues, but they are not yet perceived as substitutes for human empathy or interpersonal presence, especially during unexpected or high-stress scenarios.

Finally, public acceptance of fully automated services may depend on whether users feel that their concerns are heard and addressed. While some digital systems may include channels for submitting complaints or giving feedback, the absence of visible or immediate human contact can reduce users' trust. If passengers perceive these channels as opaque or ineffective, their confidence in the service may erode, even if technical performance remains high.

In summary, AmBs and SAVs offer opportunities to rethink customer care through digital automation and responsive system design. However, the emotional and interpersonal dimensions of care, traditionally provided by human staff, remain difficult to replicate. To ensure inclusive and trustworthy service, automated PT systems must embed mechanisms for real-time support, design for the needs of vulnerable groups, and maintain visible, responsive pathways for feedback and problem resolution. There is clear evidence that many users, particularly those who are vulnerable or new to the system, prefer some form of on-board human supervision. Until fully digital support systems can demonstrate equivalency in terms of trust and emotional security, human presence is likely to remain a critical component of perceived service quality.

Environmental impact

Environmental impact refers to the effect of public transport operations on the natural and urban environment. This includes emissions, energy consumption, noise pollution, and the overall ecological footprint of the system. According to EN 13816:2002, environmental performance is a key quality indicator, reflecting the public transport system's contribution to broader sustainability goals. The integration of AmBs and SAVs presents both promising opportunities and important challenges in this dimension.

A key potential benefit of AmBs and SAVs is their ability to reduce environmental externalities, particularly when they replace private car travel. Private passenger vehicles currently account for approximately 75% of transportation-related GHG emissions globally (Almaskati et al., 2024), making their replacement critical for climate mitigation. Studies predict that SAVs, when deployed as electric, right-sized vehicles, can reduce greenhouse gas emissions by 56–94% and energy consumption by 53–76%, depending on fleet composition and charging strategies (Axsen & Sovacool, 2019; Almaskati et al., 2024; Bala et al., 2023; Golbabaei et al., 2021). Similarly, shared autonomous buses offer greater fuel efficiency and emissions reduction when operating collectively rather than as private AVs (Azad et al., 2019).

If used to complement conventional PT, by improving first- and last-mile connectivity or serving low-density areas, AmBs and SAVs can reduce car dependency and support modal shift, ultimately contributing to improved urban air quality and climate targets (Faisal et al., 2019; Golbabaei et al., 2021). Simulation studies show that integrating SAVs with PT could lead to up to 37% energy savings compared to private cars (Golbabaei et al., 2021). Public transport promotion in urban areas has also been shown to reduce both fuel energy use and GHG emissions by over 22% over a 30-year period (Hasan et al., 2022).

Operational efficiencies also play a major role. AmBs operating on optimised schedules, especially when demand-responsive, can help reduce energy waste (Hasan et al., 2022). SAVs equipped with intelligent routing and ride-pooling algorithms can increase average vehicle occupancy, reduce vehicle-kilometres travelled (VKT), and lower overall emissions per passenger (Golbabaei et al., 2021; Milakis et al., 2017). Driving behaviour, such as smoother acceleration and deceleration enabled by automation, can yield an additional 15–20% fuel savings (Othman, 2022).

Both modes are generally quieter than conventional diesel buses, which contributes to a reduction in noise pollution, especially in residential neighbourhoods and near sensitive locations like schools and hospitals (Golbabaei et al., 2021; Karolemeas et al., 2024). This enhances the liveability and health of urban environments.

However, these environmental benefits are not guaranteed. Without proper integration into the transport ecosystem, SAVs in particular may induce additional travel, either by replacing more sustainable modes (walking, cycling, PT) or by increasing VKT through “deadheading” (vehicles driving empty to pick up passengers). Studies suggest that under certain conditions, the net environmental impact of SAV deployment could be negative, potentially doubling emissions if car dependency increases (Almaskati et al., 2024).

Induced demand is a risk: the convenience and affordability of SAVs may encourage people to travel longer distances or more frequently (Golbabaei et al., 2021). Without regulatory and pricing mechanisms, such as VKT-based pricing or incentives for shared trips, these services may undermine decarbonization goals (Faisal et al., 2019; Axsen & Sovacool, 2019).

In addition, the life-cycle environmental footprint of AVs and related infrastructure must be considered. The production and disposal of batteries, sensors, and AV-specific hardware are resource- and energy-intensive, with environmental impacts extending well beyond operational emissions (Golbabaei et al., 2023). Effective battery recycling, sustainable material sourcing, and energy-efficient manufacturing are essential to mitigate these long-term impacts.

The design of infrastructure, including charging stations, pick-up/drop-off points, and integration with walking and cycling facilities, also influences ecological outcomes. Emission reductions are amplified when electric AVs are charged using low-carbon energy sources and when charging schedules align with renewable energy availability (Narayanan et al., 2020; Golbabaei et al., 2021). Strategic placement of shared charging hubs can also reduce unnecessary vehicle travel (Narayanan et al., 2020).

Importantly, attitudes toward environmental sustainability influence SAV adoption. While findings are mixed, several studies show that individuals with strong pro-environmental values are more likely to adopt SAVs if they perceive them as a sustainable alternative to car ownership (Nazari et al., 2018; La Delfa et al., preprint; Lécureux et al., 2023). The communication of environmental benefits has been shown to strengthen this effect (Narayanan et al., 2020), suggesting that environmental framing plays a role in supporting both user acceptance and policy legitimacy.

In conclusion, AmBs and SAVs hold strong potential to support low-emission, quiet, and energy-efficient public transport, but only if their deployment is carefully managed to complement existing transit, encourage shared use, minimise empty miles, and align with sustainable energy systems. Without these safeguards, their environmental performance may fall short of expectations or even worsen existing urban challenges.

2.4 Conclusions and future research directions

This review highlights that automated PT modes, specifically AmBs and SAVs, present both opportunities and challenges for the perceived service quality of PT systems. Drawing on the European standard EN 13816 and integrating psychological frameworks from Maslow's hierarchy of needs and the Kano model, this study shows that vehicle automation can enhance several service quality dimensions, including availability, accessibility, comfort, and environmental impact, while simultaneously introducing new risks related to security, customer care, and digital inclusion.

Taken together, the reviewed evidence underscores that service design is pivotal for the success of AmBs, and that the way passengers experience and use travel time in SAVs can fundamentally shape user acceptance. In particular, AmBs appear most promising when deployed as feeder or first-/last-mile services in areas or time periods with low conventional transit supply, rather than as replacements for high-capacity lines, while SAVs have the potential to transform in-vehicle time from "lost" time into productive or enjoyable time, provided that vehicles and services meet basic expectations for comfort, privacy, and safety.

Overall, the synthesis indicates that AmBs and SAVs can strengthen the basic and hedonic layers of service quality but may compromise security and interpersonal aspects traditionally ensured by human presence. Their ability to enhance temporal and spatial efficiency is promising, yet highly dependent on the quality of service design, user experience, and governance. However, existing research remains limited to short-term trials, hypothetical experiments, or simulation-based analyses, leaving substantial uncertainty about how user perceptions evolve through real, repeated interactions with automated PT.

Viewed through the EN 13816 lens, the findings suggest that automated services can substantially improve the *Availability* of PT – by extending coverage to low-density areas and enabling late-night or off-peak service unconstrained by driver shifts – and, under suitable design, the *Accessibility* of the network, for instance via demand-responsive or door-to-door services for people living far from fixed routes or with limited mobility. If passengers are able to use in-vehicle time for work or leisure in SAVs, the *Time* dimension of quality is also enhanced, as the perceived burden of travel time decreases. At the same time, the literature and reviewed studies highlight that the benefits for *Comfort* and *Security* are far from automatic: cautious but sometimes erratic vehicle behaviour, small vehicle size, the absence of staff, and the need to share space with strangers can reduce perceived comfort and personal security, particularly among women, older adults, and other vulnerable groups. The withdrawal of drivers also affects *Customer care*, removing an important source of on-board assistance and social control, which current digital support channels cannot fully replace. As a result, the success of AmBs and SAVs will depend not only on operational performance but also on whether they deliver consistently on these quality attributes that matter most to users: reliability and travel time, but also comfort, safety, accessibility, and responsive support.

Future research should therefore extend beyond attitudinal intention to examine how actual ride experience influences perceptions of service quality across diverse user groups. It is important to understand how users adapt their expectations over time and whether satisfaction stabilises, increases, or declines as automated PT systems become normalised. This calls for longitudinal and comparative studies that consider different operational settings, such as public versus privately managed services, and diverse social and demographic contexts, including gender, age, and special needs. Moreover, future studies should explore how users balance perceived safety, comfort, and control in shared automated settings that operate at high levels of automation and accommodate multiple passengers. Governance frameworks and service models also require closer scrutiny, not only in terms of efficiency but also regarding data privacy, transparency, and equity, to ensure that automated mobility systems remain inclusive and legitimate components of public transport networks.

Building on these identified gaps, the next stage of research will focus on two primary directions. The first concerns the type of service for AmBs, examining how variations in operational design, such as routing structure, stop configuration, and service flexibility, shape user preferences and perceived service quality before and after real ride experiences. The second focuses on the use of travel time in SAVs, analysing how vehicle automation changes the way users value and utilise in-vehicle time for productive or recreational purposes. This includes assessing how these perceptions evolve after direct experience.

Ultimately, adopting AmBs and SAVs in PT involves a trade-off: these modes can substantially improve service availability and enable travellers to reclaim their travel time, but they also introduce new challenges for managing service quality and user trust. Bridging this gap will require close collaboration between transport authorities, operators, technology providers, and user groups to ensure that automated PT services are carefully integrated into existing networks, aligned with established quality standards, and supported by clear policies on issues such as role division with conventional PT, pricing, data protection, and minimum comfort and safety requirements. By addressing these design and governance questions, the potential benefits identified in this review – more flexible, efficient, and user-centred public transport – stand a greater chance of being realised in practice, in ways that are socially inclusive and sustainable.

Chapter 3

Users' Preferences for Automated Minibuses and Their Service Type

Building on the conceptual findings from Chapter 2, which identified potential areas where vehicle automation could enhance public transport service quality, this chapter shifts from a theoretical to an empirical perspective. It investigates how users evaluate one specific aspect of automated public transport – the type of service provided by automated minibuses (AmBs) – in the absence of direct ride experience. The analysis focuses on how preferences differ between regular (fixed-route, fixed-schedule) and flexible (on-demand, door-to-door) services, and how these preferences vary among user groups with distinct travel habits.

To address these questions, a stated choice experiment was conducted among travellers in the Netherlands. The experiment assessed participants' preferences for AmB service types and analysed variations across mode segments, including car users, public transport users, and active mode travellers. This approach establishes a behavioural baseline for understanding perceptions of automated minibuses prior to real-life exposure, forming a reference point for the subsequent chapter that examines the effect of actual ride experience.

This chapter is organised as follows. Section 3.1 introduces the research context and objectives. Section 3.2 outlines prospective users' expectations and concerns regarding AmBs. Section 3.3 describes the research methodology, followed by a presentation of the survey data in Section 3.4. The modelling approach is explained in Section 3.5, while Sections 3.6 and 3.7 discuss the results and present general conclusions and future research directions.

This chapter is based on the following paper:

- Öztürker, M., Homem de Almeida Correia, G., Scheltes, A., Olde Kalter, M. J., & Van Arem, B. (2022). Exploring users' preferences for automated minibuses and their service type: A stated choice experiment in the Netherlands. *Journal of Advanced Transportation*, *2022*(1), 4614848.

3.1. Introduction

In the last several decades, urban mobility has undergone a fast transformation driven by the sharing economy, electrification, and automation. A variety of travel options that complement public transport (PT) systems is provided by vehicle-sharing (e.g., cars and micromobility modes such as scooters, and bicycles) and ride-sharing services (e.g., car or vanpooling, taxi-like services, and microtransit minibus shuttles). Nowadays, an increasing number of environmentally friendly electrical models are being deployed in these services, while potentially safer and more cost-efficient automated vehicles are expected to substitute human-driven ones in the near future (Abduljabbar et al., 2021; Liao & Correia, 2022; Shaheen et al., 2020; Smolnicki & Sołtys, 2016).

In the present study, we focus on automated minibuses (AmBs) that are currently being introduced to the public around the world in pilot settings including in the Netherlands. Given the vehicle design characteristics (smaller size and low speed), prospective flexibility, and cost-efficiency of operations, the potential of AmBs' ride-sharing service to strengthen the underserved links of PT networks has attracted attention in both research and practice (Hagenzieker et al., 2021).

While automated driving technology is still undergoing tests and has to gain maturity, there is a need to understand in which application cases and contexts the AmBs' potential could be maximized so that it can serve the transport needs of the prospective end-users. Here, application cases can be defined as the area of service such as rural, (sub)urban areas, or city centres, and application contexts such as the type of service (scheduled or on-demand), the driving environment (in mixed traffic or on dedicated lanes), and the type of supervision and surveillance, etc.

So far, there is only one study in which researchers compared different application cases to determine how they influence the successful deployment of AmBs. It was conducted during the CityMobil2 project in 12 European cities (Alessandrini et al., 2014). The application cases were grouped into four categories, namely, "within city centre" (La Rochelle, Oristano, Reggio Calabria, and Trikala), "within a major facility (university campus, business district)" (Geneva, Lausanne, San Sebastian, and Sophia Antipolis), "from PT node to a major facility (hospital, exhibition centre)" (Brussels, León, and Milan), and "from PT node to the residential area" (Vantaa). At that time, researchers found a higher preference for AmBs than for conventional minibuses only in the cities with routes "within major facilities (university campus, business district)," which indicated that automated shuttles might not be attractive in all applications. Nevertheless, in the meantime, several years have passed and vehicle automation is becoming a more mainstream technology.

For understandable reasons, other studies evaluated people's experiences in a single-pilot application case and results should be interpreted bearing this limitation in mind. Among them, the application cases included city centres (Madigan et al., 2017; Portouli et al., 2017), residential areas (Salonen & Haavisto, 2019; Mouratidis & Serrano, 2021), routes within business districts (Nordhoff et al., 2018b) and university campuses (Chee et al., 2020), the route from a PT station to a hospital (Motak et al., 2017) or an airport (Cirillo & Hetrakul, 2010), the route from a parking area to an exhibition centre (Delle Site et al., 2011), and at a tourist location (Wicki et al., 2019). The overall impressions and intentions to use the AmBs in the future were estimated in those studies.

Apart from instrumental variables that characterize the mode of transport (travel time, travel distance, costs, and waiting and walking time), several context variables were also included such as time of day (Delle Site et al., 2011), weather (Delle Site et al., 2011; Wicki et al., 2019), driving environment (mixed vs dedicated lane) (Dekker, 2017), supervision and surveillance (Dekker, 2017; Winter et al., 2019), trip purpose (Ashkrof et al., 2019), and crowdedness (Wicki et al., 2019). The participants of these studies showed in general that they would prefer to travel in an AmB in the daytime, in rainy weather, in mixed traffic, and in a less crowded environment. The AmBs were found to be more attractive for long-distance trips, for leisure purposes, and were less favoured for regular commuting on short distances. Yet, preferences for supervision and surveillance had mixed results, for example.

In the present study, we focus on one fundamental aspect of AmB's future integration into PT systems, that is, the type of service offered to the clients. The on-demand and flexible features of AmB's service are frequently mentioned as an advantage of this new transport mode (Salonen & Haavisto, 2019). The flexible service (on-demand, door-to-door) can be introduced as an alternative to or operating jointly with regular (fixed route, scheduled) service. Another option is to provide a hybrid service where the AmBs follow a fixed route but can be called on-demand.

To date, there are only a few studies that focus on the type of service. The studies by Badia and Jenelius (2020) and Calabrò et al. (2022) showed that both service types could find appropriate application cases, depending on the size of the operational area, travel demand, and the length of the trips and users' value of travel time.

The travellers' perception of service types was hitherto evaluated in two stated choice studies. In the last-mile application case, from a metro station to the business park Rivium (Capelle-aan-den-IJssel, the Netherlands), respondents were given a choice between an AmB operating in a dedicated lane, an AmB driving in mixed traffic, or selecting another travel mode (Dekker, 2017). The type of service, namely, fixed one with fixed stops (regular service) or offering on-demand door-to-door trips (flexible service), was included as an attribute of the AmBs in the experiment. The preference for the latter type was found to be higher. In Winter et al. (2019), respondents were asked to choose between an AmB, a conventional bus, or another travel option. A conventional bus followed a fixed route and a fixed schedule (regular service). For an AmB operating on a fixed route as well, the respondents could select the fixed-schedule operations or call an AmB on-demand (hybrid service). It appeared that partial flexibility offered by on-demand operations in a hybrid service was not more attractive to potential users in the application case of short trips in (sub)urban areas.

From these two studies, we have initial indications that flexible service is more appreciated than a regular one, but a hybrid service (on-demand, fixed-route) does not look like an appealing solution. Nevertheless, more insights are needed to understand the decision-making process behind the preferences for the AmBs and their service type.

An additional aspect that we look at in the present study is the influence of the users' current travel mode. In other words, finding out if the travellers were grouped according to their current travel mode (car, PT, or active modes (AM) – bicycle and walking), the AmBs and their service type were perceived differently. As Roche-Cerasi (2019) showed, car users may not perceive any additional value of AmBs in the application case of the first-mile connection to public transit. The participants of the cited study stated that it would not make their travel by PT easier and more attractive. On the contrary, 37.5% of car users living in rural areas with low PT network coverage expressed their intention to switch to AmBs operating as an access mode to conventional bus stops (Bos, 2017). In the segment of current PT users, it appeared that 16 to 23% of travellers would use PT more often with the introduction of AmBs (Bos, 2017). Likewise, a positive correlation with the intention to use AmBs was found for frequent PT and AM commuters on the last-mile part of their trip (Chee et al., 2018). However, the results of the study by Pakusch & Bossauer (2017) showed that car and PT users may not differ in their intention to use automated PT, such as automated trains, trams, or buses.

From earlier studies, we see that the intention to use the AmBs in the future varies between current travellers' segments when classified by their main current mode of transport.

Therefore, accounting for it is important when evaluating the potential of the AmBs and their service type.

Aiming to contribute to the further understanding of the prospects of AmBs' integration into PT systems from the users' perspective, we can formulate the *main objective* of the present study: to explore the preferences for AmBs with respect to the service type (regular and flexible), which might be provided for the first-mile part of the trips or short (sub)urban commutes, and in comparison to the travellers' current mode (car, PT, or AM).

Therefore, we designed a stated choice experiment for a hypothetical application case of first-mile (access) connection to transit lines or short (sub)urban commuting trips in the Netherlands. We use two types of service, one being on-demand and door-to-door, called "flexible service," and the other a fixed-route and fixed-schedule service, called "regular service." Their introduction as two separate alternatives in the choice sets allows the explicit evaluation of each service type. We asked the participants to assess the two AmB alternatives compared to their current travel mode (car, PT, or AM), which was obtained in the earlier part of the survey. This disaggregated approach also allows us to evaluate the differences and similarities in the preferences between the AmB service types among the different user segments according to their current travel mode.

The paper is organised as follows. In the next section, we give a brief overview of the expectations and doubts that prospective users have about AmBs. The methodology of the research is described in Section 3.3; the collected survey data are analysed in Section 3.4. We explain the modelling approach in Section 3.5. In Sections 3.6 and 3.7, respectively, we discuss the results and finalise the paper with general conclusions and future research directions.

3.2. Literature overview of users' expectations and doubts regarding automated minibuses

The potential users of these services have started to form their initial opinions about AmBs following news about them in the media, observing demonstration drives (without passengers) or taking test rides during pilot projects. There is a common expectation that the introduction of AmBs can lead to social, economic, and environmental benefits. However, their launch has also attracted some concerns.

From a positive perspective, the users see the AmBs as part of PT systems and look forward to the improvement that can be brought upon in terms of flexibility, frequency, personalisation of trip preferences, and better network coverage (Distler et al., 2018; Dubielzig et al., 2018; Nordhoff et al., 2018a; Pakusch & Bossauer, 2017). They expect an increase in accessibility for older, disabled people, in particular when a door-to-door service is introduced (Roche-Cerasi, 2019). AmBs are seen to even replace private vehicles and, therefore, reduce congestion (Ramseyer et al., 2018). The environmental benefits are in saving energy and using clean energy sources (Nordhoff et al., 2018b).

From a negative perspective, the concerns are mainly about privacy and security from hacking or terrorist attacks, safety in traffic in general and because of the possibility of a technology failure (Herrenkind et al., 2019; Launonen et al., 2021; Piao et al., 2016; Portouli et al., 2017). The question about the ethical reasoning of AmBs in case of an unavoidable accident is frequently raised, i.e., "run over a child or crash the vehicle" type of issue (Salonen & Haavisto, 2019). Prospective users are hesitant about relying on technology, communicating their needs as passengers, and interpreting the behaviour of AmBs when driving or passing by as they do not yet have enough experience (Eden et al., 2017; Pakusch & Bossauer, 2017; Ramseyer et al., 2018; Razmi Rad et al., 2020). Therefore, people do not expect faster journeys and fewer traffic accidents (Roche-Cerasi, 2019). The increase in vehicle and infrastructure costs is of concern as well (Lopez-Lambas & Alonso, 2019).

The absence of a driver has two main consequences according to the prospective users' view. On one hand, it might save the expenditure on salaries and thus make the flexible, on-demand, door-to-door service feasible (Piao et al., 2016; Ramseyer et al., 2018). However, opinions on a possible travel cost reduction are not consensual. As opposed to the usually expected decrease (Dubielzig et al., 2018), the participants of another study (Salonen & Haavisto, 2019) were unsure if this would be a reality in the future. They would prefer the costs to be used to improve the service quality, i.e., having frequent, on-demand, round-the-clock operations. Other foreseen advantages include improved safety in traffic due to the elimination of drivers' mistakes, less rude behaviour, or reduction of unpleasant driving style, and also a more stable service as buses will not be cancelled when staff are not available (Dubielzig et al., 2018). On the other hand, travellers realize that the deployment of technology will cause the loss of jobs (Lopez-Lambas & Alonso, 2019). Not having a driver or another supervisory person onboard also raises concerns about late-night safety and security, prevention of vandalism, and compliance with paying for the trip. Problems might arise too with regards to access inside the bus for disabled and older people and the provision of first aid (Dong et al., 2019; Lundquist, 2018).

It is important that the influence of this mix of advantages and disadvantages, envisaged by the participants of the abovementioned studies, is addressed and continuously monitored for changes. Therefore, in addition to the stated choice experiment that focuses on the users' preferences for the AmBs' service type in comparison to their current travel mode, we include in the survey more aspects. Among them are the influence of the belief that AmBs would reduce the number of traffic accidents and lower the environmental impact of transport; trust in technology to drive the passengers safely; knowledge and experience with AmBs; and preferred type of supervision that would substitute the driver.

3.3. Methodology

An online stated preference survey was designed that comprised four sections. The questionnaire started by collecting information on the respondent's current travel behaviour to be used in the stated choice experiment, which is in the second section. The third section included Likert scale indicators of attitudes for different aspects related directly or indirectly to AmBs. Finally, in the last part, respondents were asked to provide information about their socioeconomic background.

3.3.1. Stated choice experiment

If a new alternative (e.g., travel mode, route, etc.) is offered to travellers, a stated choice (SC) experiment is often used (de Dios Ortúzar & Willumsen, 2011). This is a data collection technique that originated in the fields of transport and market research (Hensher, 1994). The respondents are given several sets of choices, with several alternatives that differ in their attributes and attribute levels. In its most standard configuration, they are asked to choose one of the options in the given hypothetical situation (Louviere et al., 2000). Further analysis of the data with discrete choice models allows us to evaluate the prospects of new alternatives and establish the trade-offs that respondents make (Train, 2009).

The usage of such surveys is not free of debate. The main concern is about the hypothetical nature of the choice situation, its representation of reality, and, consequently, the reliability of stated choices. To ensure realistic responses, in the following subsections, we address the issue of the realism of the SC experiment by using a reference alternative and providing a clear description of AmBs and their service types, by including relevant indicators of service quality in the choice tasks as attributes and by carefully selecting the attribute levels to represent the choice context.

Reference alternative

As mentioned above, the hypothetical essence of the choice situations that respondents face in an SC experiment has raised concerns as to whether a respondent would make the same choice in reality. Therefore, the quality of the collected data is in question. To increase the realism of an SC experiment, it is advised to use a reference point from which the respondent starts the evaluation of potential options (see Starmer (2000) as cited in Hensher (2006)).

In the first section of the survey, the participants were asked to provide information about their current travel behaviour, which was used to create a reference alternative for the SC experiment. From the question about the current occupation status of the respondents, the trip purpose was assumed and was taken as a context in the choice sets. The respondents were referred to a trip from home to work (for employed or self-employed individuals), study (for students), or any frequently visited destination (for unemployed or retired individuals). Depending on the respondents' travel pattern for the reported trip, the main transport mode for unimodal travellers or access transport mode for multimodal travellers (the main transport mode for them was, in most cases, the train) was used as a label for the reference alternative in the SC experiment. According to this travel mode, we grouped the respondents into three segments of travellers: the car users, the PT users (bus or tram), and the AM users (cycling or walking).

It is important to note that travellers have different perceptions of access and egress parts of multimodal trips; users tend to pay more attention to the characteristics of the access part, as was shown in (Hoogendoorn-Lanser et al., 2006). Therefore, we specifically asked multimodal travellers only to think about the access part of the trip and used it in the choice situations instead of generalising to first-/last-mile connections.

An additional precaution was taken to avoid the misperception that the AmBs might substitute high passenger capacity transit modes or private cars for relatively longer commuting trips. For example, in the case when in real life the respondent commutes from home to work by car for 45 min, this is probably not a trip that should be replaced by an AmB. We thus limit the application of the AmBs to a first-mile trip or a short (sub)urban trip in the Dutch context by assigning the invariant "standard" trip duration of 20 min with "standard" travel costs concerning the current travel mode.

Another rationale for using a reference alternative in this SC experiment is that we can look into similarities and differences in the preferences for the AmBs and their service type between the mentioned three segments of travellers (car, PT, and AM users).

Alternatives and their description

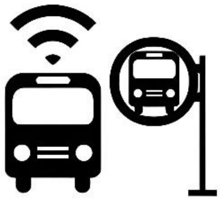
Aiming to explore the potential of two service types that the AmBs might offer in the future, we included them as two separate alternatives to the choice sets. They were designated "self-driving bus (regular service)" which follows a fixed route and has a fixed schedule, and "self-driving bus (flexible service)" which operates on-demand and picks up and drops off passengers at their requested locations.

To help the respondents imagine an AmB with the service type that it might provide in the context of their daily trips, we gave them a clear description of two main AmB alternatives (Figure 3.1).

Imagine a trip from your home to work.
You usually travel by bus and your travel time is 20 minutes.

In the next part of the questionnaire, we show **two alternatives** for this trip. In both cases, it is a **self-driving bus**, but with different characteristics:

Self-driving bus (regular service)



A self-driving bus operates on a fixed route according to a fixed timetable, comparable to a current bus, tram or metro. You can hop on and off at existing stops.

Self-driving bus (flexible service)

A self-driving bus can be called via an app on your phone and is comparable to a (shared) taxi. You will be picked up at the front door and dropped off at your destination, but the bus sometimes has to detour to pick up / drop off other people. The travel time may therefore be longer or shorter than the travel time predicted by the app.

Both alternatives have the following features:
- the bus travels **without a driver** (and also has no steering, brake and accelerator pedals)
- there is a **steward** on board, supervising the bus
- the bus has **11 seats** and **4 standing places**

Figure 3.1. Example of the description of two AmB alternatives (for an employed respondent who travels from home to work by bus)

Attributes and attribute levels

To evaluate the deployment potential of the two types of services provided by AmBs from the users' perspective, we include four instrumental variables in the SC experiment that are key attributes of service quality, as shown in previous studies (Barabino et al., 2020; Prioni & Hensher, 2001). For PT and the two AmB alternatives, the instrumental variables are in-vehicle travel time, travel costs, waiting time at the stop or doorstep, and walking time to the stop (only for "regular service"). The car trip has attributes of in-vehicle travel time and costs. We assume that the car is parked next to the respondent's home, so the walking time for the car users is negligible. Cycling or walking time is shown for AM users.

Travel time of the reference alternative (car, PT, and AM) is fixed at 20 min to limit the application case of the AmBs to the first-mile part of the trip or a short (sub)urban trip in the Dutch context. This figure is assumed based on the average trip length of 40–45 km per day for people in the 18–65 years age range (CBS, 2019).

The calculation of travel costs for car users is based on the cost per km for owning and running a vehicle. It includes fuel, insurance, maintenance costs, and tax payments for an average car, excluding parking costs (Nibud, 2020). Travel costs for PT are taken from trip-planning apps.

The attribute levels for the AmBs are pivoted around attributes of the reference trip if this is done in PT; e.g., in-vehicle travel time in the AmB (regular service) is 10 min shorter, the same or 10 min longer than in PT (Table 3.1). The attribute levels of travel time and costs for the AmB (flexible service) are assumed to be higher than those of the AmB (regular service), considering possible longer trips with detours for picking up and dropping off passengers. All alternatives, their attributes, and attribute levels are shown in Table 3.1.

Table 3.1. Alternatives, attributes, and attribute levels in the SC experiment

	Alternative 1 Current travel mode			Alternative 2 Automated minibus (regular service)	Alternative 3 Automated minibus (flexible service)
	CAR	PT	AM		
In-vehicle travel time (min)	20	20	20	10 / 20 / 30 (-10 / 0 / +10)*	15 / 25 / 35 (-5 / +5 / +15)*
Travel costs (€)	5.00	2.50	-	2.00 / 2.50 / 3.00 (-0.50 / 0 / +0.50)*	2.50 / 3.25 / 4.00 (0 / +0.75 / +1.50)*
Waiting time (min)	-	5	-	2 / 5 / 8 (-3 / 0 / +3)*	2 / 5 / 8 (-3 / 0 / +3)*
Walking time (min)	-	8	-	4 / 8 / 12 (-4 / 0 / +4)*	-

CAR – reference alternative (car users)
PT – reference alternative (PT users)
AM – reference alternative (AM users)
* applied pivot values are in parenthesis

Choice sets

The fractional factorial orthogonal design of 12 choice sets is generated in Ngene software (ChoiceMetrics, 2018). With the relatively low complexity of the choice tasks in our SC experiment, a full number of situations (12 choice sets) is presented to each respondent (see Figure 3.2 for an example).

Which mode of transport do you prefer to travel from your home to work in this situation?			
	Public transport (bus, tram)	Self-driving bus (regular service)	Self-driving bus (flexible service)
Travel time	20 min	30 min	25 min
Travel cost	2.5 euro	2 euro	3.25 euro
Waiting time	5 min	5 min	8 min
Walking time	8 min	12 min	-

Figure 3.2. Example of a choice set with PT as reference alternative

3.3.2. Socioeconomic characteristics of the respondents and attitudinal indicators

The influence of attitudes and perceptions in an individual's decision-making process can be captured by measuring the agreement or disagreement with indicators on a Likert scale. In previous research, it was shown that the inclusion of these latent variables in discrete choice models increases their explanatory power (Ben-Akiva et al., 2002; Yap et al., 2016). Another argument for the attitudinal indicators is that little is known so far about what might motivate people to use the AmBs in the future; therefore, we included this component in the survey as well.

The selection of the indicator statements is based on earlier studies where researchers showed a significant effect on the acceptance of AmBs (Table 3.2). Among them are perceived usefulness (S15, 21, 22), ease of use (S14), safety (S11, 13), enjoyment (S18, 19), intention to use (S16), environmental benefits (S20), and future applications (S12).

Additionally, we asked respondents to rate their general opinion about self-driving transport (S1), experience with technology (S6-10), and comfort of riding backwards (S17) as the AmB does not have a front or back end and can travel in both directions. We include a block that assesses sensation-seeking or risk-taking behaviour that is not yet well studied but shows high loadings on the intention to use the AmBs in the future (Nordhoff et al., 2018a). The indicators are adapted from the psychometric Domain-Specific Risk-Taking scale (DOSPERT) (Blais &Weber, 2009).

The last section of the survey contains questions about the socioeconomic background of the respondents such as gender, age, educational level, occupation, annual gross household income, region of residence in the Netherlands, possession of a driving licence and PT pass, possession of different types of vehicles, having a traffic accident in the past, having disability or motion sickness, use of car- or ride-sharing services (such as Uber and GreenWheels), having knowledge about automated driving and experience with it, and preference for the type of supervision that would substitute a driver in an AmB.

3.4. Data analysis of survey sample

3.4.1. Data

The online survey was distributed in the Netherlands in March 2020 by an external panel company. The original version was in Dutch and is shown in this paper in its translated version. Only respondents over 18 years of age were invited to take part in the research.

The total number of participants who joined the survey was 1685. Ninety respondents did not complete it, and for 230 respondents, it took less than 5 min to answer all questions. Considering the length of the survey, their answers were excluded. The resulting number of valid responses is 1365 (81.0%). The majority of the respondents (67.5%) spent 5-10 min, while it took 10-20 min for 28.3% of the sample and more than 20 min for the remaining 4.2% of the participants.

Furthermore, an analysis of the data on nontrading and lexicographic behaviour was conducted. As shown by Hess et al. (2010), sometimes participants have a strong preference for one of the alternatives, response fatigue, or just trying to influence a policy decision. Another type of selection strategy is choosing the cheapest or the fastest option and ignoring other attributes. Unfortunately, we cannot learn much from these responses because it is not possible to establish trade-offs between the attributes.

Table 3.2. Attitudinal indicators

	Indicators	Source	Likert scale
S1	What is your general opinion about self-driving transport?	This study	1 = very poor, 7 = very good
	How likely is it that you will show the following behaviour if the opportunity arises?	Adapted from (Blais & Weber, 2009)	1 = very unlikely, 7 = very likely
S2	Drive (yourself or as a passenger) without wearing your seat belt		
S3	Get into someone's car when you know that the driver has drunk more than two glasses of alcohol		
S4	Cycle or walk across the street while the traffic light is on red		
S5	Exceed the speed limit		
S6	I have a lot of experience with the use of "adaptive cruise control" in the car (automatically keeping a distance from the vehicle ahead)	This study	1 = strongly disagree, 7 = strongly agree
S7	I have a lot of experience with using "cruise control" in the car (driving automatically at a fixed speed)		
S8	I regularly use a parking assistance system in the car		
S9	I regularly have my navigation system switched on in the car		
S10	I regularly use a travel planner to plan my public transport journey		
S11	Self-driving buses without a driver are safe	Adapted from (Nordhoff et al., 2018a)	
S12	I think that in 30 years only self-driving vehicles will be on the roads	Adapted from (Jian et al., 2000)	
S13	Thanks to self-driving vehicles, there will be fewer fatal road accidents in the future		
S14	I think it takes a lot of time to learn how a self-driving bus works	Adapted from (Madigan et al., 2016) (reversed)	
S15	The use of a self-driving bus is comparable to the use of current public transport (bus, tram, and metro)	Adapted from (Nordhoff et al., 2018a)	
S16	In the future, I will use self-driving transportation for my daily trips		
S17	Riding backwards in a self-driving bus (seats facing the opposite direction of travel) is not an option for me	This study	
	A ride on a self-driving bus...	Adapted from (Kyriakidis et al., 2015)	Score from 1 to 7
S18	is fun		
S19	is relaxing		
S20	is better for the environment		
S21	is flexible		
S22	saves time		

We excluded the nontraders who selected only one of the alternatives in all the 12 choice tasks, in most cases this was their current travel mode. Notice that we are not aiming at estimating mode shares as a result of this study. Afterwards, we looked for the lexicographic choice patterns and removed those responses from the dataset. In the end, the sample consisted of 520 car users, 153 PT commuters, and 160 AM travellers. The remaining 833 responses were further analysed using discrete choice models, and in total $833 * 12=9996$ observations were collected from the SC experiment.

Table 3.3 shows the distribution of socioeconomic characteristics (SEC) in the sample (in total and separately for car, PT, and AM segments of travellers) and the population of the Netherlands. The categories of the SEC, such as gender, age, education level, occupation, and the province of residence, are slightly over- or undersampled in the whole sample and each segment, but can be considered representative of the Dutch population. In terms of annual

Table 3.3. Overview of the sample and comparison with the distribution in the Dutch population

Variable	Category	Car users (520 resp.), in %	PT users (153 resp.), in %	AM users (160 resp.), in %	Sample (833 resp.), in %	Population (CBS, 2018; 2020a, b, c), in %
Gender	Male	52.1	45.1	51.9	50.8	49.7
	Female	47.9	54.9	48.1	49.2	50.3
Age	18-24	3.3	24.2	15.6	9.5	14.6*
	25-34	17.3	22.2	13.8	17.5	15.1
	35-44	16.0	15.0	10.6	14.8	14.1
	45-54	19.6	9.8	15.0	16.9	17.2
	55-64	24.0	13.1	21.3	21.5	16.0
	65-74	16.5	14.4	21.9	17.2	13.1
	75-84	3.3	1.3	1.3	2.5	7.1
	>85	-	-	0.5	0.1	2.8
Education level	No education	0.4	-	0.6	0.4	-
	Primary education	0.6	0.7	5.0	1.5	9.4
	Secondary education	19.2	17.5	25.0	20.1	20.1
	Higher National Diploma	34.2	23.6	25.6	49.3	36.7
	Bachelor's degree	39.0	47.1	39.4	21.8	20.5
	Master's degree or PhD	6.4	11.1	4.4	6.8	11.8
	I do not know/Prefer not to say	0.2	-	-	0.1	1.5
Occupation	Employed or self-employed	67.9	56.9	41.8	60.9	68.9
	Retired	8.7	3.9	15.0	13.9	11.6
	Student or intern	14.0	10.5	16.8	7.4	3.7
	Unemployed or (partially) incapacitated	1.5	23.5	11.2	9.0	15.8 (including the last 3 categories)
	Housewife/houseman	5.2	4.6	10.6	6.1	
	Volunteer	2.1	0.6	2.9	2.0	
	Others	0.6	-	1.7	0.7	
Annual gross household income	Minimum (less than €12,500)	2.1	9.2	7.5	4.4 (5.3)**	6.4
	Below average (€12,500 - €36,000)	26.5	28.1	32.5	28.0 (33.2)	69.4
	1-2x average (€36,000 - €72,000)	48.3	34.0	33.8	42.9 (50.9)	22.3
	More than 2x average (more than €72,000)	9.8	12.4	2.4	7.8 (10.6)	1.9
	I do not know/Prefer not to say	13.3	16.3	23.8	15.8	-
Provinces	North Holland	10.6	20.9	16.2	13.6	16.5
	South Holland	18.8	28.8	16.9	20.3	21.3
	Utrecht	5.4	5.2	11.2	6.5	7.8
	Zeeland	3.7	1.3	2.5	3.0	2.2
	North Brabant	14.8	8.5	13.8	13.4	14.7
	Limburg	11.0	8.5	5.0	9.4	6.4
	Gelderland	14.0	7.2	16.2	13.2	12.0
	Overijssel	6.5	5.9	5.0	6.1	6.7
	Flevoland	3.8	2.0	5.0	3.7	2.4
	Drenthe	3.7	1.3	2.5	3.0	2.8
	Friesland	3.7	5.9	4.4	4.2	3.7
	Groningen	4.0	4.5	1.3	3.6	3.5

* This category starts from the age of 15 in the data from CBS; ** Percentages in parentheses are recalculated excluding missing data in income for comparison with the distribution in the population

household income, the sample cannot be considered representative as the percentages of below-average and middle-income (1-2x average) categories are just opposite to the distribution in the population. Due to the sensitivity of the question about income, almost 16% of respondents preferred not to answer, so the true representation is hard to establish. We have decided not to apply weights to correct the income distribution in the sample, as this would bias the choices for AmBs and their service type (checked with cross-tabulation), and because we are not aiming to estimate mode shares with this study.

The data on the daily travel behaviour of the respondents are of interest as well. The distribution of main transport modes and the trip purposes is summarised in Table 3.4. Compared to the population, it can be seen that in the sample of 520 car users, 153 PT users, and 160 AM users, there are approximately 6% fewer car users (drivers and passengers), 4% more PT users, and 8% more AM users than the population, according to CBS (2019). Therefore, we can consider that the sample is sufficiently representative of the population.

Additionally, we have found that 89.3% of the sample of respondents have a driving licence and 66.6% have a PT pass; 80% of the participants have a private or leased vehicle, and 80.6% have a scooter or bicycle; 42.7% of the sample have been in a traffic accident. Car- and ride-sharing services are popular with 10.7% of the respondents; 14.9% have some disability, and 13.6% suffer from motion sickness in one or more transport modes. The distribution of the aforementioned characteristics per segment of users is given in Table 3.5.

One of the most noteworthy findings is that 65.2% of the sample already knew about automated driving, namely, 62.7% of car users, 69.9% of PT users, and 68.8% of AM users. Meanwhile, 46.5% of the respondents in the sample used driving assistance technology and, most importantly, 14.4% had experienced a test ride in an AmB or automated vehicle (respectively, 48.8% and 13.7% of car users, 45.8% and 19.6% of PT users, and 39.4% and 11.9% of AM users).

Table 3.4. Distribution of main transport modes according to the trip purpose in the sample and the population

Transport mode / Trip purpose (%)	Work (60.9%)	Study (7.4%)	Recreational (31.7%)	Total in the sample	Distribution in the population (CBS, 2019)
Car (as a driver)	40.4	0.7	11.7	52.8	50.9
Car (as a passenger)	2.0	0.2	7.4	9.6	18.5
Train	5.5	2.3	1.6	9.4	11.3
Bus, tram, metro	4.9	2.0	2.0	8.9	2.9
Bicycle	5.2	2.2	3.7	15.4	8.4
Electric bicycle	1.2	-	3.1		
Scooter	1.0	-	0.7	1.7	-
Walk	0.7	-	1.5	2.2	2.5
Other*	-	-	-	-	6.4

* This category is absent in the survey

3.4.2. Missing data

Respondents had the option not to provide any of their personal information. From Table 3.3, we can see that there are missing data on education level (0.1%) and annual gross household income (15.8%).

The most common approach for handling missing data is a listwise deletion of the responses from the dataset. However, it is known that this might affect the size and representativeness of the sample and bias the outcomes of the models (Harrell, 2015). In the present study, the deleted responses would negatively influence the representativeness of the car segment of travellers. For this reason, it is useful to have a closer look at the data before

Table 3.5. Distribution of additional characteristics per segment of travellers (car, PT, and AM users)

Variable	Category	Car users (520 respondents), in %	PT users (153 respondents), in %	AM users (160 respondents), in %
Driving licence	Yes (any type of driving licence)	96.5	81.0	73.8
Vehicle in possession	Private or company (lease) auto	92.9	56.9	60.0
	Scooter, bicycle or electric bicycle	76.5	84.3	90.0
PT pass	Yes	57.1	96.7	68.8
Traffic accident	Yes	44.4	43.1	36.9
Disability	Yes (any type of disability)	13.5	15.7	18.8
Motion sickness	Yes (in any type of vehicle)	13.5	16.3	11.3
Use of car- or ride-sharing services (such as Uber and Green Wheels)	Yes	9.8	16.3	8.1

deciding whether to delete the incomplete responses or impute them using one of the state-of-the-art available methods.

The proportion of missing data is of importance. The education level falls below the benchmark of 3%. As the variable is categorical, the imputation of the most frequent category is used as recommended by Harrell (2015). With the proportion of over 3% of the missing values in income data, imputation methods can be applied (Harrell, 2015). We deploy the nonparametric k-nearest neighbours (kNN) method that can be used for numerical (continuous) and categorical data. It is a hot deck imputation method for cases where both the recipient variable (income) and donor variables (age, gender, education level, and occupation) are in one dataset. The advantage of this method is that, instead of a predictive model that might be misspecified, the distance metric is applied to define the connection between the recipient and donors (Beretta & Santaniello, 2016; Hastie et al., 2009). We fill in the missing values in the income variable by KNNImputer from Scikit-Learn (2021) with the mean value of 5 nearest neighbours from age, gender, education level, and occupation donor variables.

3.5. Discrete choice modelling

3.5.1. Model specification

Discrete choice models are applied for the analysis of collected data from the SC experiment. Essentially, these models try to explain and describe the decision-making process of the respondent based on the utility maximisation principle (de Dios Ortúzar & Willumsen, 2011; Hensher et al., 2005; Train, 2009). In other words, it is thought that the individual *n* chooses the alternative *i* among the presented finite or discrete number of alternatives *I*. She or he is assumed to try to maximise her or his utility (benefit) when stating their preference in $t \in 1,...T \{ \}$ choice sets. These choices are further combined into a utility U_{in} associated with each alternative.

In the present study, we use the utility function of the alternative i in the linear-additive form:

$$U_{in} = V_{in} + \varepsilon_{in} \qquad (3.5.1)$$

where V_{in} is observed or measured by the researcher, and ε_{in} contains all unobserved variables and measurement errors.

The observable or systematic part V_{in} consists of three components. The first is the vector of instrumental variables x_{ikn} and the vector of their coefficients β_{ik}. From the SC experiment, these are in-vehicle travel time, travel costs, waiting time at the stop or doorstep, and walking time to the PT stop, as in Table 3.1. The measured part of the utility V_{in} is extended with the second term comprising the respondents' socioeconomic characteristics x_{isn} with a related vector of coefficients β_{is}. The socioeconomic data are categorised and dummy-coded before entering into the models. The vector of latent variables η_{iln} with a corresponding vector of coefficients β_{il} represents the respondents' subjective perceptions and attitudes and is the third component. The inclusion of the last one is of the so-called hybrid choice models formulation that incorporates the latent constructs either sequentially or simultaneously. Even though the simultaneous way can outperform the sequential, we use the last one for its practical simplicity and clarity, which is sufficient for this exploratory study.

Equation (3.5.1) can be rewritten as follows:

$$U_{in} = \sum_k \beta_{ik} \cdot x_{ikn} + \sum_s \beta_{is} \cdot x_{isn} + \sum_l \beta_{il} \cdot \eta_{iln} \qquad (3.5.2)$$

The assumptions about the form of the distribution of the unobserved part ε_{in} of the utility function lead to different discrete choice model specifications. The error term ε_{in} is independently and identically distributed extreme value type 1 for all alternatives in a Multinomial Logit (MNL) model formulation. If the unobserved factors in the utilities are correlated over the alternatives, the distribution with generalised extreme value can capture this correlation in the most commonly used nested logit models.

The family of mixed logit models can be specified either by using (a) random coefficients β accounting for taste heterogeneity among individuals or (b) by adding a random error component that might capture the correlation in unobserved factors over time or alternatives. Mixed logit models can also take into consideration the intra-respondent heterogeneity or the correlation of the responses of the same person across the given number of choice sets.

Different model specifications are tested in this study in a search for a final model with the highest statistical significance in explaining our sample of choices.

3.5.2. Exploratory factor analysis

The exploratory factor analysis is performed in the SPSS software package to construct the latent attitudinal variables from indicator statements in Table 3.2 (IBM, 2017). As its name indicates, this statistical technique explores and groups the attitudinal indicators into common factors without a prior hypothesis about correlations between measured indicators.

The principal axis factoring model is applied, as the primary goal is to capture the latent dimensions. For ease of interpretation, a simple structure is achieved with orthogonal varimax rotation. The indicators with commonalities lower than 0.25 and factor loadings lower than 0.4 are excluded from the exploratory factor analysis. Subsequently, 19 out of 22 statements are grouped into four factors that account for 65.1% of the variance in the data and have an eigenvalue greater than 1. That is considered sufficient with the explained variance of over 60%

(Hair et al., 2009). These 4 factors correspond to trust, usefulness, and enjoyment of AmB; positive attitude towards riding in AmBs; technology experience; and risk-taking behaviour (Table 3.6). Computed factor scores for each respondent are further included in the discrete choice models.

3.5.3. Models′ estimation process

We deploy a five-stage modelling strategy to explore if there are similarities (taste homogeneity) in the preferences for the AmB service types (regular and flexible) within and between the segments of travellers (car, PT, and AM) (Figure 3.3). Even though full taste homogeneity (in all parameters included in a discrete choice model) is rare, as a matter of statistical evidence, we start with testing whether it exists in the preferences for the AmB service type within each traveller segment (Stage 1) and between the segments (Stage 2). Once the presence of full taste homogeneity is rejected, we proceed with allocating the sources of partial taste homogeneity (in some parameters) in preferences for the AmB service type, starting from within each traveller segment (Stage 3) and then between the traveller segments (Stage 4). MNL models are used for the tests of full and partial taste homogeneity in the initial four stages. Proceeding with the resulting MNL model from Stage 4, we search for the best model specification (including mixed logit) that explains the observed choices in the collected datasets and present the results of a final model at Stage 5. PythonBiogeme software package is used for the estimation of all tested discrete choice model specifications (Bierlaire, 2016).

Stage 1: Full taste homogeneity in the preferences for the AmB service type in the car, public transport, and active modes traveller segments individually

We start with base MNL models with instrumental, socioeconomic, and latent variables and estimate them for each segment of travellers independently (car, PT, or AM). The reference alternative has invariant attribute levels and remains constant in each choice set and across respondents within the segment of travellers. To account for the reference trip, the pivoted attribute levels of two AmB alternatives enter the discrete choice models as a difference (absolute deviation) from the reference alternative. All parameters are included as alternative-specific in the base MNL models.

To test whether the potential users do not distinguish the service types (regular and flexible), we estimate three general (restricted) MNL models with almost all parameters for the AmB (regular service) and the AmB (flexible service) being generic instead of alternative-specific. As the walking time to the bus stop is only given for the AmB(regular service) in the SC experiment, it remains alternative-specific.

The correctness of the specification of the general (restricted) models is verified by the likelihood ratio test (de Dios Ortúzar & Willumsen, 2011):

$$LRS = -2\{L(\beta_g) - L(\beta)\} \qquad (3.5.3)$$

where $L(\beta_g)$ and $L(\beta)$ are the final log-likelihood of the general (restricted) model with 34 generic parameters and the base model with 67 alternative-specific parameters, respectively.

Comparing the likelihood ratio statistics for car, PT, and AM segments, respectively, LRS_{CAR} = 163.308, LRS_{PT} = 242.878, LRS_{AM} = 90.326 with the critical value of χ^2 = 47.400 for 33 degrees of freedom at the 95% significance level, we can conclude that full taste homogeneity for two AmBs' service types is not present in the car, PT, and AM traveller segments.

Table 3.6. Estimation results of exploratory factor analysis

Indicators	Factors			
	Trust, usefulness, and enjoyment of AmB	Positive attitude towards AmBs	Technology experience	Risk-taking behaviour
S11: Self-driving buses without a driver are safe	0.714			
S13: Thanks to self-driving vehicles, there will be fewer fatal road accidents in the future	0.694			
S16: In the future, I will use self-driving transportation for my daily trips	0.632			
S15: The use of a self-driving bus is comparable to the use of the current public transport (bus, tram, metro)	0.591			
S12: I think that in 30 years only self-driving vehicles will be on the roads	0.533			
S1: What is your general opinion about self-driving transport?	0.527	0.492		
S21: A ride on a self-driving bus is flexible		0.803		
S22: A ride on a self-driving bus saves time		0.776		
S19: A ride on a self-driving bus is relaxing	0.519	0.636		
S18: A ride on a self-driving bus is fun	0.504	0.627		
S20: A ride on a self-driving bus is better for the environment		0.600		
S7: I have a lot of experience with using "cruise control" in the car (driving automatically at a fixed speed)			0.715	
S6: I have a lot of experience with the use of "adaptive cruise control" in the car (automatically keeping a distance from the vehicle in front)			0.646	
S8: I regularly use a parking assistance system in the car			0.639	
S9: I regularly have my navigation system switched on in the car			0.518	
S3: How likely would you be to get into someone's car when you know that the driver has drunk more than two glasses of alcohol?				0.709
S4: How likely would you be to cycle or walk across the street while the traffic light is on red?				0.676
S5: How likely would you be to exceed the speed limit?				0.652
S2: How likely would you be to travel (as driver or passenger) without wearing your seat belt?				0.593

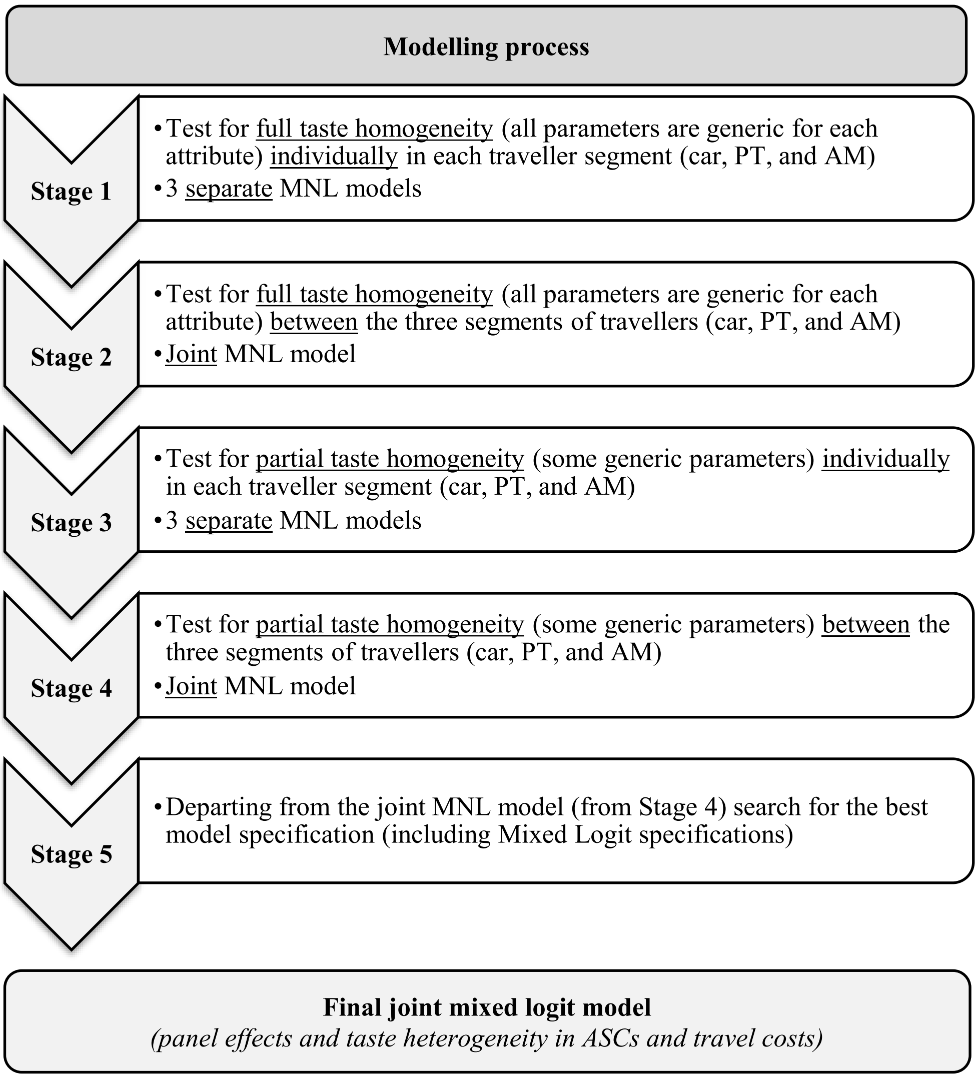


Figure 3.3. Five-stage modelling process

Stage 2: Full taste homogeneity for the AmB (regular service) and the AmB (flexible service) between three segments of travellers (car, public transport, and active modes) in the joint model

To allow for the direct comparison of preferences for two AmB alternatives between the three segments of travellers (car, PT, and AM), we create an artificial nested structure of a joint MNL model following the methodology suggested by Swait and Bernardino (2000). Three base (alternative-specific) MNL models are placed as separate nests under one root. The difference in the variance σ of error terms ε in three traveller segments (car, PT, and AM) is accounted for by the relative scale parameters μ. The scale parameter for the car users' nest is normalised to one $\mu_{CAR} = 1$, and the scale parameters for PT μ_{PT} and AM μ_{AM} nests are estimated relative to it.

From (3.5.2), we can rewrite the joint model that accounts for the difference in the scales:

$$U_{CAR} = \sum_k \beta_{CAR\,k} \cdot x_{CAR\,k} + \sum_s \beta_{CAR\,s} \cdot x_{CAR\,s} + \sum_l \beta_{CAR\,l} \cdot \eta_{CAR\,l} + \varepsilon_{CAR}$$

$$U_{PT} = \mu_{PT}\left(\sum_k \beta_{PT\,k} \cdot x_{PT\,k} + \sum_s \beta_{PT\,s} \cdot x_{PT\,s} + \sum_l \beta_{PT\,l} \cdot \eta_{PT\,l} + \varepsilon_{PT}\right) \qquad (3.5.4)$$

$$U_{AM} = \mu_{AM}\left(\sum_k \beta_{AM\,k} \cdot x_{AM\,k} + \sum_s \beta_{AM\,s} \cdot x_{AM\,s} + \sum_l \beta_{AM\,l} \cdot \eta_{AM\,l} + \varepsilon_{AM}\right)$$

Full taste homogeneity is tested under the assumption that tastes are the same in all parameters $\beta_{CAR\ k} = \beta_{PT\ k} = \beta_{AM\ k}$, $\beta_{CAR\ s} = \beta_{PT\ s} = \beta_{AM\ s}$, $\beta_{CAR\ l} = \beta_{PT\ l} = \beta_{AM\ l}$ and the only difference between the three segments exists in scales $\mu_{CAR} \neq \mu_{PT} \neq \mu_{AM}$. The sum of the final log-likelihoods of the base (alternative-specific) MNL models estimated independently is −8646.54 with a total of 201 parameters (67 in each). The final log-likelihood of the joint restricted MNL model with 67 generic parameters and 2 scale parameters is −9056.411. The likelihood ratio statistics of 819.742 is much higher than the χ^2 critical value of 159.814 for 132 degrees of freedom at a 95% significance level. Therefore, we conclude that there is no full taste homogeneity present between the segments of car, PT, and AM users.

Stage 3. Partial taste homogeneity in the preferences for the AmB service type within each traveller segment (car, public transport, and active modes) separately

Having proved that full taste homogeneity (in all parameters) is not present, in the third stage, we check whether partial taste homogeneity (in some parameters) exists in the preferences for the AmB type of service within each segment of travellers independently (car, PT, and AM users). Here, we return to the three base MNL models for car, PT, and AM users' segments with all parameters included as alternative-specific for the AmB (regular service) and the AmB (flexible service).

In the previous Stages 1 and 2, the full set of 67 parameters (including the nonsignificant ones) has been used for testing the hypothesis of full taste homogeneity (in all parameters). At this stage, we first exclude nonsignificant parameters from the base (alternative-specific) MNL models. The remaining parameters have a p-value $p>0.1$. A lower level of 10% rather than 5% is applied due to the exploratory purpose of the study.

Candidate parameters (in which taste homogeneity might be present and these should be restricted to having the same value) are identified from covariance/correlation analysis of pairs of βs based on t-test values that are less than a critical threshold of 1.96 for a 95% significance level (de Dios Ortúzar & Willumsen, 2011). The output file of PythonBiogeme (Bierlaire, 2016) contains this analysis. 8, 5, and 4 generic parameters are introduced in the MNL models for car, PT, and AM travellers' segments.

As in Stage 1, the restricted models with introduced generic parameters (designated as partially restricted) are tested for the correctness of the specification using the likelihood ratio test. At a 95% significance level, the likelihood ratio statistics between base (alternative-specific) models and partially restricted models for car, PT, and AM segments of travellers, respectively, LRS_{CAR} = 36.376, LRS_{PT} = 3.842, LRS_{AM} = 3.22 are lower than the χ^2 critical values χ^2_{CAR} = 50.998 (36 df), χ^2_{PT} = 53.384 (38 df), and χ^2_{AM} = 62.830 (46 df). Therefore, we can conclude that the partially restricted models are of the correct specification.

Stage 4. Partial taste homogeneity between segments of travellers (car, public transport, and active modes) in the joint model

We proceed with the identification of the candidate parameters that might be the source of partial taste homogeneity between the segments of travellers (car, PT, and AM) in their choices in a unified model. Following the methodology explained in Stages 2 and 3, we put three partially restricted MNL models (from Stage 3) in a joint partially restricted MNL model and introduce 7 generic parameters between the segments of travellers identified from the covariance/correlation analysis.

The likelihood ratio statistics of 7.05 between three partially restricted MNL models (estimated jointly as if there is no partial taste homogeneity between segments of travellers) and the joint partially restricted MNL model is less than the χ^2 critical value of 16.919 for 9 degrees of freedom (2 scale parameters and 7 generic parameters). From this, we can conclude that indeed car, PT, and AM users have partial homogeneity in tastes while other parameters remain heterogeneous across the segments.

Stage 5. Search for the best model specification

In the last stage, we search for the best model specification that explains the observed choices in the collected datasets. Proceeding with the joint partially restricted MNL model from Stage 4 that contains restricted parameters representing taste homogeneity in the preferences for the AmB service type within and between the segments of travellers (car, PT, and AM), we test different model specifications. These include nested logit, mixed logit with random error component or random parameters (travel time, travel costs, and alternative-specific constants (ASCs)), and mixed logit with panel effects. The panel mixed logit model with taste heterogeneity in travel costs parameters and ASCs explains the data best considering the main goodness-of-fit indicators, i.e., adjusted Rho-squared, Akaike, and Bayesian information criteria.

The results of the final joint model with socioeconomic and latent variables are given in Table 3.7. The estimated parameters are placed in columns named "CAR," "PT," and "AM" for car, PT, and AM segments of travellers, respectively. The name of each parameter in the table ends with a subscript of "BR" or "BF" indicating that it belongs to the AmB (regular service) or the AmB (flexible service) utility function. The combined "BR-BF" subscript denotes a generic parameter for the AmBs regardless of the service type. The generic parameter coefficients for the revealed similarities between the segments of travellers are in bold (e.g., $\beta_{BR\_BF\_TT}$ generic parameter for car and PT segments of travellers has a coefficient of **−0.122 (−31.1)*****).

The final joint mixed logit model includes 57 parameters. It was estimated on 10000 Halton draws from a normal distribution and showed stable results. It took 12 days and 7.5 hours for the model to converge on a computer with a 3.6 GHz frequency processor and 32GB RAM. The goodness of fit (adjusted Rho-squared) of the final model is 0.287. A value between 0.2 and 0.4 indicates a good model fit to the sample data (Louviere et al., 2000).

The scale parameters for PT and AM segments of travellers are both significantly different from 1. This shows that the difference in variance in the error terms is present. It is 22% higher in the PT users' segment than in the car segment, and 39.2% lower in the AM than in the car segment.

3.6. Discussion of results

From the final joint mixed logit model (Table 3.7), we discuss the results from the perspective of revealed similarities and differences in preferences for the AmB service type within and then between the segments of travellers (car, PT, and AM users). We go through the findings following all components of the utility functions. We start with instrumental variables, continue with latent and socioeconomic variables, and, in the end, interpret the mean of the unobserved part of utility, ASC. We finalise this section by mentioning the limitations of the present study.

3.6.1. Instrumental variables

Looking at the preferences for the type of service provided by AmBs within each segment of travellers (car, PT, and AM), we see that the AM users do not significantly prefer one service type over another in all instrumental variables (travel time, travel costs, and waiting time). Car

Table 3.7. Results of the final mixed logit model

Parameter	Description of the corresponding variable	Traveller segments		
		CAR	PT	AM
ASC	Alternative-specific constant of reference alternative and two automated minibus alternatives	0	0	0
ASC_{BR}		*0.493 (1.48)*	-	-
ASC_{BF}		-1.55 (-6.62)***	-	-
ASC_{BR_BF}		-	*-0.0169 (-0.0899)*	3.32 (8.06)***
σ_{ASC_BR}	Standard deviation of alternative-specific constant distribution (normal distribution)	1.38 (6.55)***	-	-
σ_{ASC_BF}		1.28 (10.3)***	-	-
$\sigma_{ASC\_BR\_BF}$		-	0.582 (6.69)***	0.853 (1.91)*
β_{ik}	**Instrumental variables**			
β_{BR_TT}	In-vehicle travel time in minutes	-	-0.127 (-11.3)***	-
β_{BF_TT}		-	-0.0859 (-8.14)***	-
$\beta_{BR\_BF\_TT}$		-0.122 (-31.1)***	-	-0.122 (-31.1)***
β_{BR_TC}	Travel costs in euros	-0.487 (-4.69)***	-	-
β_{BF_TC}		-1.12 (-15.6)***	-	-
$\beta_{BR\_BF\_TC}$		-	-1.36 (-10.7)***	-1.36 (-10.7)***
σ_{BR_TC}	Standard deviation of travel costs distribution in euros (normal distribution)	0.535 (6.23)***	-	-
σ_{BF_TC}		0.672 (10.2)***	-	-
$\sigma_{BR\_BF\_TC}$		-	0.844 (9.92)***	0.844 (9.92)***
β_{BR_WAITT}	Waiting time at a bus stop in minutes	-	-0.135 (-5.82)***	-
β_{BF_WAITT}		-	*-0.0411 (-1.36)*	-
$\beta_{BR\_BF\_WAITT}$		-0.115 (-10.5)***	-	-0.115 (-10.5)***
β_{BR_WALKT}	Walking time to a bus stop in minutes	-0.214 (-17.3)***	-0.214 (-17.3)***	-0.124 (-4.58)***
β_{is}	**Socio-economic variables**			
	Age (reference – Old):			
β_{BR_AGE1}	Young	-0.608 (-2.51)**	-	-
β_{BF_AGE1}		-	1.02 (5.13)***	-
β_{BF_AGE2}	Middle	-	1.29 (5.91)***	-
	Education level (reference – Low):			
β_{BR_EDU1}	Medium		0.414 (3.06)***	-0.499 (-1.89)*
β_{BR_EDU2}	High		0.528 (2.46)**	-2.73 (-3.17)***
	Occupation (reference – unemployed or retired):			
β_{BR_WORK1}	Study	-	-	-1.05 (-2.29)**
β_{BR_WORK2}	Employed	-	-	-0.601 (-2.32)**
$\beta_{BR\_BF\_WORK2}$		-0.554 (-3.64)***	-	-
	Income (reference - Low):			
$\beta_{BR\_INCOME1}$	Middle	-0.397 (-1.9)*	-	-
$\beta_{BR\_INCOME2}$	High	-0.566 (-1.65)*	-	-
$\beta_{BF\_INCOME2}$		-	0.662 (3.09)***	0.662 (3.09)***
	Region (reference - North):			
$\beta_{BF\_REGION2}$	East	-	0.508 (2.41)**	-
	Driving licence (reference - No):			
$\beta_{BR\_DR\_LICENCE}$	Yes	-	-	0.956 (3.75)***

Table 3.7. Results of the final mixed logit model *(continued)*

Parameter	Description of the corresponding variable	Traveller segments		
		CAR	PT	AM
	Vehicle in possession (reference – No vehicles):			
$\beta_{BF\_VEHICLE1}$	Auto	-	-0.517 (-3.48)***	-
$\beta_{BR\_VEHICLE2}$	Scooter, bicycle	-	-0.454 (-3.0)***	-
	PT pass (reference – No):			
$\beta_{BR\_PT\_CARD}$	Yes	1.04 (5.23)***	-	-
$\beta_{BF\_PT\_CARD}$		0.478 (2.68)***	-	-1.28 (-4.28)***
	Traffic accident (reference - No):			
$\beta_{BR\_TR\_ACCIDENT}$	Yes	-	-	-0.466 (-1.91)*
$\beta_{BF\_TR\_ACCIDENT}$		-	-0.796 (-4.98)***	-
	Knowledge about automated driving (reference - No):			
$\beta_{BR\_BF\_KNOW\_AD\_PT}$	Yes	-	-0.322 (-2.11)**	-
	Experience with automated driving (reference – No):			
$\beta_{BR\_EXP\_AD1}$	Yes (driving assistance)	-0.322 (-2.1)**	-	-0.322 (-2.1)**
$\beta_{BF\_EXP\_AD2}$	Yes (automated vehicle or minibus)	-0.45 (-1.75)*	-	-
$\beta_{BR\_BF\_EXP\_AD2}$		-	0.399 (2.2)**	-
	Supervision (reference – No supervision):			
$\beta_{BR\_BF\_SUPERVISION2}$	Remotely by operator	0.377 (2.57)***	-	-
β_{il}	**Latent variables**			
$\beta_{BR\_ATT\_BUS}$	Positive attitude towards automated minibus	-	-	0.454 (2.06)**
$\beta_{BF\_ATT\_BUS}$		-	-	1.15 (4.09)***
$\beta_{BR\_BF\_ATT\_BUS}$		0.645 (8.31)***	0.222 (2.73)***	-
$\beta_{BR\_BF\_TRUST}$	Trust, usefulness and enjoyment of automated minibuses	0.424 (6.89)***	0.424 (6.89)***	-
$\beta_{BR\_BF\_TECH}$	Technology experience	-	0.22 (2.49)**	-
μ^{a}				
μ_CAR	Scale parameters	1	-	-
μ_PT		-	1.22 (11.7)***	-
μ_AM		-	-	0.608 (11.7)***
Number of parameters			57	
Null log-likelihood			-10981.73	
Final log-likelihood			-7827.029	
Rho-square			0.287	
Akaike Information Criterion			15768.06	
Bayesian Information Criterion			16037.39	
Number of Halton draws from a normal distribution			10000	

*** = significant at a 99% confidence interval
** = significant at a 95%
* = significant at a 90%
Not significant values are in italics
[a] t-test against 1

users perceive the difference only in costs spent for travelling in the regular service, while PT users are the only segment that distinguishes and appreciates AmB's flexible service in terms of in-vehicle travel time and waiting time at the doorstep.

Notably, there are important similarities and differences between the segments of travellers. The in-vehicle travel time is associated with similar disutility regardless of the service type for car and AM users and in the AmB (regular service) for PT users. Only the latter demand segment of travellers (PT users) has a better perception of the in-vehicle travel time in the AmB with flexible service. The same pattern holds for the waiting time marginal values, although the disutility of the waiting time for the flexible service loses its significance for PT users. No need to walk to the bus stop and the possibility to wait for the AmB in the comfort of your home are known reasons for opting for on-demand services (Yan et al., 2019; Yan et al., 2021). That is why PT users might prefer to spend their travel time in the AmB operating as a flexible service rather than a regular one. Whilst car and AM users already do not need to spend time waiting and walking, therefore, that is probably the reason why the in-vehicle travel time in the AmBs with flexible service is not preferred.

Car users perceive the travel costs for the regular service less negatively than the costs of the flexible service. The explanation for the latter might be that the on-demand and door-to-door features are not something the car users would prefer to pay for at the cost of following an uncertain route due to other travellers' pick-ups and drop-offs versus a predefined route of more conventional regular service. In fact, car users are known to value independence, convenience, and control over their travels (Innocenti et al., 2013; Steg, 2003). A significant taste heterogeneity for the travel costs parameter has been detected in all segments of users, which goes to show the uncertainty that exists regarding the sensitivity of travellers towards transport prices.

Walking time to the bus stop is statistically speaking of less concern for AM users than for the other two segments (car and PT users). This might be connected to them being inclined to more physically demanding modes of transport (so-called active) than the other user segments are.

3.6.2. Latent attitudinal variables

The results also indicate the importance of psychological factors when explaining the preferences for the AmBs and their service type. One out of four constructs, risk-taking behaviour, does not show a significant influence in all segments of travellers, which might be explained by the self-reporting nature of the answers. The respondents might be concerned with sharing their misbehaviour (Sullman & Taylor, 2010). The average score for the four statements that formed the risk-taking factor varied from 1.74 to 3.17 points on a 1 (no risk) to 7 (high risk) scale.

Three other attitudinal constructs, i.e., positive attitude towards riding in AmBs; trust, usefulness, and enjoyment; and experience with technology, have a positive influence on the preference for AmBs. Besides, in most cases, there is no significant preference for one service type over another. The AM users are the only traveller segment for which a positive attitude towards riding in AmBs is of more importance when choosing flexible service.

Again, there are some similarities and differences in the attitudes between traveller segments. The positive attitude towards riding in AmBs (the perception of the ride in the minibus as being flexible, saving time, relaxing, fun, and eco-friendly) plays a significant role in the choices for the minibuses in all segments. However, no taste homogeneity is found for this variable in three segments of travellers. The flexible service preference as explained by the positive attitude towards riding in AmBs is highest in the AM segment, whereas the preference for regular service is more modest. The car and PT users do not distinguish their preference for

AmBs depending on the offered service but differ in magnitude. Regardless of the service type preference, the results reflect potential users' expectations from the deployment of AmBs to improve the quality of PT service in terms of convenience and comfort and reduce environmental impact as expressed in previous studies (Distler et al., 2018; Dubielzig et al., 2018; Nordhoff et al., 2018a, b; Salonen & Haavisto, 2019). We were able to confirm that having a positive image of future trips in AmBs is an important determinant of preference for AmBs.

The joint construct of trust, usefulness, and enjoyment of the AmB has a positive effect on the preference for both types of service with no difference between car and PT commuters. Initial trust in the capabilities of AmBs to drive safely without a driver, recognizing the usefulness for daily trips, the pleasure of commutes, and being driven are some of the most important predictors of prospective use of AmBs (Dekker, 2017; Herrenkind et al., 2019; Nordhoff et al., 2018b; Winter et al., 2019), though not for AM users in the present study. It cannot be said with certainty why AM users do not assign importance to these constructs. The possible reasons might lie in their socioeconomic characteristics and personality traits.

For the PT segment, the experience with technology (namely, driving and parking assistance and route-planning apps) positively influences the preference for AmBs offering both services but does not affect car and AM travellers' choices. It appears that PT users might be more concerned than car and AM users with the ability of AmBs to perform driving tasks without a driver, so for them, the experience with lower levels of automation might assure this ability. Our findings are in line with the results from earlier studies where the participants with technology experience used AmBs more frequently and indicated that they were comfortable with delivering driving tasks to the automated driving system and were willing to pay more for the trip in AmBs (Madigan et al., 2016; Portouli et al., 2017).

3.6.3. Socioeconomic variables

The travellers' segments have different socioeconomic characteristics that are significant or, if present in several segments, they show the opposite effect on the preference for AmBs. Therefore, only two similarities are detected, namely, having a high income when choosing flexible service (between PT and AM users) and an experience with driving assistance when opting for regular service (between car and AM users). As a consequence, we describe the influence of users' characteristics per traveller segment (car, PT, and AM) in the following order: parameters for both service types (generic), for regular service, for flexible service, and from positive to negative impact.

Employed car users do not feel enthusiastic about the new transport mode despite the service options offered. Having a PT card has a positive influence on choosing AmBs but a different impact, i.e., the marginal utility for regular service is the highest among parameters of socioeconomic variables (1.04) and roughly half of it for flexible service (0.478). Young car commuters with middle and high income have a negative perception of the regular service provided by the AmBs.

Medium and high levels of education is a positive determinant for the regular service preference of PT users. Young- and middle-aged PT commuters with high income and living in the eastern region of the Netherlands tend to favour the flexible service. Having a scooter or a bicycle has a negative impact on the choice of the regular service. At the same time, PT commuters who possess a car or have had a traffic accident in the past have a negative perception of the flexible service.

For AM users, the possession of a driving licence has a positive impact on the preference for regular service and a high income for flexible service. Students or employed individuals with a medium and high level of education who have had a traffic accident in the past show a negative preference for the regular service. Holding a PT card has a negative influence when choosing a flexible service.

There are three more variables of particular interest, namely, knowledge about automated driving, experience with it, and preference for the type of supervision. As is shown in Section 3.4.1, 65.2% of the participants stated that they have knowledge about automated driving, 46.5% have experience with driving assistance technology, and 14.4% have experience travelling in an AmB or an automated vehicle (AV). However, only for PT users, the knowledge about automated driving has a significant negative influence on the preference for both service types. Similar results were obtained by Chee et al. (2021) though without accounting for the current travel mode of the participants. As explained by Pernestål et al. (2018), individuals who have knowledge about automated driving technology are likely to have less trust in safe driving. Contrary to this, Dong et al. (2019) have found that participants with prior knowledge about automated driving are more willing to use automated buses.

Car and AM users who have had experience with driving assistance technology are not inclined to prefer regular service. For PT users, ride experience in an AmB or an AV is a positive factor when choosing the AmB, regardless of the provided service. However, based on this experience, car travellers see the flexibility of the service as a disadvantage. Experience with automated driving technology has a mixed influence on the willingness to use AmBs. The positive effect of taking a ride in an AmB is found in (Chee et al., 2018; Pakusch & Bossauer, 2017; Wicki et al., 2019) and, in particular, on preference for on-demand operations (Bos, 2017). However, just the opposite result is seen in (Pernestål et al., 2018). As we see, there is a mixed influence on the preferences for AmBs of car and PT users with previous journey experience in an AmB or an AV. This incongruence might be derived from the differences in the expectations of automated driving technology. While for car users the experience might lead to disappointment with its current level, PT users may still give some credit for the early stages of deployment.

The absence of a human driver on board is considered to be the most noticeable change for passengers riding in AmBs. Therefore, the preferences for a driver's substitute (steward, operator, or both) that would help passengers feel safe are frequently addressed in research. Although we may see in the results of some studies that respondents indicate that they would be comfortable with remote control by an operator or even without any supervision (Nordhoff et al., 2018b; Pernestål et al., 2018), in other studies, the participants support the idea of having a steward on board to deal with any unexpected situations (Dekker, 2017; Dong et al., 2019; Portouli et al., 2017; Winter et al., 2019). In the present study, car users prefer remote control by an operator in both types of services. A similar result was found in (Pernestål et al., 2018). As we have said above for the ride experience, car users might have higher expectations for the capabilities of automated driving technology; thus, they do not want to have a steward on board. While PT and AM users do not show a clear preference for the type of supervision.

3.6.4. Alternative-specific constants

Interpreting the mean of the unobserved part of utilities under the assumption of all other parameters remaining the same, we see the highest relative preference for the AmBs regardless of the service type in the AM users' segment. In contrast, car users show an indication of a negative preference for the AmB (flexible service). The slight negative generic ASC for the AmB is not significant in the PT users' segment. Statistically significant standard deviations for the ASCs indicate that taste heterogeneity is present in the unobserved part of utility. The recent study by Guo et al. (2021) sheds light on possible sources of this heterogeneity when evaluating the influence of different context parameters through an SC experiment.

3.6.5. Study limitations

First of all, the limitations of this study are related to the hypothetical nature of the SC experiment and the difficulties associated with imagining future commutes in the AmB alternatives. Another caveat comes from the design of the experiment itself, namely, the precautions we have taken. The respondent's current travel patterns are not reflected in full. Instead, the fixed reference trip attributes are imposed on the participants to represent either the first-mile parts of the trip or short (sub)urban commutes. At last, the survey was distributed online with the help of a panel company. Therefore, the distribution was limited to the participants of the panel, and those were groups of the population who have access to and use the Internet.

Despite the aforementioned limitations, the results of the present study give a starting point for developing integration strategies targeting different segments of travellers (car, PT, and AM). However, in time, this strategy should be checked and aligned with possible changes in the preferences of more experienced AmB users.

3.7. Conclusions

This paper explores the deployment potential of AmBs with respect to the service types, namely, "regular" (fixed route, fixed schedule) and "flexible" (door-to-door, on-demand) in first-mile trips or short (sub)urban commutes in the Netherlands. Additionally, it accounts for the preferences of travellers' segment according to their current travel mode (car, PT, and AM).

The results of the present study reveal some distinctive preferences for the AmBs and their service type by car, PT, and AM users. These findings give the initial indications for the development of integration strategies that consider the needs and interests of these three segments of travellers specifically.

Public transport users are the most likely segment of travellers that would appreciate the AmB offering flexible service. They show a higher preference for its on-demand and door-to-door features which they might lack in conventional-like regular service today. PT users have less sensitivity to the increase of in-vehicle travel time due to pick-ups and drop-offs of other passengers which is offset by the possibility to wait in the comfort of their homes with no need to walk to the bus stop. However, high sensitivity to the travel costs in both service types might indicate that the expectations of cheaper trips in AmBs are not met (in the SC experiment, the travel costs are set at the level of the conventional bus service). Regardless of the service type, a positive attitude towards riding in AmBs, having trust, and seeing an AmB as useful and enjoyable are important indicators of AmBs' preference by PT users. On the contrary, knowledge about automated driving technology in general negatively affects the choice for AmBs. However, having experience with driving assistance technologies and a ride experience in an AV or an AmB reassures their belief in the capabilities of the AmBs to drive safely. Meeting the expectations in travel costs reduction, building realistic knowledge about automated driving through information sessions and creating a positive ride experience might enhance the preferences of PT users for AmBs.

Car users show a higher appreciation for AmBs' regular service as indicated by the less negative perception of travel costs for this type of service. They might prefer to pay for a more predictable regular service rather than for flexible service due to the uncertainty associated with picking up and dropping off other passengers. Nevertheless, this may just indicate a certain level of lack of interest for PT since car users already enjoy flexibility with their current travel mode. Therefore, their perception of in-vehicle travel time and waiting time for AmBs regardless of the service type remains on the level of PT users' perception of AmBs' regular service. Nonetheless, similar to PT users, the preferences for AmBs regardless of the provided service are supported by a positive attitude towards riding in AmBs, trust in their safe operations, and recognition of AmBs' usefulness and pleasure of commutes. For car users, experience with driving assistance technology and ride experience in an AV or an AmB negatively influence their preferences for regular and flexible service, respectively, while they would prefer the remote control by an operator in both service types. To attract current car users to switch to multimodal PTcommutes with AmBs' regular service on the first mile is not an easy task. The emphasis should be on a seamless connection to other transit modes, as transfers are known to have the most negative impact on PT service satisfaction (Liu et al., 2021), in addition to the positive difference in the travel costs between the use of a car and an AmB providing regular service. Reassurance with a positive ride experience is of the essence as well.

Active modes users do not show a specific preference for service type as explained by the attributes of the trip in an AmB (in-vehicle travel time, travel costs, and waiting time). However, they have lower sensitivity to the walking time to the bus stop when choosing a regular service than car and PT users which can be explained by using more physically demanding modes. For AM users, having a positive attitude towards riding in AmBs plays the strongest role in preferences for flexible service; the influence on the choices for regular service is more modest. Similar to car users', AM users' experience with driving assistance technology has a negative impact on their preferences for regular service. While the modal shift of AM users is the least desirable as they already prefer sustainable travel options for daily use, they might become occasional users of AmBs providing both service types, with a higher probability of choosing the flexible service. Similar to other segments of travellers (car and PT), a positive image of future trips in AmBs needs to be confirmed with a positive ride experience in AmBs.

The findings of the present study could be useful for city planners and transport operators when considering the introduction of AmBs for first-mile trips or short (sub)urban commutes. These results give insights into the decision-making process behind the preferences of the current car, PT, and AM users for the service type that might be provided by AmBs. We need to underline that up to today only a very small percentage of the population had a ride experience in AmBs. Therefore, irrespective of the segment, prospective users' expectations should be monitored while gaining more experience with AmBs.

Policy-wise, this study underlines the importance of accounting for the current modality segment of the users when looking into application cases and contexts for the prospective integration of AmBs into PT systems. While the parsimonious generalization of the main instrumental variables may result in generic policy measures that fail to consider the specific needs of distinct target groups, the opposite is valid as well, developing different policy measures targeted at many groups can lead to an unnecessary increase in effort and cost. Hence, the sources of taste heterogeneity should be properly investigated.

In the end, we can suggest several follow-up research directions. The high resulting values of alternative-specific constants and their standard deviations (in the car and AM travellers' segments especially) signal that a substantial part of trade-off behaviour remains unexplained. More insights are needed about the reasons for choosing AmBs in different segments of travellers. When contemplating the future application cases and contexts for the AmBs, the prospective modal share of the AmBs among conventional transport modes would be of interest. Another aspect to consider is the temporary nature of stated choices. The introduction of AmBs is still at a very early stage, and time is needed for potential users to get accustomed to them. The opinion of the users might change over time as they gain more experience of and confidence in AmBs. Thus, longitudinal studies could give more insights.

Chapter 4

Ride Experience in Automated Minibuses

Following the baseline analysis in Chapter 3, which examined users' preferences for automated minibuses (AmBs) without prior exposure, this chapter investigates how a real ride experience influences those preferences. Experiencing an automated service firsthand can alter perceptions of safety, comfort, and reliability, potentially shifting attitudes and choice behaviour. Understanding this experiential effect is essential, as most prospective users still lack direct interaction with automated public transport and rely instead on assumptions or media portrayals.

To capture these effects, a pilot trial with an automated minibus was conducted in the city of Helmond, the Netherlands. Participants completed stated choice experiments both before and after taking a real ride in an AmB. This pre-post design enables the identification of changes in preferences resulting from direct experience and provides insight into how exposure shapes preferences for automated public transport.

The remainder of the chapter is structured as follows. Section 4.1 introduces the research context and objectives. Section 4.2 describes the pilot trial and research setup. Section 4.3 applies discrete choice modelling to analyse the data, Section 4.4 discusses the results, and Section 4.5 summarises the main conclusions.

This chapter is based on the following paper:

- Öztürker, M., de Almeida Correia, G. H., & van Arem, B. (2024). Ride experience in automated minibuses: measuring users' transport mode preferences before and after a test ride. *Transportation Research Procedia*, *78*, 335-344.

4.1 Introduction

The introduction of automated driving technology is associated with high uncertainty. Without a reference technology to rely on, making realistic predictions about the adoption of automated driving becomes challenging. Additionally, not only is the technology not ready, but also the potential users might have higher expectations of automated transport modes than what they are currently able to deliver.

One particular type of automated transport mode is the automated minibus (AmB), which is being tested in short trials across Europe and around the world (Hagenzieker et al., 2021). AmBs have the potential to serve as a viable alternative for short-distance transportation, particularly for connecting transit lines with rapidly growing urban areas that lack sufficient public transport coverage. Presenting this transport innovation and providing ride experience in trials at different stages of the automated driving development process allows not only to test the advancements of technology but also to capture the process of users' formation of attitudes and preferences for these solutions over time. Understanding these changes in attitudes and preferences can contribute to better predictions regarding the future deployment of AmBs.

According to the Diffusion of Innovation theory (Rogers, 2003), the process of formation of attitudes and preferences encompasses five stages that ultimately lead to the final decision of adopting or rejecting the innovation, AmBs in this study. From acquiring knowledge about AmBs at the knowledge stage, and forming initial attitudes and preferences towards them at the persuasion stage, potential users may decide to participate in pilot trials to get their first ride experience in AmBs, marking the decision stage. Afterwards, they reassess their attitudes and preferences towards AmBs and may continue to monitor the progress of the innovation during implementation in other pilot trials until it loses its novelty and becomes like a conventional transport mode (implementation stage). Lastly, during the confirmation stage, potential users seek validation and support for their decision, which can lead to the final adoption or rejection of AmBs based on their satisfaction and perceived advantage of this new transport mode. Following this process, individuals may change their opinions in favour of or against the use of AmBs.

Through pilot trials of AmBs, we can observe the transition from individuals' knowledge-persuasion stages to decision-implementation-confirmation stages. However, trying to capture the process of the formation of potential users' attitudes and preferences towards innovations is not an easy task due to the difficulties associated with recruiting the participants before the trials and the drop-off rates at the later stages of research. Consequently, there are limited longitudinal studies available.

Among the few studies on relatively recent innovations, there are longitudinal studies on electric vehicles (Jensen et al., 2013, 2014; Hinnüber et al., 2019), vehicle-to-grid charging for electric vehicles (Ghotge et al., 2022), and hydrogen buses (Loria Rebolledo et al., 2019). The results from these studies demonstrate that even a first-time ride experience in an electric vehicle (Hinnüber et al., 2019) or a short experience with vehicle-to-grid charging by current electric vehicle drivers (Ghotge et al., 2022) can influence participants' attitudes and evaluations of these innovations. In a longer 3-month trial, experience with an electric vehicle significantly impacted participants' preferences regarding driving range, top speed, fuel cost, battery life, and charging locations (Jensen et al., 2013, 2014). Comparing frequent, occasional, and non-users of hydrogen buses, the more experienced frequent users were willing to pay more for comfort and emission reductions provided by an environmentally friendly fleet of buses (Loria Rebolledo et al., 2019).

Regarding automated transport, several longitudinal studies have focused on the formation of attitudes as predictors of behavioural intention to use such technology. The combination of a real ride experience and a ride experience in a simulator was used in two studies by Hartwich et al. (2019) and Classen et al. (2021). Younger and older participants' trust and acceptance of automated vehicles were positively influenced by initial system experience in a driving simulator and remained stable for young drivers after test rides in a BMW i3 vehicle equipped with automated longitudinal control (Hartwich et al., 2019). For older drivers, exposure to automated vehicle technology in both a simulator as drivers and an AmB as passengers increased their perceptions of safety, trust, and perceived usefulness (Classen et al., 2021). Two other studies by Chee et al. (2021) and Guo et al. (2022) took place in Stockholm, Sweden where an AmB provided public transport services in two areas of the city. The results indicated that users' intentions to use AmBs were positively influenced when the users' needs were met and they received favourable recommendations from others (Guo et al., 2022). While the participants who were satisfied with the safety and travel time reliability of the bus service continued to use it and valued its comfort, in contrast to those who chose to discontinue its use (Chee et al., 2021).

While these few longitudinal studies with varying experimental setups provide clear evidence of changes in potential users' attitudes towards AmBs over time, there is still a lack of research on transport mode preferences that include both AmBs and conventional modes of transportation (cars, public transport (tram, bus), and bicycles) and the process of preference formation under the influence of ride experience in close-to-realistic traffic conditions.

To address this research gap, our study aims to answer the following research questions: a) Do potential users exhibit a preference for AmBs over traditional transportation options (cars, buses, or bicycles) when considering the first- and last-mile segments of their public transport trips? b) Does this preference remain stable under the influence of ride experience in AmBs in close-to-realistic traffic conditions?

We use the case study of the connection between the Brandevoort train station and the newly developing working and living area in Helmond (the Netherlands), in which an AmB followed a route on public roads in mixed traffic. This case study represents an application case of the first-/last-mile connection between a transit line and rapidly growing urban areas that lack sufficient public transport coverage. Presently, there is no public transport service operating on this specific route. We consider buses as a conventional mode of public transport service that is currently used in Helmond. We define the ride experience as a first ride experience and a consecutive ride experience in an AmB.

The remainder of the paper is structured as follows. We describe the pilot trial in the city of Helmond and our research setup in Section 2. Then, in Section 3, we apply discrete choice modelling to analyse the data, followed by a discussion of the results in Section 4. Finally, we summarise the main conclusions in Section 5.

4.2 Pilot in Helmond and research setup

The pilot trial of an AmB that we studied in this paper took place in Helmond, the Netherlands, in February-March 2021. The Navya Arma minibus operated along a 3.1 km route connecting the Brandevoort train station and the Automotive Campus (Figure 4.1). The route included four stops, two roundabouts and an overpass over a highway. The AmB's maximum speed was 16 km/h. To ensure safety and smooth operation, road signs were used to alert other traffic users, and parking and overtaking were prohibited along the route.

The AmB's operation in this pilot was not entirely smooth as it experienced some interruptions and challenges. During the trial's second week, the minibus was unable to operate due to icy road conditions caused by snow. Additionally, there were a few days when the rides

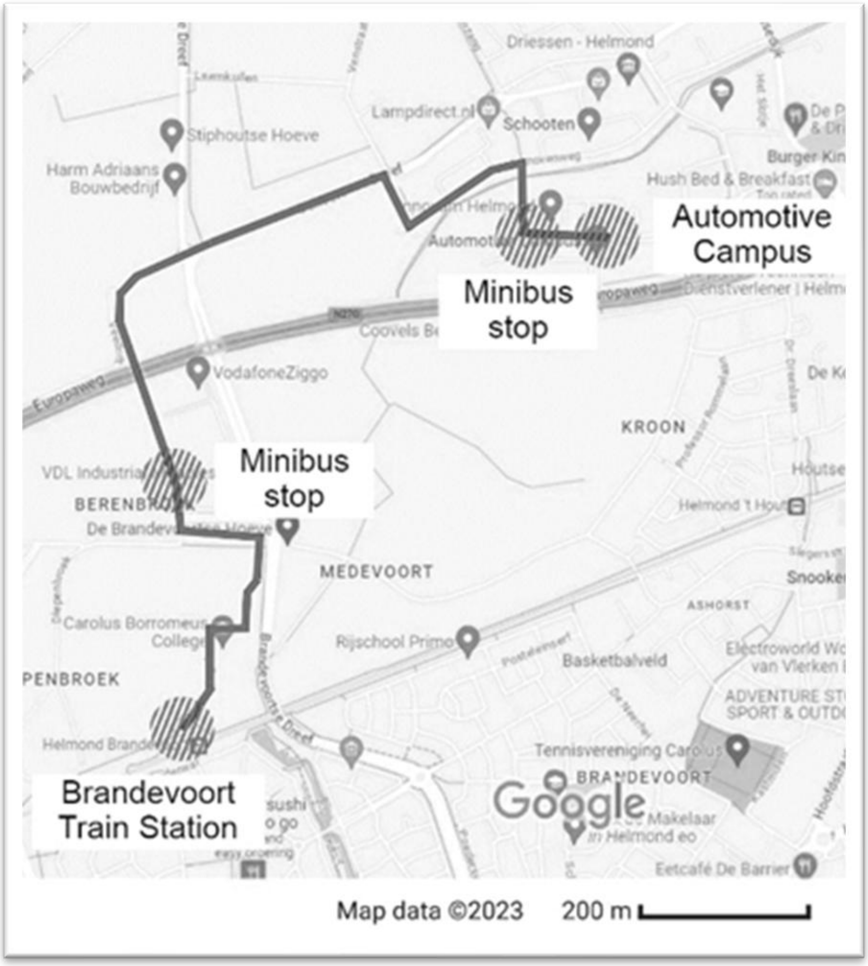


Figure 4.1. The route of the automated minibus between the Brandevoort train station and the Automotive Campus in Helmond, the Netherlands (Google Maps, n.d.).

had to be cancelled due to a malfunction in the software. The timing of the pilot trial coincided with the COVID-19 pandemic and the lockdown measures implemented in the Netherlands. As a result, only two passengers, next to the host and steward, were permitted to ride in the AmB despite its normal capacity of accommodating 11 seated passengers. To manage the limited capacity, participants were required to reserve a time slot for their ride.

The experiment conducted with a sample of system users consisted of three parts: an online stated choice survey administered before the test ride, the actual test ride, and a follow-up online survey conducted after the test ride. This experimental design allows us to track the influence of the ride experience gained during the pilot trial by comparing the survey responses before and after the test ride. Also, (it's important to understand at which stage of the adoption process the user is) participants could have a previous ride experience in an AmB in other pilot trials. To get this information, a question is also included in the first survey.

The first survey before the test ride included (a) questions about respondents' current travel behaviour, (b) a stated mode choice experiment, (c) indicator statements measuring attitudes towards AmBs and (d) questions about respondents' socio-economic background. While in the second survey after the test ride, the participants were asked to repeat the stated choice experiment and to give scores on the indicator statements once again. The participants who booked a test ride received the survey links by email before and after their test ride.

The starting section of the first survey included questions about respondents' current travel behaviour such as their current transport mode, frequency and duration of travel, and changes in their travel due to the pandemic.

In the stated choice experiment section, a conventional bus, a private car, a bicycle, an AmB providing regular service, and an AmB providing flexible service were the alternatives whose attributes were orthogonally combined to form choice sets using Ngene software (Choice Metrics, 2018). Each survey (before and after a test ride) included six choice sets for respondents to evaluate. In this context, regular service refers to a service with a fixed route and schedule, while flexible service represents an on-demand service following a flexible route. Classical attributes in the choice sets are in-vehicle travel time, travel costs, waiting time at the bus stop or the doorstep and walking time to the stop (Table 4.1). The attribute levels were selected based on the data from trip-planning apps.

Table 4.1. Alternatives, their attributes and attribute levels in the stated choice experiment

Attributes and attribute levels	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5
	Auto	Bus	Bicycle	Automated minibus (regular)	Automated minibus (flexible)
In-vehicle travel time (min)	10 / 15 / 20	6 / 11 / 16	15 / 20 / 25	6 / 11 / 16	10 / 15 / 20
Travel costs (€)	3.0 / 4.0 / 5.0	1.1/1.6/2.1	-	1.1 /1.6 / 2.1	2.0 / 2.5 / 3.0
Waiting time at the bus stop or doorstep (min)	-	2 / 5 / 8	-	2 / 5 / 8	2 / 5 / 8
Walking time to the bus stop (min)	-	4 / 7 / 10	-	4 / 7 / 10	-

The subsequent section consisted of 13 indicator statements used to assess attitudes towards the AmB itself such as perceived usefulness, ease of use, and safety and to evaluate the overall experience of the test ride (Table 4.2).

The final section of the first survey included inquiries regarding participants' socioeconomic background such as gender, age, educational attainment, occupation, and annual gross household income. Additionally, we asked them to indicate their affiliation with a specific group, i.e., residents of Helmond, individuals with a professional interest in participating, or individuals working in the Automotive Campus. We also sought to understand their preference for the type of supervision that would replace a human driver (steward, remote supervision, or a combination of both).

4.3 Data analysis and discrete choice modelling

Despite the challenges posed by the COVID-19 pandemic, interruptions due to weather conditions and software malfunction, a total of 112 individuals participated in the pilot trial. Among them, 78 participants completed either the first or second survey, with 45 individuals responding to both surveys, which are the focus of further analysis.

The final sample comprises 47.8% residents of Helmond, 46.7% participants with a professional interest in automated driving, and 5.5% transport professionals residing in Helmond. Notably, 40% of the participants had prior ride experience in an AmB. The distribution in the sample is positively skewed towards the male gender (77.8%), age above 50 (64.1%), and those with a higher education level (74.3%). While the percentage of employed participants (69.2%) is representative of the population in the Netherlands. 25.8% of

Table 4.2. Attitudinal indicators: mean scores and model structure based on multi-group confirmatory factor analysis

	Indicator statements[1]	Scores (mean / standard deviation) Before test ride	Scores (mean / standard deviation) After test ride
	Factor 1. Benefits and Usefulness of AmBs		
S1[2]	I think that in 30 years only self-driving vehicles will be on the roads	4.02 (1.889)	4.22 (1.704)
S2[2]	Thanks to self-driving vehicles, there will be fewer fatal road accidents in the future	4.98 (1.5)	5.2 (1.531)
S3[3]	In the future, I will use self-driving transportation for my daily trips	4.11 (1.787)	4.44 (1.645)
S4[4]	A ride on a self-driving bus is better for the environment	5.15 (1.762)	5.19 (1.45)
S5[4]	A ride on a self-driving bus is flexible	4.43 (1.536)	4.62 (1.346)
S6[4]	A ride on a self-driving bus saves time	3.78 (1.304)	3.73 (1.178)
	Factor 2. Enjoyment of Rides in AmBs		
S7[5]	Do you like self-driving transport?	5.73 (1.0282)	5.68 (1.132)
S8[4]	A ride on a self-driving bus is fun	5.41 (0.999)	5.32 (1.258)
S9[4]	A ride on a self-driving bus is relaxing	4.7* (1.348)	4.99* (1.24)
	Factor 3. Ease of Use and Safety of AmBs		
S10[3]	Self-driving buses without a driver are safe	4.78 (1.363)	5.04 (1.551)
S11[3]	The use of a self-driving bus is comparable to the use of current public transport (bus, tram, and metro)	5.16 (1.492)	5.09 (1.607)
S12[6]	I think it takes a lot of time to learn how a self-driving bus works (reversed)	4.82 (1.898)	4.71 (1.829)
S13[5]	Riding backwards in a self-driving bus (seats facing the opposite direction of travel) is not an option for me (reversed)	4.8** (1.841)	5.24** (1.773)

The difference between the two scores is significant:

** at a 95% level based on Wilcoxon signed-rank test statistics (Z= -2.512, p=0.012);

* at a 90% level based on Wilcoxon signed-rank test statistics (Z= -1.886, p=0.059).

[1] Statement S7 is on a Likert scale from 1 = dislike extremely to 7 = like extremely. All other statements are on a Likert scale from 1 = strongly disagree to 7 = strongly agree.

[2] Adapted from Jian et al. (2000)

[3] Adapted from Nordhoff et al. (2018a)

[4] Adapted from Kyriakidis et al. (2015)

[5] Adapted from Öztürker et al. (2022)

[6] Adapted from Madigan et al. (2016)

Results of confirmatory factor analysis. Model fit: for wave 1 before the test ride (RMSEA – 0.14, CFI – 0.969, TLI – 0.97) and for wave 2 after the test ride (RMSEA – 0.123, CFI – 0.976, TLI – 0.961).

Multi-group confirmatory factor analysis confirmed weak (restricted factor loadings) and strong (restricted factor loadings and intercepts) model structure invariance against the configural model.

participants did not provide information about their annual gross household income, leading us to exclude this variable from the analysis.

Analysing the responses to the attitudinal statements (Table 4.2), we performed an initial check on whether there was a significant difference between the scores given before and after the test ride. To do so, we employed a nonparametric Wilcoxon Signed-Ranks test suitable for Likert scale data using SPSS (IBM, 2017). Then, the potential model structure was extracted using maximum likelihood estimation and tested using confirmatory factor analysis. Its fit to both waves of responses was verified with multi-group confirmatory factor analysis (Rosseel, 2012). The final model consists of three latent variables: the benefits and usefulness of AmBs, enjoyment of rides in AmBs, and ease of use and safety of AmBs. Lastly, the structural equation models were pre-estimated before these latent variables sequentially entered the choice model.

We estimated a hybrid mixed logit model with panel effects jointly on the data collected in the two waves (before and after a test ride) in Biogeme (Table 4.3) (Bierlaire, 2023). The difference in the data variance between the two waves is accounted for by the scale parameter. Examples of this approach can be found in the studies by Jensen et al. (2013) and González et al. (2016). It allows us to assess the significance of the variations in attitudes and preferences influenced by the ride experience in the Helmond pilot trial. Additionally, the participants' previous ride experience in other trials was incorporated into the model as an interaction term.

4.4 Discussion of results

From the estimated choice model (Table 4.3), we discuss the results from the perspective of the relative changes in the preferences for AmBs in comparison to conventional transport modes (car, bus, or bicycle) under the influence of ride experience in the Helmond pilot and previous ride experience in other pilots. We go through the outcomes based on each component of the utility functions, starting with instrumental variables and subsequently exploring latent and socioeconomic variables.

4.4.1. Instrumental variables

In terms of perception of in-vehicle travel time in AmBs compared to conventional modes of transportation, such as cars, buses, or bicycles, participants in this pilot show a clear preference for spending their travel time in AmBs that offer flexible service. This preference remains consistent even after the participants have experienced the test ride, indicating that the ride experience does not significantly alter their choice. Moreover, participants perceive the travel time in AmBs (flexible service) as similar to the travel time in a car before the test ride (the travel time perception in a car loses its significance after riding in the AmB).

On the other hand, participants show a lower preference towards in-vehicle travel time in AmBs providing regular service. Notably, the ride experience in the Helmond pilot influences their perception, as the travel time parameter gains its significance after the test ride. Furthermore, participants perceive their travel time in regular-service AmBs as comparable to that of bus and bicycle alternatives.

These similarities in the perception of travel time between an AmB (flexible service) and a car, and between an AmB (regular service), a bus and a bicycle might indicate that an AmB with flexible service is associated with higher convenience and comfort, akin to a private car, as it offers doorstep pick-up and drop-off for passengers. While an AmB with regular service is considered alike to conventional public transport, and, surprisingly, the use of active modes. This unexpected association with active modes could be attributed to the physical effort involved in riding a bike, which can be linked to the effort of walking to and from the bus stop

Table 4.3. Modelling results of joint hybrid mixed logit model with panel effects

Parameter	Corresponding variable	Parameters		
		Specific for wave 1	Specific for wave 2	Generic
βik	**Instrumental variables**			
β_busreg_TT	In-vehicle travel time (min)	-	-0.144***	-
β_busflex_TT		-	-	-0.0889***
β_bus_TT		-	-	-0.186***
β_car_TT		-0.097*	-	-
β_car_TT * exp		-	-0.203***	-
β_bike_TT		-	-	-0.137***
β_busreg_TC	Travel costs (€)	-1.26***	-	-
β_busflex_TC		-	-	-0.626***
β_bus_TC		-	-	-0.757***
β_car_TC		-	-	-1.17***
β_car_TC * exp		-	0.916***	-
β_busreg_waitT	Waiting time at a stop or a doorstep (min)	-	-0.106**	-
β_busreg_walkT	Walking time to a stop (min)	-	-0.0945*	-
β_busreg_walkT * ride_exp		-0.129**	-	-
β_bus_walkT		-	-0.25***	-
βis	**Socio-economic variables**			
β_busflex_gender	Female (ref. - Male)	-	1.85***	-
β_busflex_gender * ride_exp		-	-2.67***	-
β_bus_age	Old (above 50)	-	0.78**	-
β_car_age	(ref. – Young (below 50))	1.83***	-	-
β_bike_age		1.13***	-	-
β_bike_age * ride_exp		-1.62***	-	-
β_busreg_ocuppation	Employed	-	-1.71***	-
β_busflex_ocuppation	(ref. – Student, retired, unemployed and others)	-	-2.68***	-
β_busflex_ocu * ride_exp		-	1.16*	-
β_car_ocuppation		4.04***	-	-
β_car_ocu * ride_exp		-3.02**	-	-
β_bike_ocuppation		2.54***	-	-
β_busreg_steward	Steward in the minibus	-	0.558*	-
β_busflex_steward * ride_exp	(ref. – No supervision)	-	1.44***	-
β_bus_steward * ride_exp		2.27***	-	-
β_bike_steward		-1.54***	-	-

Table 4.3. Modelling results of joint hybrid mixed logit model with panel effects *(continued)*

Parameter	Corresponding variable	Parameters		
		Specific for wave 1	Specific for wave 2	Generic
β_busreg_operator	Remotely by operator	1.12***	-	-
β_busflex_operator		1.98***	-	-
β_bus_operator	(ref. – No supervision)	1.09**	-	-
β_car_part	Participants with a professional interest	-2.72**	-	-
β_car_part * ride_exp		4.4***	-	-
β_bike_part	(ref. – Residents of Helmond)	0.911*	-	-
β_{il}	**Latent variables**			
β_busreg_F2	Enjoyment of rides in AmBs	-	0.375*	-
β_bike_F2		-	-0.732***	-
β_car_F3	Ease of use and safety of AmBs	1.54*	-	-
β_bike_F3		-1.12*	-	-
μ	**Scale between waves**			
μ_wave2	Scale parameter	1	1.19^{a}	-
σ	**Panel effects**			
σ_{μ}	Standard deviation for panel effects	-	-	1.01***
Number of parameters		59^{b}		
Sample size / Number of observations		45 / 540		
Initial log-likelihood / Final log-likelihood		-869.0965 / -577.6521		
Rho-square / Adjusted Rho-square		0.335 / 0.29		
Akaike / Bayesian Information Criterion		1233.304 / 1303.764		
Number of Halton draws from a normal distribution		1000		

[a] t-test against 1

[b] parameters from structural equations for latent variables are not shown in this table

∗∗∗ significant at a 99% confidence interval

∗∗ significant at a 95%

∗ significant at a 90%

when taking an AmB (regular service).

Considering the travel costs, participants consistently express a preference for AmBs offering flexible service regardless of the ride experience. The travel costs for AmBs providing regular service are less favoured. Yet, this parameter loses its significance once participants gain ride experience in the pilot. However, in contrast to the similarities in the perceptions of travel time parameters between the travel options in this experiment, participants prefer paying for AmBs (flexible service), similar to the bus alternative and evaluate the travel costs for AmBs (regular service) as negative as the travel costs of using a car alternative.

One potential explanation could be that participants perceive flexible-service AmBs as being similarly affordable as conventional public transport options, at the same time offering greater convenience and travel comfort. As a result, the perception of paying for regular-service AmBs, which do not possess these advantages, is akin to the perception of paying for using cars. Here, the benefits of flexibility provided by cars are counterbalanced by their generally higher travel costs particularly in the presence of flexible-service AmBs as an alternative option.

As for AmBs providing regular service, the disutilities associated with waiting time at a bus stop and walking time to the bus stop gain significance after participants have experienced a ride in this pilot. Moreover, those participants who have previous ride experience in an AmB perceive walking time to the bus stop more negatively, but only before the test ride in the Helmond trial. Additionally, participants prefer to walk to the bus stop to board an AmB with regular service rather than a conventional bus.

The more negative perception of walking time among participants with prior AmB experience may be attributed to their higher expectations for the service. They might anticipate a more seamless and efficient experience when selecting AmBs with regular service, leading them to view walking time as a more significant drawback. However, regardless of previous ride experience, all participants become more aware of the negative impact that both walking and waiting time have on their preferences for this travel option after experiencing a ride.

The preference for walking to the bus stop to take an AmB rather than a conventional bus could be attributed to the excitement surrounding automated driving technology. Participants might be drawn to the novelty of AmBs.

Consistent with the current study, the studies conducted by Dekker (2017) and Öztürker et al. (2022) also demonstrated a higher value placed on flexible service compared to regular one, particularly among current public transportation users in the latter study. However, these findings contrast with the results of the study by Winter et al. (2019) where regular service was preferred over hybrid service (on-demand, following a fixed route).

4.4.2. Latent variables

Two out of three latent attitudinal variables have a significant impact on the preferences in this experiment, namely, enjoyment of rides in AmBs, and ease of use and safety of AmBs. Yet, only the enjoyment of the rides in AmBs directly and positively affects the preferences for AmBs with regular service. As for the other alternatives, choosing a bicycle before the test ride in the Helmond pilot happens with a lower probability on average for participants who envision AmBs as safe and easy to use. On the contrary, participants opt for a private car even though they recognise AmB's safety and ease of use features. While after a test ride, those who enjoyed their ride experience in the AmB expressed their preference against a bicycle alternative.

AmBs could be viewed as a safe and effortless alternative to cycling, and this perception is supported by having an enjoyable ride experience in this trial. However, even though participants recognise the safety and ease of use offered by AmBs, the convenience provided by cars is hard to outweigh due to the comfort and freedom associated with them.

4.4.3. Socioeconomic variables

The participants' choices, as explained by their socioeconomic characteristics, undergo a significant change from the pre-ride wave to the post-ride wave. Female participants demonstrate a preference for AmBs with flexible service after a test ride in the Helmond pilot. However, this preference is negatively affected by prior ride experience in AmBs. In the case of older participants (aged 50 and above), their initial choice favours car and bicycle travel options before a test ride. However, their preference changes when selecting a bicycle, influenced by their previous ride experience. After a test ride, older participants opt for a bus travel option.

Employed participants, before gaining ride experience in the pilot, tend to choose a car and a bicycle. However, those with prior ride experience hold an opposing opinion on the car alternative. After a test ride, employed participants do not enjoy AmBs with regular or flexible service. Nevertheless, previous ride experience softens their negative preference for AmBs providing flexible service. This dislike of AmBs is not surprising, as employed participants have higher time pressure to reach their work destinations, while the travel is not that efficient with the current speed of AmBs in test conditions (the max speed was 16 km/h).

Participants who have a professional interest in joining the pilot trial tend to dislike the car alternative and prefer a bicycle before a test ride. However, those with previous ride experience in AmBs reverse their perception and return to their choice of car alternative. The explanation of this pattern could be that the participants who experience the AmB for the first time might feel excited because of trying it in reality, whereas the experienced participants may feel disappointed with the slow progress from their previous experience to the current one.

The preference for supervision in AmBs, regular or flexible, shifts from remote supervision by an operator before the test ride to supervision by a steward inside the AmB after the ride. Witnessing the current state of technology could explain this change. Apart from that, participants without prior ride experience in AmBs who opt for supervision by a steward in the minibus dislike bicycles. On the other hand, participants with previous ride experience in AmBs who select steward supervision show a positive inclination towards a bus alternative. Additionally, participants who choose remote supervision by an operator before the test ride, regardless of previous experience, show a preference for a bus.

In summary, the aforementioned findings revealed participants' strong inclination towards flexible-service AmBs, specifically regarding travel time and costs. The preferences for less popular regular-service AmBs underwent a significant change in the perception of all instrumental variables due to participants' ride experience in the Helmond pilot, as well as their previous experiences from other trials.

Finally, it's important to highlight some limitations of this study. The first one arises from the hypothetical scenario presented in the SC experiment. While the provided ride experience aimed to mitigate this limitation, participants still had to imagine their commutes using AmB alternatives, as the case study in Helmond and the SC experiment design did not fully mirror their current travel patterns. The second constraint is due to the modest sample size, with nearly half of the participants having a professional interest in AmBs. This makes it challenging to generalise the results to the population. The third limitation stems from the low speed of the AmB in the Helmond pilot trial, which could have influenced participants' perceptions of safety during the test rides. This limitation remains consistent across various pilot studies, reflecting ongoing concerns about the safety of automated driving until the technology proves itself.

While taking into account these limitations, the findings of this study can be seen as the initial phase in exploring how participants' real ride experiences (initial and consecutive) with AmBs influence their preferences for this mode of transportation in comparison to conventional transport options (in the case of this study, car, bus, and bicycle).

4.5 Conclusions

In a pilot trial conducted in Helmond, the Netherlands, we examined how the ride experience in AmBs influenced users' attitudes and preferences for this transport solution compared to traditional transport options (car, bus, and bicycle). Participants took a test ride in an AmB on a public road with mixed traffic, and we collected data from pre- and post-ride surveys. Our analysis using a joint hybrid mixed logit model revealed that participants exhibited a clear preference for flexible-service AmBs in terms of travel time and costs. Moreover, they perceived travel time to be analogous to that of cars, while their willingness to allocate travel costs for flexible-service AmBs resembled that of choosing a bus. Notably, preferences for less favoured regular-service AmBs underwent a shift in the perception of travel time and travel costs and waiting and walking time parameters influenced by participants' ride experience. After the test ride, the disutility of travel time in regular-service AmBs gained significance, opposite to the travel costs. Additionally, participants perceived the travel time to be on par with both buses and bicycles, while viewing the travel costs with the same unfavourable perspective as those associated with car usage. The inconveniences related to the waiting time at a bus stop and walking time to the bus stop became significant for participants after they had experienced a ride in this pilot. Those participants with prior ride experience demonstrated a propensity for walking to the bus stop when considering regular-service AmBs, favouring it over conventional buses. As for underlying psychological attitudes, having an enjoyable ride experience in this pilot reinforced the preference for AmBs with regular service. While preference for supervision in AmBs, whether with regular or flexible service, transitions from remote operator supervision before the test ride to onboard steward supervision inside the AmB after the ride.

These findings highlight the significant impact of ride experience (initial and consecutive) in AmBs on participants' preferences for this transport mode. This emphasises the importance of panel studies in understanding changes in attitudes and preferences for AmBs over time. However, it is important to acknowledge that our conclusions are specific to this particular case study in Helmond. Expanding this research to encompass a wider geographical and demographic context will be crucial for establishing the broader applicability of our results.

It is important to note that there is still a long way from the full-scale implementation of AmBs. Therefore, it is recommended to adopt an iterative monitoring process that closely tracks the advancements in automated driving technology and its perception among potential users. Additionally, longer pilot trials are needed to give potential users more time to form their opinions while using AmBs as a daily transport option. Moreover, engaging potential users in participatory studies during these trials can steer the development and deployment of AmBs towards a transport solution that is specifically designed to meet their needs.

Chapter 5

Use of Travel Time in a Shared Automated Vehicle for Work and Leisure

Building upon the empirical insights from Chapter 4 on how direct experience influences users' perceptions of automated public transport, this chapter shifts the focus from automated minibuses to shared automated vehicles (SAVs) and explores how vehicle automation may transform the use of travel time during rides. As SAVs typically provide a private or semi-private travel environment, they offer greater potential for productive or relaxing activities compared to conventional public transport. Understanding how users perceive and experience these opportunities is crucial for evaluating the broader benefits of vehicle automation beyond traditional performance metrics such as speed or cost.

This chapter investigates how engagement in non-driving-related tasks (NDRTs), such as work or leisure, affects user preferences and the perceived value of travel time in SAVs. It further examines how direct, experiential exposure to these activities influences attitudes and mode choices. To address these questions, a Wizard-of-Oz simulator-on-wheels experiment was conducted, combining subjective and video-based observational data on head position to capture user engagement and behavioural responses under realistic travel conditions.

The chapter is organised as follows. Section 5.1 introduces the research context and objectives. Section 5.2 describes the experimental setup, based on a review of existing AV study configurations. Section 5.3 outlines the four-step methodology integrating subjective data with video-based observations of head position. The modelling approach and discussion of results are presented in Sections 5.4 and 5.5. Finally, Section 5.6 summarises the main conclusions.

This chapter is based on the following paper:

- Öztürker, M., Nordhoff, S., Hoogendoorn-Lanser, S., van Arem, B., & Homem de Almeida Correia, G. (2026). Use of travel time in a shared automated vehicle for work and leisure: Results from a field experiment with a Wizard-of-Oz simulator-on-wheels vehicle. *Transportation Research Part C: Emerging Technologies*, *188*, 105646.

5.1 Introduction

"In the future, driving a vehicle might become like horse riding. Just a hobby"
Anonymous participant 1

"Staying curious helps to stop anxiety when daring to ride in a self-driving vehicle"
Anonymous participant 2

In contemporary society, commuting constitutes a significant part of individuals' daily routines, often seen as an unproductive yet unavoidable activity. For instance, in the Netherlands, average one-way door-to-door commutes last approximately 80 min by train, 45 min by urban public transport (bus, tram, or metro), and 25 min by car or bicycle (CBS, 2023c). To mitigate time loss and improve commute experience, passengers of trains, urban public transport (PT), and cars commonly engage in non-driving-related tasks (NDRTs), also known as travel-based multitasking. Common activities are working, reading, socialising with fellow passengers, or relaxing, which allow travellers to use their time productively or enjoyably (Keseru et al., 2020; Rizki et al., 2021; Singleton, 2020; Sun and Wong, 2022).

Innovations in transport technology, such as automated vehicles (AVs), present opportunities to transform commuting by enhancing both productivity and travel satisfaction. Driverless AVs operating at SAE Levels 4 and 5 eliminate the need for active driver engagement, allowing travellers to dedicate their commute entirely to NDRTs, such as sleeping, working, or socialising (SAE International, 2021; Wadud and Huda, 2019). However, the deployment of AVs comes with challenges. Simply replacing conventional vehicles with privately owned AVs may exacerbate urban congestion and increase travel demand, undermining potential benefits (Barreto et al., 2022; Meyer et al., 2017; Milakis et al., 2017). A more sustainable approach involves deploying AVs as car- or ride-sharing services in urban areas and integrating them with PT systems (Acheampong et al., 2021; Bala et al., 2023; Carrese et al., 2023; Fan et al., 2023).

Shared automated vehicle (SAV) services, exemplified by companies like Waymo, Baidu, Didi, and Apollo, are actively testing their technology through pilot programs in cities across China and the USA. While these programs demonstrate advancements in vehicle automation, empirical research is needed to assess how effectively travellers can utilise SAV commute time for NDRTs and whether such activities enhance travel productivity and satisfaction, which can become a catalyst for SAV adoption. This is particularly relevant given that, in conventional transport modes like trains and urban PT, engaging in NDRTs has been shown to improve travel satisfaction by reducing the perceived disutility and value of travel time (VoTT) (Kouwenhoven and de Jong, 2018; Malokin et al., 2021; Molin et al., 2020; Varghese and Jana, 2018; Wardman et al., 2020). However, despite well-documented evidence of travel-based multitasking in traditional modes, research on NDRT engagement in SAVs remains limited. Understanding these dynamics is essential for fostering SAV adoption and ensuring that AVs as car- and ride-sharing services contribute to sustainable urban mobility rather than exacerbating congestion.

Prior research on travel time use for NDRTs in AVs has shown that potential users express preferences for activities such as sleeping, watching movies, reading, or messaging, with preferences varying based on the AV's level of automation and whether it is privately owned or shared (Kyriakidis et al., 2015; Bansal et al., 2016). Travel distance further shapes NDRT preferences, with shorter trips favouring smartphone use and longer trips encouraging resting or working, especially among AV-oriented users (Lee et al., 2021). While AVs are unlikely to replace fixed-location activities (i.e., activities previously done at home or the office), they expand the range of NDRTs performed during travel, particularly among individuals with higher income and education levels (Pudāne et al., 2018; 2019; 2021).

Vehicle interior design also plays a role in facilitating NDRTs. AVs with work-oriented interior redesigns showed lower VoTTs compared to those redesigned for leisure. However, contrary to expectations, AVs with redesigned interiors had higher VoTTs compared to chauffeur-driven vehicles with the same interior modifications (Correia et al., 2019).

Few empirical studies have directly assessed individuals' ability to engage in NDRTs inside AVs, as most research focuses on responses to takeover requests during NDRTs rather than the tasks themselves (De Winter et al., 2014; Naujoks et al., 2018; Shahini and Zahabi, 2022). For instance, Ko & Ji (2018) measured the flow experience of reading and watching videos in Level 3 AVs in a driving simulator experiment. Their findings suggest that moderate task difficulty can induce a state of flow, a mental state characterised by complete immersion and focus. Similarly, Klingegård et al. (2020) demonstrated through a Wizard-of-Oz experiment that participants could perform mentally demanding tasks in Level 4 AVs on highways as effectively as in an office environment.

While prior research provides valuable insights, it addresses either behavioural or experiential aspects of travel time use for NDRTs in AVs, leaving the interplay between NDRT engagement, mode preferences, and changes in the VoTT in the context of SAVs largely unexplored.

Three key research gaps emerge. First, survey-based studies, often using stated choice experiments, rely on hypothetical scenarios, potentially introducing hypothetical bias (Haghani et al., 2021). This bias may cause participants to overestimate their preferences and attitudes toward AVs, limiting insights into realistic engagement with NDRTs in SAVs. Second, empirical studies focus on the feasibility of engagement in NDRTs under real-world conditions, in which factors such as vehicle dynamics, automated driving-induced motion sickness, physical efforts and cognitive demands affect travellers' experiences (Bellem et al., 2018; Cornet et al., 2022; Elbanhawi et al., 2015; Singleton, 2019). While these studies benefit from the collection of physiological data – such as heart rate, electrodermal activity, electroencephalography, glance behaviour, and head posture estimation – to provide objective insights into the ability to engage in NDRTs inside AVs, they do not capture how such engagement affects travellers' attitudes, preferences, and VoTT for AVs. Third, prior research has largely focused on AVs in general, often in comparison with conventional private vehicles, rather than specifically investigating how SAVs, as a distinct transport mode, facilitate engagement in NDRTs. To the best of our knowledge, only one study has explicitly examined NDRTs in the context of SAVs, finding that car-sharing AVs were generally preferred over ride-sharing AVs and public transport. Preferences were strongly influenced by the ability to perform NDRTs, such as reading, using social media, and gaming, though certain activities, like writing, negatively impacted SAV choice (Hamadneh & Esztergár-Kiss, 2022). However, this study also relied on hypothetical scenarios, highlighting the ongoing gap between perceived and real-world behaviours.

These gaps underscore the need for robust empirical research to accurately assess how the use of travel time for NDRTs in SAVs influences travellers' attitudes, preferences, and VoTT under real-world conditions. Addressing these gaps is essential to inform strategies for integrating SAVs into urban PT systems and maximising their potential benefits on the individual and societal levels.

To address the gaps, this study employs a Wizard-of-Oz (WoZ) experiment, a controlled alternative setup for real-world testing that simulates SAV operations while minimising safety risks and navigating regulatory restrictions, as pilot programs with SAVs are not yet permitted in most countries, particularly across Europe. Participants will experience both work- and leisure-related NDRTs while travelling in urban areas, providing a realistic context for evaluating their attitudes and preferences toward SAVs. This division into work- and leisure-related activities is adopted to simplify participants' understanding, as it aligns with familiar, everyday scenarios and reflects common distinctions in travel-based multitasking (Cornet et al., 2022; Keseru and Macharis, 2018). Changes in participants' attitudes, preferences, and associated VoTTs before and after the WoZ experiment are assessed through stated choice (SC) surveys, capturing the influence of experiencing NDRTs in SAVs. SAVs are evaluated in comparison with other travel alternatives that include not only private conventional cars but also urban PT modes, such as buses and trams, as well as bicycles, which are widely used in the Netherlands. Finally, the study measures the extent of participants' engagement in NDRTs during SAV rides, offering further insights into how these activities affect travel behaviour and perceptions of SAVs.

Building on this experimental framework, the present study advances the understanding of behavioural and experiential aspects of travel time use for NDRTs in SAVs through the following contributions:

- Development and deployment of a WoZ experiment that allows participants to experience work- and leisure-related NDRTs while travelling in urban areas.
- Investigation of how using travel time for work- and leisure-related NDRTs in SAVs influences users' attitudes, preferences, and associated VoTTs compared to conventional transport modes, including conventional cars, urban PT (bus or tram), and bicycles, as evaluated through a stated preference experiment.
- Examination of consistency in users' attitudes, preferences, and associated VoTTs for SAVs, conventional cars, urban PT, and bicycles before and after the field experiment, capturing the effect of experiencing NDRTs.
- Measurement of user engagement levels in work- and leisure-related NDRTs during SAV rides to assess the depth and quality of involvement.

5.2 Experimental configurations for studying travel time use in automated vehicles

Real-life AV experiences are essential for addressing the limitations of studies that rely on mental images and perceptions of automated driving technology. These experiences enhance research validity by providing accurate assessments of user attitudes and preferences. However, conducting experiments in complex traffic conditions presents challenges due to safety risks and legal restrictions (Etzioni et al., 2021; Farooq et al., 2018; Greifenstein, 2024; Lukovics et al., 2023; Zou et al., 2021). Despite advancements in commercial AV operations in some regions, pilot programs involving AVs remain restricted or entirely prohibited in most countries, particularly across Europe.

To overcome these challenges, researchers have developed alternative experimental configurations categorised as in-lab, on-road, and mixed setups. These configurations differ in terms of perceived realism, safety, costs, and data collection feasibility – key factors for ensuring the validity and practicality of experiments. This section reviews these setups, highlighting their application in studying NDRTs. Based on this review, we adopt a WoZ simulator-on-wheels vehicle to explore the impact of travel time use on attitudes and preferences for SAVs.

5.2.1. Experimental configurations: in-lab, on-road, and mixed

Experimental configurations for studying AV-related phenomena can be broadly divided into in-lab, on-road, and mixed setups, each offering distinct advantages and limitations.

In-lab experimental configurations rely on traditional driving simulators and virtual reality (VR) simulators to recreate driving environments within controlled settings. Traditional simulators typically include a driver's seat, steering wheel, and pedals, with fidelity ranging from simple setups using basic screens to high-fidelity systems mounted on motion platforms that replicate vehicle dynamics (De Winter et al., 2014; Ko and Ji, 2018; Minhas et al., 2020).

VR simulators enhance immersion through head-mounted displays (HMDs) or Cave Automatic Virtual Environments (CAVEs), where a virtual environment is projected onto surrounding walls (Ejichukwu et al., 2024; Kettle and Lee, 2022; Riegler et al., 2021). These setups are cost-effective, safe, and enable streamlined data collection across controlled scenarios. While CAVE systems represent a more advanced form of immersive simulation, they, and VR setups more broadly, often lack the full range of multisensory and physical stimuli present in real-world travel, such as vehicle motion, road surface vibration, dynamic lighting, and noise variability. As a result, such setups may fall short in replicating the unpredictability and associated experience of real-world traffic conditions, thereby limiting ecological validity.

On-road experimental configurations take place on test tracks or public roads. Test tracks can range from simple closed circuits to advanced proving ground facilities simulating urban environments with diverse road types and intersections (Hartwich et al., 2019; Lukovics et al., 2023; Shi and Bengler, 2022; Chen et al., 2020; Yang et al., 2021). They offer a safer and more predictable alternative to real traffic. These controlled conditions also facilitate reliable and consistent data collection, making test tracks particularly effective for studying specific driving scenarios.

Public road experiments, often conducted on highways, provide the highest realism by exposing participants to genuine traffic conditions. However, they involve greater safety risks, logistical challenges, and difficulties in collecting consistent data due to the dynamic and unpredictable nature of real-world environments (Dillmann et al., 2023; Feys et al., 2021; Naujoks et al., 2016; Noble et al., 2021; Solís-Marcos et al., 2018).

Vehicles in on-road experiments include AVs with lower automation levels (Levels 1–3) (Hartwich et al., 2019; Liu et al., 2019; Liu et al., 2021) and WoZ vehicles simulating higher levels of automation (Levels 3–5), where concealed drivers mimic automation while maintaining safety (Ekman et al., 2019; Naujoks et al., 2019; Osz et al., 2018).

Mixed setups combine elements of in-lab and on-road experiments, offering hybrid environments. Examples include the WoZ simulator-on-wheels vehicle, which integrates real-world driving with simulator-like displays (Baltodano et al., 2015; Detjen et al., 2020), and the WoZ VR simulator-on-wheels, where participants experience a virtual overlay of real-world traffic through HMDs while riding in a vehicle (Zou et al., 2021). These configurations balance realism, safety, cost, and data collection feasibility, making them promising for AV research.

5.2.2. Exploring non-driving related tasks across experimental configurations

In-lab and on-road experiments are widely used to study engagement in NDRTs during automated driving, whereas mixed experimental setups remain limited overall and particularly for studying NDRT engagement.

In-lab simulator studies primarily examine drivers' reaction times, workload, and situational awareness during transitions from NDRTs to manual control (Naujoks et al., 2018; Riegler et al., 2021; Shahini and Zahabi, 2022; Gerber et al., 2020; Li et al., 2020). However, research on NDRT performance in AVs using VR simulators is limited due to the technology's low fidelity in replicating the complexity of NDRTs. Additionally, HMDs restrict natural movement, making them unsuitable for tasks requiring a full range of motion or intricate physical actions (Riegler et al., 2021).

On-road experiments explore how NDRTs affect drivers' ability to monitor lower-level automation (Levels 1–2) and take over control in Level 3 AVs. These studies also examine how automation level and driver experience influence NDRT performance (Naujoks et al., 2016; Naujoks et al., 2019; Noble et al., 2021; Shi and Bengler, 2022; Solís-Marcos et al., 2018). While offering high realism, these setups face challenges in ensuring participant safety and consistent data collection.

Mixed setups, such as the WoZ simulator-on-wheels and the WoZ VR simulator-on-wheels, allow participants to experience dynamic urban environments. However, NDRTs have only been studied in the WoZ simulator-on-wheels, where participants' self-selection of tasks during rides was monitored (Detjen et al., 2020). The WoZ VR simulator-on-wheels, while promising, inherits limitations of HMD-based VR simulators, including restricted movement and reduced feasibility for tasks requiring full motion (Zou et al., 2021).

Across all setups, NDRTs typically involve everyday activities (e.g., reading) or standardised tasks (e.g., n-Back tasks), with tasks typically performed on handheld devices, mounted displays, or head-up displays. However, most studies focus on functional performance metrics, neglecting deeper aspects of the feasibility of NDRT engagement – a gap highlighted earlier in Section 1. Exceptions include Ko and Ji (2018), who measured flow experience in simulators, and Klingegård et al. (2020), who evaluated NDRT engagement using a WoZ vehicle in a Level 4 highway scenario.

5.2.3. Evaluating and selecting the experimental configuration

To identify the most suitable experimental setup for studying travel time use for NDRTs in SAVs operating in urban environments, this evaluation considers four key factors: perceived realism, safety risks, costs, and data collection feasibility. These factors are derived from reviewed studies and additional sources reflecting key elements that influence the validity, practicality, and replicability of experimental research (Baltodano et al., 2015; De Winter et al., 2012; Detjen et al., 2020; Eriksson et al., 2017; Hartwich et al., 2019; Riegler et al., 2021; Weidner et al., 2017; Zou et al., 2021). Table 5.1 summarises the differences between the experimental configurations based on these factors.

A mixed experimental setup emerges as the optimal choice for this study, offering a balance between realism, safety, cost, and feasibility. Among mixed configurations, the WoZ simulator-on-wheels vehicle provides distinct advantages by combining the high realism of on-road experiments with the safety and control of in-lab setups. This configuration enables participants to engage in realistic NDRT scenarios while experiencing urban traffic conditions.

The WoZ simulator-on-wheels addresses the ecological validity limitations of in-lab studies and mitigates the safety risks of public road experiments. Its ability to simulate higher levels of automation (Levels 3–4) further enhances its relevance for future SAV research. While mixed setups involve higher costs and logistical complexities, their benefits outweigh these challenges, making the WoZ simulator-on-wheels a robust platform for exploring how productive travel time use influences user attitudes and preferences toward SAVs.

Table 5.1. Comparison of experimental configurations across key factors

Experimental configuration	Key factors			
	Perceived realism[1]	Safety risks[2]	Costs[3]	Data collection feasibility[4]
In-lab	Low	High	Low	High
On-road (test track)	Moderate	Moderate	Moderate	Moderate
On-road (public road)	High	Low	High	Low
Mixed	High	Moderate	Moderate-High	Moderate

[1] (de Winter et al., 2012; Detjen et al., 2020; Eriksson et al., 2017; Hartwich et al., 2019; Riegler et al., 2021; Weidner et al., 2017; Zou et al., 2021)
[2] (de Winter et al., 2012; Detjen et al., 2020; Eriksson et al., 2017; Riegler et al., 2021; Zou et al., 2021)
[3] (Baltodano et al., 2015; Eriksson et al., 2017; Riegler et al., 2021; Zou et al., 2021)
[4] (de Winter et al., 2012; Eriksson et al., 2017; Riegler et al., 2021)

5.3 Methodology

This field study employs a convergent mixed-method approach that combines subjective data collection methods with video-based observational data on head position to explore the impact of using travel time for work- and leisure-related NDRTs in SAVs on users' attitudes, preferences, and associated VoTTs compared to conventional transport modes, including cars, urban PT (bus or tram), and bicycles.

The core element of the study involves two test rides in a WoZ vehicle, where participants engage in both work- and leisure-related NDRTs while travelling through urban areas. Subjective data are gathered through pre- and post-test online surveys, complemented by semi-structured interviews. In addition, camera-based observations are collected during the test rides and used to derive participants' head direction as a proxy for their engagement in NDRTs.

The experimental design included a main experimental group and a control group. Participants in the main experimental group completed both work- and leisure-related NDRTs, with the order of these tasks balanced to reduce potential order effects, while the control group completed the pre-test survey only and served as a baseline comparison.

The methodology is structured around a four-step process, outlined in Figure 5.1. The subsequent sections provide a detailed overview of this approach.

5.3.1. Procedure

Experimental vehicle

The test rides were conducted using a Wizard-of-Oz (WoZ) simulator-on-wheels vehicle to simulate a Level 5 SAV (MICD, 2022), a setup similar to Detjen et al. (2020). The vehicle, a Nissan e-NV200 Evalia van provided by LeasePlan, was modified to create the illusion of full automation while being manually driven by a "safety driver". To maintain this illusion, a wall partition was installed behind the first row of seats (Figures 5.2, 5.3), fully enclosing the passenger compartment. Inside, three OLED screens simulated a driver's seat view by displaying real-time footage of the driving environment, captured via cameras mounted on the

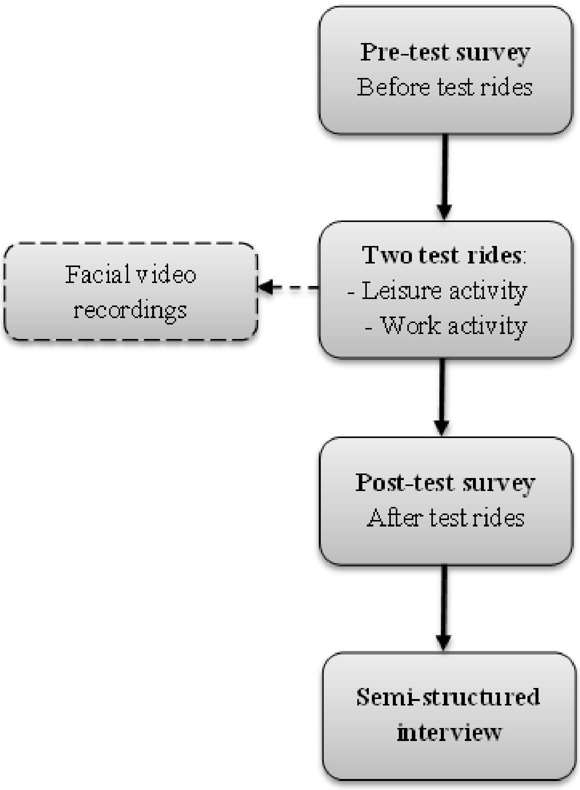


Figure 5.1. Four-step methodological approach

front and side windshields. Participants had no access to driving controls, such as the steering wheel or pedals, reinforcing the perception of a fully autonomous ride.

The passenger compartment was designed to provide privacy and comfort, allowing one participant at a time to engage in work- and leisure-related NDRTs in a distraction-free setting. The seating arrangement ensured that the participant sat in the rear seat, directly behind the partition, with an unobstructed view of the simulated road environment.

To ensure the participant's safety and comfort, an emergency stop button was installed on the left side of the seat, allowing participants to terminate the experiment immediately if they experienced any discomfort or negative effects.

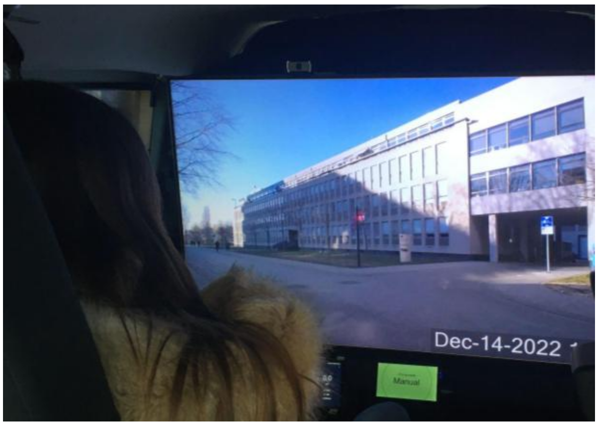
A camera mounted above the central front display recorded participant behaviour during the test rides, providing data on NDRT engagement levels. Facial video recordings, captured by this camera, were used to assess the extent of participants' engagement in NDRTs. This video data was chosen as a non-invasive method to allow participants to freely use handheld devices and materials during the test rides without interference. Inspired by camera-based driver monitoring systems (Pech et al., 2019; Seaman et al., 2022; van Gent et al., 2017), head orientation served as a proxy for attention allocation and engagement level. Facial video recordings were processed after the experiment using a computer-vision algorithm that classified head orientation into five categories (forward, left, right, up, and down), with the percentage of time spent looking down used as a proxy for engagement in the NDRTs.

Pre-test

Given that only one participant at a time could be in the experimental WoZ vehicle, participants were invited to book a timeslot via a link provided in the recruitment advertisement. The advertisement included a brief study description, outlining its stages and time commitment, which consisted of approximately 20 min for the pre-test survey and 1.5 h on the day of the experiment.

a) Exterior view

b) Interior set-up



c) Passenger during a test ride

Figure 5.2. Wizard-of-Oz simulator-on-wheels vehicle

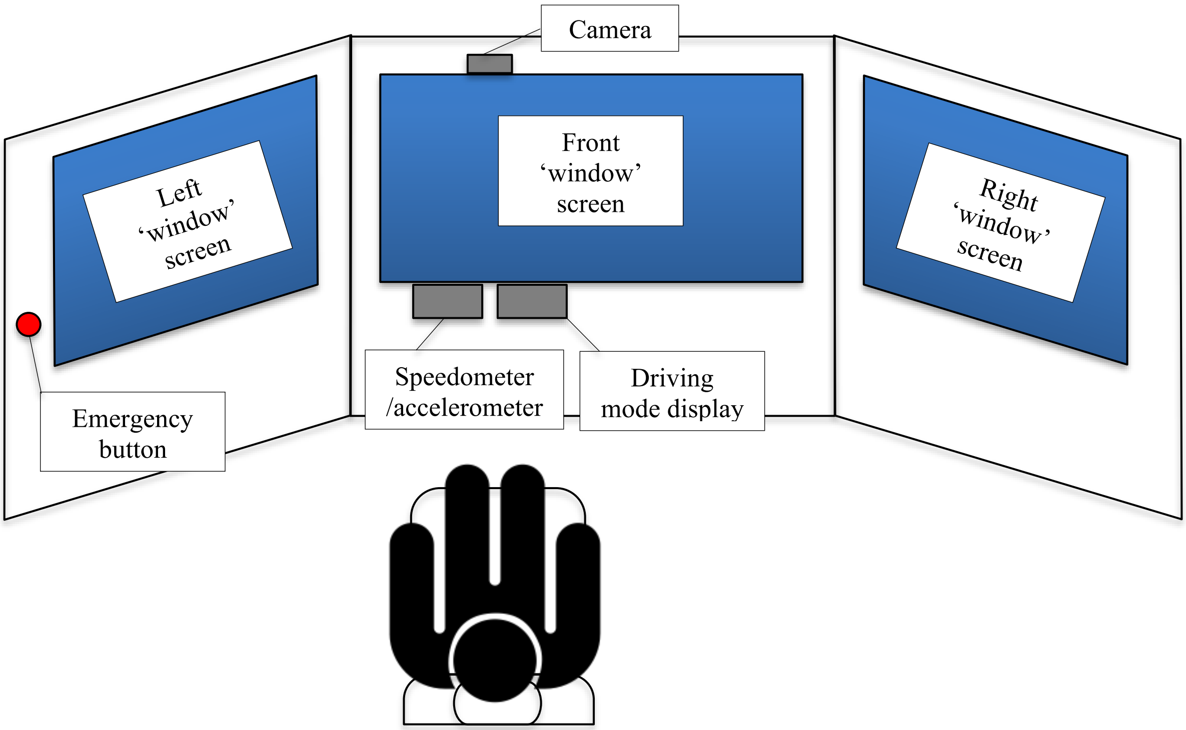


Figure 5.3. Schematic setup of the passenger's compartment

One week before their scheduled appointment, participants received an email containing a link to the pre-test survey, which they were required to complete at home. The survey assessed their initial attitudes and preferences toward SAVs compared to conventional transport modes.

Before accessing the pre-test survey, participants were required to sign a consent form, which, along with the standard description of the research procedure and data handling practices, also included a confidentiality clause. This clause prohibited participants from discussing the experimental setup until the study was completed, preventing them from revealing the true nature of the experimental vehicle to others.

Along with the survey, participants received a detailed description of the study procedure, outlining the steps they would follow on the day of the experiment. This included a 10-minute introduction, followed by two test rides of approximately 20 min each. After each ride, participants would complete a post-test survey and take part in a short interview during a 20-minute break to discuss their experience. Additionally, they were provided with a list of materials required for work- and leisure-related NDRTs to ensure they were adequately prepared.

The work- and leisure-related NDRTs were carefully selected to be actively engaging, cognitively demanding, and intrinsically motivating, based on criteria from Cornet et al. (2022) and Keseru & Macharis (2018). To ensure ecological validity and accommodate diverse participant interests, the selection of specific tasks was left to participants. They were provided with an example list of possible tasks prior to the test day (Appendix B) and encouraged to choose their own tasks similar to those examples, specifically, activities they would normally perform during travel or idle time.

Given the 20-minute test ride duration, suitable work-related tasks included planning an agenda, responding to emails, or reading. Participants were asked to bring their laptops and prepare work-related tasks in advance; for unemployed or retired participants, laptops were provided on-site along with example tasks such as writing a letter or email, creating a grocery list, or planning a weekly agenda. Leisure activities included reading paper-based materials or using a smartphone, with participants either bringing their own or selecting from provided options. This approach aimed to maintain high engagement, allow personal relevance, and simulate realistic travel time use during SAV rides.

Experimental day

During the introduction session, participants were first introduced to the experimental scenario, in which they were asked to imagine calling an SAV via an app, which would then arrive at their doorstep to take them to their destination.

To ensure their comfort and safety, participants were informed that they could terminate the experiment at any time by pressing an emergency button (Figure 5.3) if they felt uncomfortable. They were also advised to use the initial minutes of the ride to acclimate before beginning their assigned tasks. The “safety driver” was introduced as being present to oversee the vehicle’s operation and ensure a safe driving experience.

Following the introduction, each participant took two test rides in the WoZ simulator-on-wheels vehicle, engaging in both work- and leisure-related NDRTs. To control for potential order effects, participants were randomly assigned to start with either work-related or leisure-related tasks, ensuring a balanced experimental design.

The vehicle followed a 7.2 km route through Delft, the Netherlands, covering an urban driving environment with a mix of roundabouts, regulated intersections, busy city streets (max 50 km/h), a bascule bridge, and a provincial road (max 80 km/h) (Figure 5.4). Test rides were conducted on weekdays during daylight hours to ensure optimal lighting for NDRT engagement and to maintain consistent traffic conditions by avoiding peak hours. A team of seven “safety drivers” was instructed to drive calmly and cautiously, reflecting safe driving style of an AV.

After each test ride, participants took a 20-minute break, during which they completed a post-test survey and participated in semi-structured interviews to discuss their experience.

At the end of the 1.5-hour session, researchers disclosed the Wizard-of-Oz setup, clarifying that the vehicle was manually driven. Participants were also reminded of the confidentiality agreement, ensuring they would not share details about the experiment until the study period was completed.

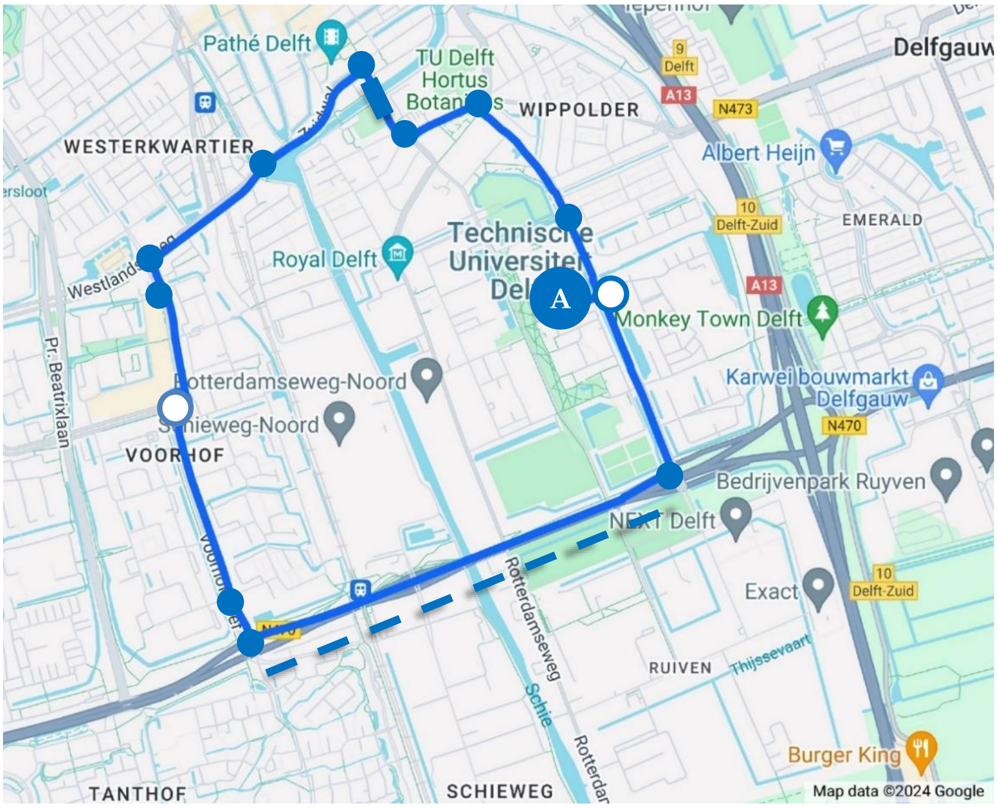


Figure 5.4. Test rides route in Delft (approximately 20 minutes)

A Start/end point

Busy roundabouts

Controlled intersections

Provincial road N470

Bascule bridge

5.3.2. Instrument

Pre- and post-test surveys

The pre-test survey conducted before the test rides encompassed (a) questions regarding the participants' current travel behaviour, (b) an SC experiment on mode choice, (c) indicator statements to gauge attitudes towards SAVs, and (d) questions about the participants' socio-economic background.

In the post-test survey after each test ride, participants were asked to repeat the SC experiment and reassess the indicator statements. The surveys were available in Dutch and English.

The opening section of the pre-test survey contained questions about the respondents' current travel behaviour, such as current travel mode, trip frequency and duration. The final section included questions regarding the respondents' socio-economic background, covering aspects such as gender, age, educational level, occupation, annual gross household income, possession of a driving license and PT pass, ownership of various types of vehicles, history of traffic accidents, presence of mobility restrictions or motion sickness, use of car- or ride-sharing services, and experience with AVs.

The SC experiment was designed to explore the preferences for SAVs, considering the possibility of performing NDRTs when using this car-sharing service. Before presenting the choice sets, participants were provided with detailed instructions about the SC experiment (Figure 5.5).

Imagine a trip **from home to your work**.

You open your travel planning app and see a **new alternative** for this trip.
It is a **self-driving car** which drives without a driver and has no steering, brake and gas pedals.
It picks you up at your doorstep and drops you off at your workplace.
You travel alone and can comfortably spend your time on working or leisure activities.

In the next part of the questionnaire, we ask you to choose between **four options** for your trip **(9 choice tasks):**

Self-driving car | Conventional car | Public transport (bus or tram) | Bicycle

For each choice card, the properties of the four travel options will differ in terms of:

Travel time | Travel costs | Waiting time at PT stop | Walking time to PT stop or parking place | Activity during trip | Level of crowdedness

Figure 5.5. Instructions shown to participants before starting the SC experiment

The choice sets included four labelled alternatives: an SAV (referred to as a self-driving car for clarity), a conventional car, PT (bus or tram), and a bicycle. Participants were asked to choose their preferred mode of transportation under scenarios where in-vehicle travel time, travel costs, waiting time at the PT stop or doorstep, and walking time to the PT stop or parking place were provided. For the SAV alternative, the attribute "Activity during trip" had two levels: working and leisure. Additionally, the level of crowdedness was included as an attribute of the PT (bus or tram) alternative.

The attribute levels were primarily determined based on data from trip-planning applications for mid-sized cities in the Netherlands (Table 5.2). The travel costs for the conventional car alternative were calculated for middle-class vehicles (i.e., vehicles typically priced and categorised between economy and luxury, offering moderate features and performance) and included expenses for fuel, insurance, maintenance, and taxes, excluding parking costs (Nibud, 2023). The travel costs for SAVs offering car-sharing services were assumed to be similar to those for the conventional car alternative.

Based on the participants' indicated occupation, the purpose of the trip was specified in the choice sets in the direction from home to the workplace for employed or self-employed individuals, a place of study for students, or any frequently visited location for unemployed or

Table 5.2. Attribute levels

Attributes and attribute levels	Alternative 1	Alternative 2	Alternative 3	Alternative 4
	Self-driving car	Conventional car	Public transport (bus or tram)	Bicycle
Travel time (min)	15 / 25 / 35	15 / 25 / 35	15 / 25 / 35	20 / 30 / 40
Travel costs (€)	3.0 / 4.0 / 5.0	3.0 / 4.0 / 5.0	2.4 / 3.4 / 4.4	–
Waiting time (min)	2 / 5 / 8	–	2 / 5 / 8	–
Walking time (min)	–	2 / 4 / 6	4 / 7 / 10	–
Activity	(0) Leisure (1) Work	–	–	–
Crowdedness	–	–	(0) Not crowded (1) Light crowdedness (2) Crowded	–

retired individuals.

Each respondent was presented with a total of nine hypothetical choice tasks, repeated in pre-test and post-test surveys (see example of a choice task in Figure 5.6). The choice tasks were generated using Ngene software through an orthogonal design, resulting in 36 choice sets divided into four blocks (ChoiceMetrics, 2018).

Card 1. Which mode of transport do you prefer to travel from your home to work in this situation?

	Self-driving car	Conventional car	Public transport (bus or tram)	Bicycle
Travel time	**35 min**	**35 min**	**25 min**	**20 min**
Travel costs	**4 euro**	**3 euro**	**2.4 euro**	**-**
Waiting time	**5 min**	**-**	**2 min**	**-**
Walking time	**-**	**4 min**	**10 min**	**-**
Activity	**Working**	**-**	**-**	**-**
Crowdedness	**-**	**-**	**Light crowdedness**	**-**

Figure 5.6. Example of a choice task (for employed or self-employed participants)

Moreover, in the pre-test and post-test surveys, participants rated their agreement with 18 attitudinal statements on a 7-point Likert scale, representing six psychological constructs: enjoyment of AVs and the ride experience, perceived safety and trust in their technological capabilities, intention to use SAVs, service quality, and perception of work and leisure activities. The last two constructs specifically assess the importance of using travel time for work or leisure, as well as the comfort and ability to concentrate on these activities during the ride (Table 5.3).

Semi-structured interviews

To gain a deeper understanding of participants' perceptions of SAVs, their experiences of riding in the Wizard-of-Oz simulator-on-wheels vehicle and engaging in work- and leisure-related NDRTs, we conducted semi-structured interviews, which took place with participants during the breaks after the first and the second test rides, after participants filled in the post-test surveys.

The interviews followed a short interview guide covering five core themes: (1) participants' motivation for joining the experiment; (2) their prior knowledge of and interest in automated driving technology; (3) their perceived safety and trust in the vehicle during the test rides; (4) their perception of the vehicle's driving style compared with that of a human driver; and (5) their experience of engaging in work- and leisure-related NDRTs. After the second ride, participants were also asked to compare both ride conditions and reflect on whether one activity type was easier or more comfortable to perform than the other.

An additional aim of the interviews was to assess participants' belief in the experimental setup, namely, whether they initially believed they were riding in a self-driving vehicle. To avoid influencing participants' responses during the rides, this was assessed indirectly during the conversation and confirmed after the nature of the Wizard-of-Oz setup had been disclosed. Participants' responses were manually annotated using predefined categories, including motivation for participation, interest in automated driving, trust and perceived safety, perceived driving style, experience with work- and leisure-related NDRTs, and belief in the experimental setup. The interview analysis followed a deductive content analysis approach (Elo & Kyngäs, 2008), in which responses were classified according to these predefined categories and used to identify recurring patterns in participants' experiences.

5.3.3. Participants

A total of 104 participants took part in the five-week experiment conducted between November and December 2022. This main sample was recruited from the Delft panel with support from the Delft municipality. As an incentive, participants had the opportunity to win one of ten €50 gift cards.

Because the main sample consisted of volunteers from an existing panel, there was a risk of self-selection bias: these participants might have been more curious or enthusiastic about experiencing SAVs than the general population. To address this concern, we recruited a control group of 35 participants through social media, personal networks, and paper-based advertisements, following recommendations from Feys et al. (2021) and Liu et al. (2019). Unlike the main sample, participation in the control group was voluntary and non-incentivised. These participants completed a pre-test survey that excluded the experimental scenario and served as a baseline to check for the differences in choices.

Although the recruitment strategies differed (panel vs open call), both groups included individuals from Delft and surrounding areas with diverse backgrounds in age, gender, education, and travel patterns. Appendix C summarises the socio-economic characteristics of both groups (Table C.1), mode choices by trip purpose (Table C.2), and additional participant details (Table C.3).

Table 5.3. Attitudinal indicators and underlying psychological constructs

	Indicators*	Source	Likert scale
Enjoyment of AVs			
S1	I like self-driving cars	Adapted from Öztürker et al. (2022)	1 = dislike extremely, 7 = like extremely
S2	I think that a ride in a self-driving car is enjoyable (A ride in a self-driving car was enjoyable)	Adapted from Nordhoff et al. (2018a)	1 = strongly disagree, 7 = strongly agree
S3	I think that a ride in a self-driving car is stressful (A ride in a self-driving car was stressful)	Adapted from Yap et al. (2016)	
Perceived safety and trust			
S4	I trust that a system can drive a self-driving car with no assistance from me	Adapted from Yap et al. (2016)	1 = strongly disagree, 7 = strongly agree
S5	I dislike that I don't have control of how the car drives	Adapted from Kyriakidis et al. (2015)	
S6	I can entrust the safety of a close family member to a self-driving car		
S7	I think that a ride in a self-driving car is safe (A ride in a self-driving car was safe)		
Work activity			
S8	It is important for me to use my travel time productively when I'm riding in a self-driving car (I would use my travel time productively when I ride in a self-driving car)	Created for this study	1 = strongly disagree, 7 = strongly agree
S9	I think I will be (I was) able to concentrate on working in a self-driving car		
S10	I think it will be (It was) comfortable to work in a self-driving car		
S11	I think that a ride in a self-driving car is comfortable (A ride in a self-driving car was comfortable)	Adapted from Kyriakidis et al. (2015)	
Leisure activity			
S12	I think I will be (I was) able to concentrate on my leisure activities in a self-driving car	Created for this study	1 = strongly disagree, 7 = strongly agree
S13	I think it will be (It was) comfortable to spend time for leisure activities in a self-driving car		
S8 and S11		See above	
Intention to use shared automated vehicles			
S14	I like that an electric self-driving car does not produce pollutant emissions	Adapted from Yap et al. (2016)	1 = strongly disagree, 7 = strongly agree
S15	In the future, I will use self-driving cars for my daily trips	Adapted from Nordhoff et al. (2018b)	
S16	I think that a ride in a self-driving car saves time (would save my time)	Adapted from Kyriakidis et al. (2015)	
Service quality			
S17	I am afraid that there will be no car available when I request one	Adapted from Yap et al. (2016)	1 = strongly disagree, 7 = strongly agree
S18	I am worried that the car is not clean after its previous use		

* The statements were modified for the post-test survey, see in parentheses

5.4 Modelling approach

5.4.1. Joint model specification

In this study, we employed a mixed logit model with panel effects, jointly estimated on pre- and post-test datasets, following methodologies from Jensen et al. (2013) and González et al. (2016). This approach allowed us to compare participants' preferences before and after experiencing work and leisure activities during test rides in the experimental vehicle while accounting for correlation in repeated choices from the same individuals. To account for potential heteroscedasticity between the pre- and post-test datasets, a scale parameter was included in the joint model formulation. This is a common approach in stated preference studies to address differences in unobserved utility variance, which can arise due to variations in geographic regions, datasets, or, in our study, the two survey waves (Train, 2009; Jensen et al., 2013; González et al., 2016). More flexible specifications, such as random scale mixed logit or latent class models (Hess & Train, 2017), can also capture variation in scale across individuals or subgroups, but they require larger samples and add estimation complexity. Given that our joint model incorporated a panel structure and was estimated on the available sample (n = 104), a fixed scale adjustment was selected as the most suitable choice for our objective of assessing before-after changes in preferences following experimental SAV exposure. The model was estimated using the PandasBiogeme software package (Bierlaire, 2023).

In the joint mixed logit model with panel effects, $U_{in}^{pre-test}$ and $U_{in}^{post-test}$ represent utilities that individual n assigns to alternative i before and after the test rides, respectively (Eq. 5.1).

$$\begin{aligned} U_{in}^{pre-test} &= \sum_k \beta_{ik}^{pre-test} \cdot x_{ikn} \\ &\quad + \sum_l \beta_{il}^{pre-test} \cdot x_{ln}^{pre-test} + \sum_s \beta_{is}^{pre-test} \cdot x_{sn} + \gamma_{in}^{pre-test} + \varepsilon_{in}^{pre-test} \\ U_{in}^{post-test} &= \mu \Bigg(\sum_k \beta_{ik}^{post-test} \cdot x_{ikn} \\ &\quad + \sum_l \beta_{il}^{post-test} \cdot x_{ln}^{post-test} + \sum_s \beta_{is}^{post-test} \cdot x_{sn} + \gamma_{in}^{post-test} + \varepsilon_{in}^{post-test} \Bigg) \end{aligned} \tag{5.1}$$

Where:

x_{ikn} and β_{ik} is the vector of instrumental variables and their estimated parameters;
x_{ln} and β_{il} is the vector of latent variables and their estimated parameters;
x_{sn} and β_{is} is the vector of socio-economic variables and their estimated parameters;
γ_{in} is a normally distributed error component capturing panel effects (mean 0, standard deviation σ);
ε_{in} is an independent and identically distributed (i.i.d.) extreme value type 1 error term;
μ is a scale parameter to normalise error variances across pre- and post-test data.

The first component of the utility function includes instrumental variables x_{ikn} that represent observable attributes of the travel alternatives in the SC experiment, such as in-vehicle travel time, travel costs, waiting time at the PT stop or doorstep, walking time to the PT stop or parking place, activity during the trip, and level of crowdedness (see Table 5.2). Level of crowdedness for the public PT (bus or tram) alternative was dummy-coded with three levels: "Not crowded" (reference category), "Light crowdedness", and "Crowded". For the SAV alternative, the variable "Activity during trip" enters the model as an interaction term with in-vehicle travel time, travel costs, and waiting time at the doorstep, allowing the effect of on-board activity to vary depending on these trip attributes.

The second component comprises latent variables x_{ln} that capture unobservable psychological constructs derived from attitudinal statements on perceptions, concerns, and beliefs about automated transport. Because latent variables cannot be directly observed, confirmatory factor analysis (CFA) was applied to a set of 18 attitudinal indicators (see Table 5.3). Unlike exploratory factor analysis (EFA), which uncovers latent structures without prior assumptions, CFA is suited to testing hypothesised structures (Brown, 2015). In our case, the same attitudinal indicators were collected in two waves (pre- and post-test), and we required a consistent factor structure to meaningfully compare latent constructs across them. EFA tends to yield different factor solutions across datasets, particularly when applied separately to each wave, which complicates longitudinal comparisons. We therefore used CFA to confirm the hypothesised structure and assessed measurement invariance via multi-group CFA to confirm stability across waves (Brown et al., 2017).

After confirming the latent variable structure through CFA, we specified structural equations to integrate the constructs x_{ln} into the discrete choice model, estimated separately for the pre-test and post-test stages S, as the attitudes of a participant n could change after engaging in work and leisure activities during test rides

$$x_{ln}^{S} = k^{S} + \sum_{s} \varphi_{s}^{S} \cdot x_{sn} + \omega_{n}^{S} \tag{5.2}$$

where k is the intersept, x_{sn} and φ_s is the vector of socio-economic variables and their estimated parameters and ω_n is the error term with zero mean and standard deviation σ_ω.

The relationship between each latent variable x_{ln} and $r = 1 \ldots R$ indicators I_{rn} associated with it was modelled through measurement equations

$$I_{rn}^{S} = k_{r}^{S} + \sum_{l} \alpha_{r}^{S} \cdot x_{ln}^{S} + \lambda_{rn}^{S} \tag{5.3}$$

where k_r is the intersect, x_{ln} is the latent variable, α_r is the factor loading linking the latent variable to indicator r and λ_{rn} is the error term with zero mean and standard deviation σ_λ.

Given the complexity of estimating the model with several latent variables, we integrated the latent variables into the discrete choice model sequentially, as this approach helps to manage the computational challenges involved. This sequential integration approach is recognised in the literature as a practical, though less statistically efficient, alternative to full-information estimation. In complex hybrid models, sequential estimation allows latent constructs to be incorporated stepwise without overburdening the estimation routine, while still yielding meaningful and statistically significant results (Bahamonde-Birke & Ortúzar, 2014; Johansson et al., 2006).

The third component accounts for individual socio-economic characteristics x_{sn} such as age, gender, and education, as well as mobility-related attributes like car ownership and current main transport mode (see Tables C.1 – 3). By including these variables, the model captures systematic heterogeneity in mode choice that cannot be explained by instrumental attributes or latent attitudes. To incorporate categorical socio-economic variables into the model, we applied dummy coding. The variable categories and their corresponding reference categories used in the coding scheme are detailed in Tables C.1 – 3.

In the utility functions (Eq.5.1), the parameters β_{ik}, β_{il}, β_{is} of instrumental, latent, and socio-economic variables, respectively, were initially estimated as specific to the pre- and post-test experimental stages. This was done to determine whether work and leisure activities during the test rides influenced participants' preferences. When no significant differences were found between pre- and post-test preferences, generic parameters were introduced.

The utility functions specified in Eq. (5.1) include two types of error terms that reflect different sources of unobserved variation. First, the term γ_{in} is a normally distributed error component (mean zero, standard deviation σ) that accounts for panel effects by capturing unobserved individual-specific variation across repeated choices. The term ε_{in} is an independent and identically distributed extreme value type 1 (EV1) error, capturing random noise at the observation level. To account for potential differences in error variance between the pre- and post-test datasets, a scale parameter μ is introduced. This normalises the variance across waves, allowing a joint model to be estimated (Jensen et al., 2013; González et al., 2016).

Finally, two interaction terms were included in the post-test utility functions to account for participants' test-ride experiences. The first captures the engagement levels in work- and leisure-related NDRTs derived from video analysis and dummy-coded into three levels: "Full concentration", "Partial concentration" (either on work or leisure activities), and "No concentration" (reference category). The second interaction accounts for whether participants believed in the experimental setup, based on post-ride interviews, and was coded as "Believed", "Hesitant", and "Did not believe" (reference). These variables interact with instrumental, latent, and socio-economic variables in the post-test model to assess whether engagement and belief moderated mode preferences. As a result, Eq. (5.1) was extended to incorporate these interaction effects in the post-test utility specification, where C stands for "Concentration" and B stands for "Belief":

$$
\begin{aligned}
U_{in}^{pre-test} &= \sum_k \beta_{ik}^{pre-test} \cdot x_{ikn} \\
&\quad + \sum_l \beta_{il}^{pre-test} \cdot x_{ln}^{pre-test} + \sum_s \beta_{is}^{pre-test} \cdot x_{sn} + \gamma_{in}^{pre-test} + \varepsilon_{in}^{pre-test} \\
U_{in}^{post-test} &= \mu \Bigg(\sum_k \beta_{ik}^{post-test} \cdot x_{ikn} + \sum_l \beta_{il}^{post-test} \cdot x_{ln}^{post-test} + \sum_s \beta_{is}^{post-test} \cdot x_{sn} \\
&\quad + \sum_{conc \cdot k} \delta_{ik}^{post-test} \cdot x_{ikn} \cdot C_{in} + \sum_{conc \cdot l} \delta_{il}^{post-test} \cdot x_{ln} \cdot C_{in} \\
&\quad + \sum_{conc \cdot s} \delta_{is}^{post-test} \cdot x_{sn} \cdot C_{in} + \sum_{belief \cdot k} \delta_{ik}^{post-test} \cdot x_{ikn} \cdot B_{in} \\
&\quad + \sum_{belief \cdot l} \delta_{il}^{post-test} \cdot x_{ln} \cdot B_{in} + \sum_{belief \cdot s} \delta_{is}^{post-test} \cdot x_{sn} \cdot B_{in} \\
&\quad + \gamma_{in}^{post-test} + \varepsilon_{in}^{post-test} \Bigg)
\end{aligned}
\tag{5.4}
$$

Finally, a similar modelling approach (based on the utility specification in Equation (5.1)) was used to compare the pre-test preferences of the main sample with those of the control group.

5.4.2. Modelling steps

The modelling process followed a stepwise approach (Figure 5.7).

Step 1. Half of the participants began with work-related activities, and the other half with leisure activities. To test whether responses differed systematically depending on activity order, we estimated a joint multinomial logit (MNL) model with instrumental variables.

Full taste homogeneity was tested under the assumption that preferences were identical across all instrumental parameters ($\beta_{post-first\,ride} = \beta_{post-second\,ride}$), with potential differences existing only in scale ($\mu_{post-first\,ride} \neq \mu_{post-second\,ride}$). The correctness of the joint model specification was verified using the likelihood ratio test (de Dios Ortúzar & Willumsen, 2011):

$$LRS = -2\{L(\beta_j) - L(\beta)\} \tag{5.5}$$

where $L(\beta_j)$ is the final log-likelihood of the joint model, and $L(\beta)$ is the sum of the final log-likelihoods of the independently estimated post-first and post-second ride models. The independent models produced a combined log-likelihood of $L(\beta)$ =−1911.3333 with a total of 32 parameters (16 each), while the joint model with 16 generic parameters and one scale parameter yielded $L(\beta_j)$ =−1913.849. The likelihood ratio statistic (5.0314) was far below the χ^2 critical value of 24.996 for 15 degrees of freedom at a 95% significance level. We therefore conclude that responses exhibit full taste homogeneity between the post-first and post-second test rides. As a result, subsequent analysis focused on responses collected after the second test ride, when participants had experienced both activities.

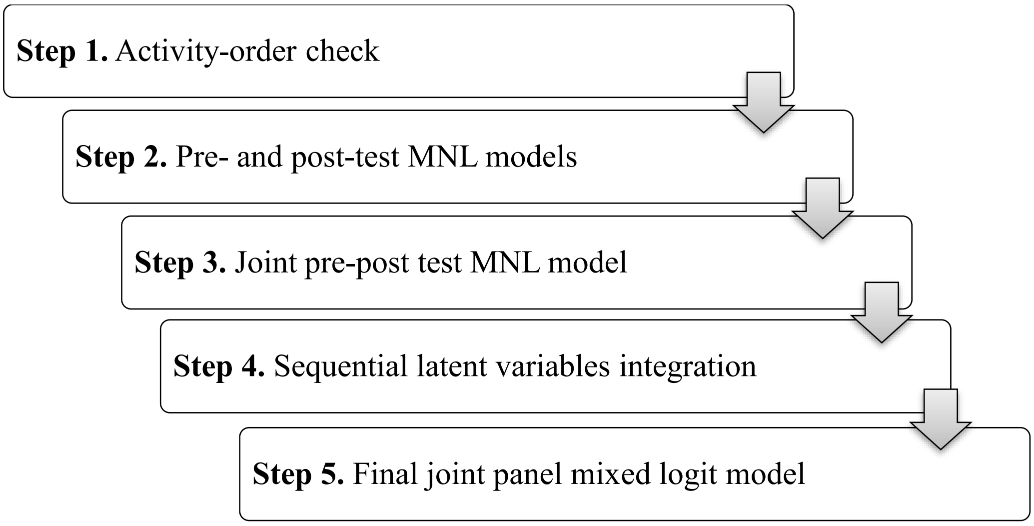


Figure 5.7. Modelling steps

Step 2. We then estimated separate MNL models for the pre-test and post-test datasets using instrumental and socio-economic variables ($MNL_{pre\text{-}test}$ – 21 parameters, $LL_{pre\text{-}test}$= -957.4702; $MNL_{post\text{-}test}$ – 26 parameters, $LL_{pre\text{-}test}$= -856.3805). At this stage, non-significant parameters were excluded at a 10% significance level, given the intermediate nature of this step in the modelling process.

Step 3. The two MNL models were subsequently combined into a joint pre-/post-test MNL under the assumption of partial taste homogeneity. Full homogeneity was considered unlikely, so candidate parameters were identified using covariance/correlation analysis of parameter pairs with t-values below 1.96 (95% significance) (de Dios Ortúzar & Willumsen, 2011). PandasBiogeme (Bierlaire, 2023) reports this analysis, and 8 generic parameters and a scale parameter were introduced into the joint model (MNL_{joint} – 38 parameters, LL_{joint}=

-1818.304). As in Step 1, the model specification was tested using the likelihood ratio test (Eq. 5.5). At the 95% significance level, the likelihood ratio statistic (8.9066) was lower than the χ^2 critical value of 16.919 (9 df), confirming correct specification of the joint model.

Step 4. After validating the latent constructs through CFA, we conducted multi-group CFA to test measurement invariance, confirming that the same attitudinal constructs could be meaningfully compared across both waves (see Section 5.5.1). This provided the foundation for the structural part of the MIMIC model, in which socio-demographic variables were specified as causes of the latent constructs. To manage computational complexity, we first pre-estimated the latent variables model (see Section 5.5.1) and then introduced the latent variables sequentially into the joint model, ensuring that each construct could be incorporated without overburdening the estimation routine.

The order of inclusion follows theoretical priority and ensures comparability across time points. Constructs most central to our research focus, namely perceived work activity and perceived leisure activity, are integrated first, followed by the remaining constructs in decreasing order of measurement reliability as indicated by the CFA. For each construct, we first added the pre-test latent variable, immediately followed by its post-test counterpart. This ordering allowed a balanced assessment of attitudinal changes across the two survey waves. While sequential estimation is less efficient than simultaneous full-information approaches, it is widely applied in hybrid choice modelling as a pragmatic solution when estimation complexity prevents joint estimation (Bahamonde-Birke & Ortúzar, 2014; Johansson et al., 2006).

Step 5. In the final step, we estimated a joint mixed logit model that incorporated an error component, γ_{in}, to account for panel effects. This component is normally distributed with mean zero and standard deviation σ, and captures unobserved individual-specific variation across repeated tasks. The results of the final joint mixed logit model with panel effects are presented in Table 5.10 and discussed in Sections 5.5.4 and 5.5.5.

We repeated Steps 2 – 5 using only the pre-test responses, comparing the main sample with the control group. The corresponding results of the joint mixed logit model with panel effects are reported in Table 5.13 and further examined in Section 5.5.6.

5.5 Results and discussion

5.5.1. Results of the latent variables model

Validating the latent constructs through CFA

Latent variables in the second term of the utility functions (Eq. 5.1) represent unobservable psychological constructs that form a latent variables model. The hypothesised structure of the latent variables model consists of 6 latent variables, namely "Enjoyment of AVs", "Perceived safety and trust", "Work activity", "Leisure activity", "Intention to use shared automated vehicles" and "Service quality" (see Table 5.3).

Before validating the structure of the latent model, we first examined the average scores that participants assigned to the indicators (Appendix D, Table D.1). Both the main sample and the control group showed generally positive attitudes toward SAVs and the potential for productive use of travel time while travelling in them. Notably, the scores in the main sample increased significantly after the test rides (see Pre-test – Post-test column in Appendix D, Table D.1), whereas no significant differences were observed between the pre-test scores and those given by the control group on nearly all indicators (see Control group – Pre-test column in Appendix D, Table D.1).

Afterwards, CFA was performed separately on the pre-test, post-test, and control group datasets to validate the latent variables model. In other words, it was used to assess the relationships between attitudinal indicator statements and their corresponding latent constructs.

In the main sample, the first run of CFA with the hypothesised model structure revealed low and non-significant standardised loadings for all indicators of the "Service quality" latent construct. Due to this poor measurement performance and limited contribution to the structural model, the construct was excluded from the final estimation (Appendix D, Tables D.2 and D.6). Additionally, the factors "Enjoyment of AVs" and "Perceived safety and trust" were highly correlated when checked for discriminant validity using the Fornell-Larcker criterion, leading to their combination into a single factor (Appendix D, Tables D.3, D.4 and D.7, D.8). The final model consisted of four latent constructs: "Perceived safety, trust, and enjoyment of AVs", "Work activity", "Leisure activity", and "Intention to use SAVs". Each latent construct was represented by at least two indicators, and factor loadings were estimated using maximum likelihood estimation with the lavaan R package (Rosseel, 2012). The CFA results for the pre-test and post-test datasets are detailed in Appendix D, Tables D.5 and D.9.

The goodness-of-fit indices, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA), for both the pre-test and post-test models indicated an acceptable fit (Appendix D, Tables D.5, D.9). RMSEA reflects how well the model fits the population covariance matrix, with values below 0.08 indicating acceptable fit and values below 0.05 considered good. CFI and TLI assess model fit relative to a baseline model, with values above 0.90 generally indicating acceptable fit and values above 0.95 considered good (Brown, 2015). These indices were selected because they are widely accepted in CFA as indicators of model adequacy.

Indicators with insignificant or weak factor loadings (<0.6) were removed from both models. While a loading of 0.7 is typically recommended, loadings of 0.6 or above are considered acceptable when supported by theory and model fit (Hair et al., 2021). All remaining loadings were significant ($p < 0.001$) and strong indicators of their respective latent constructs.

To further assess the reliability and validity of the latent variables, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were calculated (Appendix D, Tables D.5, D.9). Thresholds of 0.70 for Cronbach's alpha and CR, and 0.50 for AVE, are commonly used to indicate acceptable internal consistency and convergent validity (Hair et al., 2021; Cheung et al., 2024). Both pre-test and post-test models met these criteria, with Cronbach's alpha values exceeding 0.70, except for the "Intention to Use SAVs" factor in the pre-test model, which was kept for consistency with the post-test model. CR values also surpassed the 0.70 threshold, and AVE values confirmed convergent validity.

A multi-group confirmatory factor analysis was conducted in lavaan R package (Rosseel, 2012) to ensure model consistency across pre-test and post-test data (Brown et al., 2017). The results confirmed good model fit for both datasets, supporting measurement invariance across groups. This confirmation established that the latent constructs were stable across waves, thereby justifying their use in the structural part of the MIMIC model. Multi-group CFA indicated good fit (CFI =0.966; RMSEA = 0.081), and invariance tests (metric: ΔCFI = –0.003, ΔRMSEA = –0.001, scalar: ΔCFI = –0.009, ΔRMSEA = +0.013) showed ΔCFI $\leq$ 0.01 and ΔRMSEA $\leq$ 0.015, confirming the equivalence of constructs across waves.

Although the pre-test and control groups did not differ significantly in their average responses to attitudinal indicators, multi-group CFA revealed that the underlying factor structure was not comparable across the two groups (Appendix D, Table D.13). Specifically, the configural model for the control group showed poor fit (CFI = 0.796, RMSEA = 0.178, SRMR = 0.100), indicating that participants organised the items differently into latent constructs (see Appendix D, Table D.10, Table D.11, Table D.12 for model development stages). As outlined in Section 5.4.1, meaningful comparison of latent constructs across groups requires a consistent factor structure; without this, estimates of latent means or relationships are not valid. To avoid drawing misleading conclusions from non-equivalent latent variables, we therefore excluded the latent constructs from the joint model.

Latent variables model

Following the specification in Equation (5.2), each latent construct was regressed on socio-economic characteristics as part of the MIMIC model, namely gender, age, education level, occupation, and income. In this framework, the structural equations (Eq. 5.2) capture the influence of socio-demographic causes on the latent constructs, while the measurement equations (Eq. 5.3) link each construct to its observed indicators. The results of both the multiple indicators and multiple causes parts are presented in Appendix D, Tables D.14 (pre-test) and D.15 (post-test). In what follows, we discuss how socio-economic characteristics shaped each of the four latent constructs, comparing pre-test results (Appendix D, Table D.14) with post-test results (Appendix D, Table D.15).

For the first factor, representing perceptions of safety, trust, and enjoyment of AVs, pre-test results suggest that women, the highly educated, and higher-income respondents held more positive perceptions, whereas older and employed participants expressed negative views. Post-test results reveal substantial shifts: the effect of gender and income turns negative, and the contribution of education strengthens considerably. The age penalty remains but diminishes, while the effect of employment is no longer significant. These results indicate that direct exposure reshaped perceptions in ways that attenuated or reversed several of the pre-test socio-demographic gradients.

The second factor, relating to the perceived suitability of working in SAVs, was initially evaluated more positively by women and higher-income respondents, while older participants and those in employment expressed more negative views. After the test rides, the gender advantage remained but was smaller, the negative age effect became stronger, the employment penalty decreased sharply, and the income effect disappeared altogether. These patterns suggest that experience with the vehicle reduced income-related differences but reinforced age-based scepticism about working during rides.

The third factor, reflecting leisure-related activities in SAVs, displayed a contrasting pattern. Before the rides, women, older respondents, those with higher education, and higher-income participants reported less favourable attitudes, while the employed expressed stronger support. After exposure, the age effect flipped to a significant positive, female and income effects became non-significant, and the employment effect remained positive though weaker. Only the modest negative effect of education persisted. These findings suggest that riding experience was particularly effective in improving older participants' views of SAVs as spaces for leisure activities.

For the fourth factor, intention to use SAVs, pre-test results revealed stronger intentions among women, the highly educated, and higher-income respondents, while employment had a significant negative effect. After the rides, these relationships were reconfigured: higher income was linked to reduced intention, the effect of employment turned strongly positive, and the effects of gender and age disappeared. Education remained a small but consistent positive driver. Post-test intentions, therefore, became more closely aligned with being employed, while the pre-test prominence of income and gender weakened.

Taken together, the results show that direct exposure to SAVs reshaped how socio-economic characteristics influence perceptions and intentions. Before the rides, gender and income were strong predictors across several constructs, but their effects largely weakened or reversed afterwards. Education emerged as a consistently positive predictor of perceptions of safety, trust, and enjoyment as well as of intention to use SAVs. Employment, which was initially associated with more negative perceptions and intentions, became a positive predictor after the rides. Older participants remained sceptical about working in SAVs but became more favourable toward their leisure use. Overall, these patterns suggest that riding experience reduces pre-existing socio-economic divides, with education and employment emerging as the most important post-test determinants across the four latent constructs.

5.5.2. Quantifying the extent of engagement in NDRTs during test rides

To analyse participants' engagement in work- and leisure-related NDRTs during the test rides, facial video recordings from a camera installed above the central “front windshield” screen (Figure 5.3) were processed using a computer vision algorithm estimating visual attention through head orientation (Nielsen, 2021). The algorithm calculated the percentage of time participants looked in five directions: forward, left, right, up, and down (Figure 5.8), corresponding to the front screen, side “window” screens, the upper area of the front screen, and down at the task, respectively. Downward head orientation was used as a proxy for engagement, as gaze tracking was not feasible from the overhead camera position. When participants looked down at a task, their eyes were typically occluded from view, making head pose a practical and non-intrusive indicator of engagement for our experimental setting.

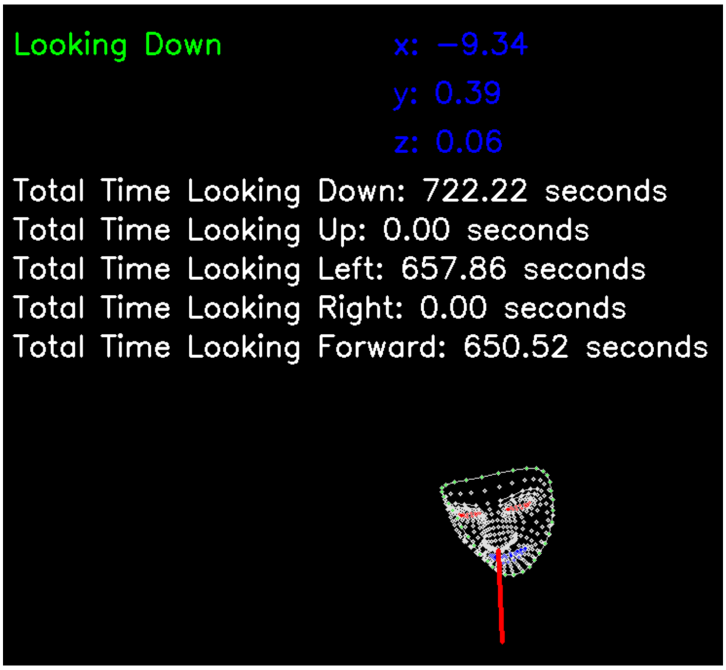


Figure 5.8. Example of processed video output

The use of head pose as a non-intrusive indicator of engagement is well established in naturalistic settings where direct eye tracking is either impractical or may alter participant behaviour. Hernandez et al. (2013) demonstrated that sustained head orientation toward a screen can reliably distinguish between high and low engagement when monitoring television viewers, even without eye-movement data. Levordashka et al. (2023) similarly used head pose to capture audience attention during live events, showing its sensitivity to engagement patterns while allowing participants to behave naturally. In an educational context, Yu et al. (2021) applied head-pose estimation to monitor student engagement during lectures, further supporting its validity as an unobtrusive engagement metric in seated-task environments. These findings support our choice of head pose over more intrusive methods, which could have disrupted participants’ self-selected NDRTs.

Participants who looked down for more than 70% of the ride were considered fully concentrated on the task. This threshold accommodates the preparatory phase at the start of the ride, when participants were instructed to first settle in the vehicle, observe their surroundings, and familiarise themselves with the interior before beginning their chosen task, as well as natural off-task glances to check the driving situation and posture adjustments. Our cut-off also aligns with previous engagement research: notably, Eriksson et al. (2018) reported that maintaining approximately 80% head orientation toward the relevant screen reflected an acceptable engagement level in an e-learning context, placing our 70% threshold within an empirically supported range while allowing for realistic off-task time in a naturalistic, in-ride setting.

Comparable thresholds appear in driver monitoring literature. In conventional driving, the NHTSA (2012) defines visual distraction when the Percent Road Center (PRC) falls below 60% in a given time window, and Kircher et al. (2009) use a similar 58% cut-off. Large-scale naturalistic studies report that attentive drivers keep their eyes on the road roughly 75 - 80% of the time (European Commission, 2015; 2022). In Level 3-4, on-road and simulator studies show that when drivers are fully engaged in a visual-manual NDRTs, they allocate 80-90% of gaze to the task (Britten, 2021; Klingegård et al., 2020).

Although our study was conducted in a vehicle simulating a Level 5 SAV, where occupants are not required to monitor the driving task, these established ranges support 70% as a conservative and empirically grounded cut-off. It ensures that "full concentration" reflects a clear majority of ride time dedicated to the task while preserving the naturalistic, non-intrusive character of the experiment.

Based on this criterion, 53.8% were fully engaged in both work and leisure activities, 10.6% focused only on work, 7.7% only on leisure, and 27.9% were not engaged in either. These results were dummy-coded into a parameter, "Concentration on NDRTs", with three levels: "Full concentration", "Partial concentration" (either on work or leisure activities), and "No concentration" (reference category).

This parameter was included as an interaction term in the discrete choice model (Eq. 5.4) to explore whether preferences differed among participants based on their engagement levels. This provided insights into how varying engagement in NDRTs influenced mode choices and the associated VoTTs.

5.5.3. Belief in the experimental setup: results from semi-structured interviews

The semi-structured interviews provided additional experiential insights into participants' perceptions of SAVs, their trust in automated driving technology, their ability to engage in NDRTs during the rides, and their belief in the Wizard-of-Oz experimental setup. The results are reported according to the main interview categories: motivation for participation, perceived safety and trust, comparison between the first and second ride, experience with work- and leisure-related NDRTs, perceived driving style, and belief in the experimental setup.

The interview responses were manually annotated using predefined categories, including reasons for joining the study, knowledge of and interest in automated driving technology, trust in SAVs and safety perception, comparison of driving styles, experience with work- versus leisure-related NDRTs, and belief in the experimental setup. A deductive content analysis approach (Elo & Kyngäs, 2008) was followed to classify participant responses within these categories and identify key patterns in their perceptions. Participants' belief in the authenticity of the experimental setup was grouped into three categories: those who believed the setup was genuine, those who did not, and those for whom it was unclear. After researchers disclosed the nature of the experimental setup, participants were asked to confirm whether they had initially believed the vehicle was self-driving.

The majority of participants cited curiosity as their primary motivation for joining the field study, followed by an interest in automated driving technology. Despite their curiosity, many were initially hesitant to fully trust the vehicle to drive autonomously. This hesitation was particularly evident among participants who appeared visibly nervous before the test rides. The presence of a “safety driver” reassured participants and contributed to their overall sense of security during the rides. Although most participants reported feeling safe, many were uncertain whether their confidence stemmed from the safety driver’s presence or trust in the automated system itself.

Participants generally found the second test ride to be more relaxed, attributing this to their familiarity with the route and experimental settings from the first ride. However, no clear pattern emerged regarding whether work or leisure activities were easier or more difficult to perform, regardless of the order. This observation is further supported by the test model results (Subsection 5.4.2).

When asked whether they noticed a difference between the driving style of the automated system and a human driver, most participants reported little to no difference, primarily comparing it to their own driving behaviour. During the discussion, 58.7% of participants expressed amazement at the vehicle’s automated driving capabilities, forming the initial group who believed the setup was genuine. In contrast, 1.9% immediately recognised that the vehicle was not a true AV, while 39.4% were uncertain about their belief in the setup until the experiment’s nature was disclosed.

After researchers revealed that the vehicle was manually driven, 74% of participants confirmed they had genuinely believed they were riding in an AV, 18.3% remained uncertain until the disclosure, and 7.7% never believed the vehicle was fully automated. These findings indicate that the experimental setup created a realistic simulation of a self-driving vehicle for the majority of participants, reinforcing its relevance for studying user preferences and engagement in work- and leisure-related NDRTs during SAV rides. To examine whether these differences in belief affected participants’ stated preferences, a “Belief in experimental setup” variable was derived from the post-ride interviews and included in the discrete choice model as an interaction term (Eq. 5.4), dummy-coded as “Believed,” “Hesitant,” and “Did not believe” (reference category).

To further examine whether belief in the experimental setup varied systematically across participant groups, we conducted a series of Chi-square tests of independence. These analyses explored associations between belief categories and socio-demographic characteristics, as well as the order in which activities were performed during the rides. No significant associations were found with age ($\chi^2 = 2.475$, $p = 0.116$, Phi = 0.154), education level ($\chi^2 = 0.41$, $p = 0.522$, Phi = 0.063), occupation ($\chi^2 = 0.45$, $p = 0.502$, Phi = 0.066), or income ($\chi^2 = 1.522$, $p = 0.217$, Phi = 0.121). Similarly, belief did not differ depending on whether participants began with a work or leisure activity ($\chi^2 = 0.184$, $p = 0.668$, Phi = 0.042).

Notably, two quotes included at the beginning of this paper were drawn from these interviews, highlighting the participants' reflections on the experiment:

> *"In the future, driving a vehicle might become like horse riding. Just a hobby."*
> Anonymous participant 1

> *"Staying curious helps to stop anxiety when daring to ride in a self-driving vehicle."*
> Anonymous participant 2

5.5.4. Results of the final joint discrete choice model

The results of the joint panel mixed logit model are detailed in Table 5.4. Parameters are organised into three columns: the first two display stage-specific parameters for the pre- and post-test phases, which showed significant differences at the 95% level, reflecting the impact of engaging in work- and leisure-related NDRTs during the test rides. The third column includes generic parameters with no significant differences between the stages.

Parameter names include suffixes such as _SAV, _CAR, _PT, and _BIKE, which indicate the corresponding travel alternatives: shared automated vehicle, conventional car, public transport (bus or tram), and bicycle, respectively.

The following suffixes indicate reference to a specific instrumental, latent, or socio-economic parameter, with their meanings and category labels explained in the "Corresponding variable" column. For a complete overview of instrumental variables, see Table 5.2. Latent variables and their measurement indicators are provided in Tables D.5 and D.9 in Appendix D, while socio-economic variables and their categorical coding are detailed in Tables C.1-C.3 in Appendix C.

The final model, comprising 51 parameters, was estimated using 1,000 Halton draws from a normal distribution, yielding stable results. The adjusted Rho-squared value of 0.287, within the 0.2–0.4 range, indicates a strong fit to the data (Louviere et al., 2000). The model is intended to be exploratory and explanatory rather than predictive, aiming to uncover behavioural mechanisms rather than maximise out-of-sample forecasting performance. As shown in Table 5.5, the staged estimation process demonstrates a systematic improvement in model fit as additional behavioural structure is introduced: the inclusion of socio-economic variables increases the adjusted Rho-squared from 0.214 to 0.285, while the subsequent integration of latent variables yields a further improvement to 0.287, accompanied by a substantial gain in log-likelihood. While the Akaike Information Criterion (AIC) continues to decrease, indicating improved explanatory fit, the Bayesian Information Criterion (BIC) increases slightly in the final specification, reflecting its stronger penalty for model complexity. This trade-off is consistent with the exploratory nature of the model and suggests that the latent variables add explanatory insight at the cost of increased complexity, rather than indiscriminate overfitting. Additionally, the scale parameter for the post-test data significantly differs from 1, revealing a 23% higher variance in the post-test error terms compared to the pre-test data.

5.5.5. Discussion

When discussing the results in the following subsections, we focus on three key aspects that align with the main objectives of this study. First, we explain how participants' experience of engagement in work- and leisure-related NDRTs during the test rides affected their preferences for SAVs compared to traditional transport modes such as conventional cars, urban PT (bus or tram), and bicycles. Second, we clarify whether the preferences of participants who could concentrate on both activities during the test rides differ from those who could focus on only one activity or none. Third, we describe how the choice between work and leisure activity influenced preferences for SAVs.

We organise the discussion of results according to the components of the model (Eq. 5.4), starting with instrumental variables, then moving on to latent variables, and finally addressing socio-economic variables. Finally, using the estimated parameters for in-vehicle travel time and costs, we compute the corresponding VoTTs.

Table 5.4. Results of the final joint mixed logit model with panel effects

Parameter	Corresponding variable	Parameters		
		Specific for pre-test	Specific for post-test	Generic
βik	**Instrumental variables**			
β_SAV_TT	In-vehicle travel time (min)	-	-	-0.0911***
β_PT_TT		-	-	-0.103***
β_CAR_TT		-	-	-0.0952***
β_BIKE_TT		-	-	-0.152***
Interaction effects with Activity during trip (Ref. - Leisure)				
β_SAV_TT * activity	Work	-	0.0139**	-
Interaction effects with Concentration on NDRTs (Ref. – Partial concentration or No concentration)				
β_CAR_TT * concentration	Full concentration	-	-0.0314***	-
β_SAV_TC	Travel costs (€)	-	-	-0.321***
β_CAR_TC		-	-	-0.439***
β_PT_TC		-	-	-0.527***
Crowdedness in PT (Ref. - Not crowded or Light crowdedness)				
β_PT_crowded	Crowded	-0.522*	-	-
βil	**Latent variables**			
β_PT_safety	Perceived safety, trust and enjoyment of AVs	-	1.15***	-
σ_safety	Standard deviation of error term	-	-0.000595	-
β_SAV_work	Perceived work activity	-	1.11**	-
β_PT_work		1.02***	-	-
σ_work	Standard deviation of error term	-0.155	0.00385	-
β_SAV_leisure	Perceived leisure activity	-	1.4**	-
β_CAR_leisure		-	1.42***	-
σ_leisure	Standard deviation of error term	-	0.853**	-
β_SAV_int	Intention to use SAVs	-	-1.47***	-
β_PT_int		-1.54***	-	-
σ_int	Standard deviation of error term	-0.398	0.0192	-
βis	**Socio-economic variables**			
Age (Ref. - Young)				
β_SAV_age	Old (above 50)	-	2.1***	-
Interaction effects with Belief in experimental set-up (Ref. – Hesitant or Did not believe)				
β_SAV_age * belief	Believed	-	-1.14***	-
β_BIKE_age * belief		-	0.766***	-
Education level (Ref. – Low)				
β_CAR_education	High	-	1.38***	-
Interaction effects with Belief in experimental set-up (Ref. – Hesitant or Did not believe)				
β_CAR_education * belief	Believed	-	-1.22***	-

Table 5.4. Results of final joint mixed logit model with panel effects *(continued)*

Parameter	**Corresponding variable**	**Parameters** Specific for pre-test	Specific for post-test	Generic
Occupation (Ref. - Other)				
β_CAR_occupation	Employed	-0.947***	-	-
β_BIKE_occupation		-	1.04***	-
Interaction effects with Belief in experimental set-up (Ref. – Hesitant or Did not believe)				
β_BIKE_occupation * belief	Believed	-	-1.09***	-
Main transport mode (Ref. – Car or Other)				
β_PT_tr_mode_PT	PT	0.747**	-	-
β_BIKE_tr_mode_PT		-0.792**	-	-
Interaction effects with Concentration on NDRTs (Ref. – Partial concentration or No concentration)				
β_BIKE_tr_mode_PT * concentration	Full concentration	-	-1.59***	-
Interaction effects with Belief in experimental set-up (Ref. – Hesitant or Did not believe)				
β_CAR_tr_mode_PT * belief	Believed	-	-1.29***	-
Main transport mode (Ref. – PT or Other)				
β_CAR_tr_mode_car	Car	-	-	0.945***
β_PT_tr_mode_car		-	-	-1.26***
β_BIKE_tr_mode_car		-1.37***	-0.907***	-
Interaction effects with Concentration on NDRTs (Ref. – Partial concentration or No concentration)				
β_CAR_tr_mode_car * concentration	Full concentration	-	0.718**	-
Previous ride experience in AVs (Ref. - No)				
β_PT_ride_exp	Yes	-	2.83***	-
Interaction effects with Concentration on NDRTs (Ref. – Partial concentration or No concentration)				
β_PT_ride_exp * concentration	Full concentration	-	-2.09***	-
Interaction effects with Belief in experimental set-up (Ref. – Hesitant or Did not believe)				
β_PT_ride_exp * belief	Believed	-	-1.77**	-
Use of car- or ride-sharing services (Ref. - No)				
β_SAV_car_shar	Yes	0.766***	-	-
β_CAR_car_shar		0.688**	-	-
Motion sickness (Ref. - No)				
β_CAR_car_sick[1]	Yes	-	-	0.644***
Mobility restrictions (Ref. - No)				
β_SAV_mob_restr	Yes	-0.895***	-	-
Traffic accident (Ref. - No)				
β_CAR_tr_accident	Yes	-0.66***	-	-
μ	**Scale between waves**			
μ_wave2	Scale parameter	-	1.23*** [a]	-
σ	**Panel effects**			
σ	St. deviation for panel effects	0.684*	0.55	-
Number of parameters			51	
Sample size / Number of observations			104 / 1872	
Initial log-likelihood / Final log-likelihood			-2595.143 / -1800.632	
Rho-square / Adjusted Rho-square			0.306 / 0.287	
Akaike / Bayesian Information Criterion			3703.265 / 3985.538	
Number of Halton draws from a normal distribution			1000	

∗∗∗ significant at a 99% confidence interval; ∗∗ at 95%; ∗ at 90%; [a] t-test against 1

[1] Generic variable between Motion sickness (before test rides) and Motion sickness (after test ride with leisure activity)

Table 5.5. Staged model estimation and goodness-of-fit statistics

	Joint MNL model (instrumental variables)	Joint MNL model (instrumental and socio-economic variables)	Final joint ML model (instrumental, socio-economic, and latent variables)
Sample size		104	
Number of observations		1872	
Number of parameters	16	40	51
Initial log-likelihood		-2595.143	
Final log-likelihood	-2024.611	-1816.269	-1800.632
Rho-square	0.22	0.3	0.306
Adjusted Rho-square	0.214	0.285	0.287
Akaike Information Criterion	4081.222	3712.537	3703.265
Bayesian Information Criterion	4169.779	3933.928	3985.538

Instrumental variables

The study's findings from the main sample of participants reveal several patterns regarding the disutility of travel time and cost across four transportation alternatives (SAVs, conventional cars, urban PT (bus or tram), and bicycles), as well as the impact of engaging in work- and leisure-related NDRTs.

At first glance, the disutility of travel time for SAVs is similar to that of PT (bus or tram) and conventional cars, with participants' engagement in activities during the test rides showing no significant impact. This lack of difference may be attributed to the relatively small size of Delft, where travel distances and times are generally short.

However, when considering the ability to perform work or leisure activities while travelling in SAVs, participants show a clear preference for work-related tasks, which reduces the perceived disutility of travel time. Work tasks are seen as productive and purposeful, making travel time feel more valuable. In contrast, leisure activities may feel less rewarding. This distinction became apparent to participants only after experiencing both work and leisure activities firsthand during the test rides.

These findings align with prior research. Correia et al. (2019) highlighted a general preference for work over leisure activities in AVs, while Susilo et al. (2012) observed that performing work activities positively influenced train commuters' perceptions of travel time.

Additionally, those able to concentrate on both work and leisure during the rides perceived travel time in a conventional car more negatively. This may be explained by the fact that, unlike in SAVs, conventional car drivers must focus on driving and cannot make use of their travel time for other activities.

In contrast to the other three alternatives, the disutility of travel time for bicycles is significantly higher compared to other modes. This may be because cycling involves physical effort and lower comfort levels, so longer trips feel more tiring and less pleasant than travel by motorised modes.

Regarding travel costs, the parameters for SAVs, conventional cars and PT (bus or tram) remained stable before and after the test rides. Perceived travel costs were least negative for SAVs, followed by conventional cars, and most negative for PT. Similar patterns have been observed in earlier studies: PT is often associated with higher generalised costs due to fares, waiting, and transfers, making it less attractive compared to the private car (Wardman, 2004; Chowdhury et al., 2015). In contrast, emerging modes such as SAVs are perceived more favourably in cost terms, as they are expected to reduce or eliminate fixed expenses related to car ownership, parking, and maintenance (Nazari et al., 2018; Pakusch et al., 2018; Yap et al., 2016). This combination of lower fixed costs and higher convenience may explain why participants in this study viewed the cost of SAVs more positively than that of cars and PT.

Additionally, the choice for the PT (bus or tram) alternative was negatively affected by the level of crowdedness before the test rides. Possibly, the novelty or positive aspects of the SAV experience could have reduced the weight of pre-existing concerns about crowdedness in public transport, making this PT attribute less influential in participants' choices.

Walking and waiting times were not significant factors in choosing between conventional car, PT (bus or tram), or SAV alternatives, possibly due to Delft's relatively small city size, which reduces the perceived burden of these factors.

Latent attitudinal variables

Latent attitudinal variables provide further insights into the travel mode preferences of participants based on underlying psychological factors. The four constructs, namely, perceived safety, trust and enjoyment of AVs, perception of work and leisure activities and intention to use SAVs, significantly influenced preferences for SAVs, conventional cars and urban PT (bus or tram), except for bicycles.

Before the test rides, participants' preference for PT, such as buses or trams, was positively influenced by the perception of work activities. This is likely because they were already familiar with working during their travel in these conventional modes. The relatively stable and predictable environment that PT offers, such as designated seating, consistent travel speeds, and the absence of driving responsibilities, may have made it an appealing option for those who value the ability to work during their journeys. After the test rides, preferences shifted toward SAVs based on the perception of work activities. This shift suggests that participants recognised SAVs could provide similar opportunities for productive use of travel time as PT, while also offering greater flexibility and privacy.

Based on the perception of leisure activities, participants favoured both SAVs and conventional cars after test rides without significantly different preferences between them, suggesting that cars, either conventional or automated, are viable for leisure on the way, possibly due to comfort and privacy. Unlike work activities, leisure may not require a stable environment, making both SAVs and traditional cars suitable choices for passengers who prioritise relaxation or entertainment during their journeys.

Moreover, participants who lack trust in AVs, perceive them as unsafe and generally have a negative opinion about them, tend to favour the PT transport alternative after the test rides. This preference for PT can be explained by the fact that public transport is more familiar and perceived as a safer option for those sceptical about AV technology.

Participants who initially intended to use SAVs in the future, also believing they could save them travel time, tend to avoid choosing PT. However, after gaining ride experience, their intentions shifted, leading them to no longer prefer SAVs as a mode of transport. This change could be due to the realisation that the expected time savings were not as substantial as they had thought, or they found other aspects of the SAV experience, such as comfort or convenience, less appealing than expected. This finding underscores the importance of experience in shaping perceptions and preferences, as perceived benefits may not always align with real-world experiences.

Socioeconomic variables

Socioeconomic factors also played a role in the preferences for SAVs, PT (bus or tram), conventional cars and bicycles, albeit in a limited way. Older participants, particularly those over 50, showed a preference for SAVs after test rides, although this preference was less pronounced among those who believed in the experimental setup. In addition, a significant interaction effect was found: older participants (over 50) who expressed belief in the experimental setup showed a stronger preference for the bicycle alternative. After the test rides, participants with higher education levels showed a positive preference for the car alternative, although this preference was reduced among those who believed in the experimental setup.

Employment status influenced choices, with employed participants initially showing a significant negative preference for cars, but shifting to a positive preference for bicycles after the test rides. Meanwhile, the use of car-sharing services predicted initial preferences for both SAVs and cars but lost significance after the test rides, indicating that direct experience with SAVs might diminish the appeal of shared services.

Predictably, current PT users preferred PT and avoided bicycles before the test rides. After the rides, those PT users who could fully concentrate on activities in SAVs continued to avoid bicycles, while those who believed in the experimental setup showed less preference for cars. In contrast, habitual car users consistently preferred their own mode and avoided PT (no significant difference between pre- and post-test rides). Their aversion to bicycles was stronger before the test rides but became less negative afterwards, and the preference for cars was further reinforced among those able to fully concentrate on activities during the SAV rides. These findings suggest that while direct experiences can shift perceptions and preferences to some extent, deeply ingrained habits and personal circumstances still significantly influence travel choices.

Additionally, participants with mobility restrictions tended not to prefer SAVs before the test rides, possibly due to concerns about accessibility in an automated driving environment. Similarly, individuals who had previously been involved in traffic accidents demonstrated an aversion to cars before the test rides, likely reflecting heightened safety concerns or anxiety associated with car travel, concerns that lost their significance after the test rides. Participants who reported a tendency to experience motion sickness before test rides and after the test ride with leisure activity showed a significantly higher likelihood of choosing the car alternative. Interestingly, participants with prior ride experience in AVs showed a preference for PT after the test rides. However, this preference was weaker among those who could fully concentrate on activities during the rides and among those who believed in the experimental setup. Overall, these results underscore how past experiences and personal circumstances influence how people evaluate and choose between emerging mobility options like SAVs.

Value of travel time

Using the disutilities of travel time and costs, we calculated the corresponding VoTTs for the SAV, PT (bus or tram) and conventional car alternatives, except for bicycles, where we assumed no associated travel costs (Table 5.6). When compared to the average VoTTs in the Dutch population (Kouwenhoven et al., 2023), which are 10.42 €/h for cars and 7.12 €/h for PT, the pattern of higher VoTTs for cars (13.0 €/h) and lower ones for PT (11.7 €/h) is consistent, albeit at a higher scale. This higher scale is most naturally a result of a very specific population, the one of Delft, being part of the experiment and not the average population in the Netherlands.

Examining further the impact of using travel time for NDRTs in SAVs, we observe the anticipated reduction of the VoTT for the SAV option (14.4 €/h) when travellers can engage in work-related activities (interaction variable). This finding aligns with earlier observations that VoTTs in traditional PT decrease when travel time is utilised productively for work (Kouwenhoven & de Jong, 2018; Molin et al., 2020). Importantly, this interaction effect only became significant in the post-test, after participants experienced the experimental SAV rides, underlying the role of exposure in revealing realistic trade-offs. Conversely, for those participants who could focus on both work and leisure activities (interaction variable with Full concentration) during their experimental SAV test rides, the VoTT for the conventional car

Table 5.6. Value of travel time before and after test rides

Transport mode	Travel time (min)		Travel costs (€)		Value of travel time (€/h)	
	Wave 1. Before test rides	Wave 2. After tests rides	Wave 1. Before test rides	Wave 2. After tests rides	Wave 1. Before test rides	Wave 2. After tests rides
Shared automated vehicle	-0.0911		-0.321		17.0	
	Travel time x Work activity					
	Not sign.	0.0139			-	14.4
Public transport (bus or tram)	-0.103		-0.527		11.7	
Conventional car	-0.0952		-0.439		13.0	
	Travel time x Full concentration					
	n/a	-0.0314				17.3

alternative increased. This increase among some participants could be due to their heightened expectations of travel comfort and productivity, set by their positive experiences with multitasking in the experimental SAVs.

5.5.6. Comparison between the main sample and control group

When comparing the main sample of participants (pre-test responses) to the control group, several notable similarities and differences emerge in their travel preferences for the SAV, PT (bus or tram), conventional car and bicycle alternatives (Table 5.7). Both groups exhibit similar perceptions of in-vehicle travel time for all four travel options and a preference for current modes of transport, with habitual car users typically opting for cars and expressing a dislike for PT. Notably, factors such as activity on the way (work or leisure), waiting and walking times did not significantly influence mode choice across different transport alternatives in either sample.

Differences between the groups, however, highlight distinct influences on transport preferences. In the control group, travel costs did not significantly affect preferences for cars, PT (bus or tram), or SAVs, contrasting with the main sample. Crowded environments significantly deterred only participants from the main sample from choosing PT.

Demographic factors also played a role: female participants in the control group showed a preference for bicycles, while older participants avoided this transport alternative, unlike in the main sample, where older participants tended to shun PT. Higher education levels in the control group correlated with a preference for bicycles over cars, and higher income was a deterrent for selecting PT. While the use of shared services was a positive factor in choosing SAVs and cars in the main sample, it negatively affected SAV choices in the control group, who instead showed a preference for bicycles. Participants with motion sickness preferred cars in the main sample but bicycles in the control group. Unique to the main sample, mobility restrictions negatively impacted the choice of SAVs, possession of a driving license discouraged PT use, and past traffic accidents deterred car use.

In conclusion, the comparison between the main sample (pre-test responses) and the control group revealed that both groups shared common perceptions of in-vehicle travel time and mode loyalty, and were similarly unaffected by factors such as activity on the way (work or leisure), waiting times, and walking times. However, the main sample showed greater sensitivity to factors like travel costs and crowding. Socioeconomic characteristics, on the other hand, did not yield consistent patterns across the two groups. Longitudinal studies conducted during the first application cases of SAVs could help identify the socio-economic profiles of potential users more clearly.

Table 5.7. Comparison between the main sample and control group: model results

Parameter	Corresponding variable	Parameters		
		Specific pre-test	Specific control group	Generic
βik	**Instrumental variables**			
β_SAV_TT	In-vehicle travel time (min)	-	-	-0.0617***
β_CAR_TT		-	-	-0.11***
β_PT_TT		-	-	-0.0991***
β_BIKE_TT		-	-	-0.138***
β_SAV_TC	Travel costs (€)	-0.358***	-	-
β_CAR_TC		-0.616***	-	-
β_PT_TC		-0.559***	-	-
Crowdedness in PT (Ref. - Not crowded or Light crowdedness)				
β_PT_crowded	Crowded	-0.483*	-	-
βis	**Socio-economic variables**			
Gender (Ref. - Male)				
β_BIKE_gender	Female	-	0.484*	-
Age (Ref. - Young)				
β_PT_age	Old (above 50)	-0.567**	-	-
β_BIKE_age		-	-1.0***	-
Education level (Ref. - Low)				
β_CAR_edu	High	-	-1.28***	-
β_BIKE_edu		-	1.4***	-
Occupation (Ref. - Other)				
β_CAR_occupation	Employed	-1.01***	-	-
Income (gross annual per household) (Ref. – Blow 50k)				
β_PT_income	Above 50k	-	-0.907**	-
Main transport mode (Ref. – Car or Other)				
β_PT_tr_mode_PT	PT	0.697**	-	-
β_BIKE_tr_mode_PT		-0.67**	-	-
Main transport mode (Ref. – PT or Other)				
β_CAR_tr_mode_car	Car	-	-	1.37***
β_PT_tr_mode_car		-	-	-0.838***
β_BIKE_tr_mode_car		-1.06***	-	-
Use of car- or ride-sharing services (Ref. - No)				
β_SAV_car_shar	Yes	0.638***	-0.517*	-
β_CAR_car_shar		0.706**	-	-
β_BIKE_car_shar		-	0.821**	-
Motion sickness (Ref. - No)				
β_CAR_car_sick	Yes	0.621*	-	-
β_BIKE_car_sick		-	1.35***	-
Mobility restrictions (Ref. - No)				
β_SAV_mob_restr	Yes	-1.5***	-	-
Driving license (Ref. - No)				
β_PT_dr_license	Yes	-0.96***	-	-
Traffic accident (Ref. - No)				
β_CAR_tr_accident	Yes	-0.683***	-	-
μ	**Scale between waves**			
μ_wave0	Scale parameter	-	1.14*** [a]	-
σ	**Panel effects**			
σ_μ	Standard deviation for panel effects	1.28***	*0.951*	-

Number of parameters	32
Sample size main group / Number of observations	104 / 936
Sample size control group / Number of observations	35 / 315
Initial log-likelihood / Final log-likelihood	-1734.254 / -1248.155
Rho-square / Adjusted Rho-square	0.28 / 0.262
Akaike / Bayesian Information Criterion	2560.31 / 2724.524
Number of Halton draws from a normal distribution	1000
∗∗∗ significant at a 99% confidence interval; ∗∗ at 95%; ∗ at 90%; [a] t-test against 1	

5.5.7. Study limitations and future research directions

This study faces several limitations that should be considered when interpreting the results.

Two limitations stem from the SC experiment. First, participants were asked to make decisions based on hypothetical scenarios, which becomes challenging when envisioning innovative transport options like SAVs, with which they have no prior experience. Second, the study focused exclusively on SAVs operating as car-sharing services, excluding ride-sharing or pooling scenarios, which remain less preferred due to barriers like the discomfort of sharing confined spaces with strangers (Correia & Viegas, 2011; Hamadneh & Esztergár-Kiss, 2022).

To mitigate the challenge of limited familiarity with SAVs, participants were provided with a ride experience in a Wizard-of-Oz simulator-on-wheels vehicle, a proven tool for simulating AVs (Detjen et al., 2020; Dillmann et al., 2023; Klingegård et al., 2020). However, the experimental setting itself introduced limitations. The presence of a 'safety driver' and the vehicle's setup (partitions, screens, and cameras) led to suspicions among 26% of participants. Additionally, variability in driving styles from seven test drivers may have influenced ride experiences. To reduce this effect, drivers were instructed to maintain a calm and cautious style to mimic AV behaviour to minimise the variability. However, it is important to note that evaluating driving style was not the objective of this study. Instead, the focus was on passenger perceptions and behavioural responses under the belief that the vehicle was operating autonomously. Future studies using real SAVs are therefore needed to validate the findings and assess how genuine automated driving behaviour shapes user perceptions and preferences.

As shown in Table C.3 in Appendix C, the vast majority of participants had no prior experience with automated driving systems. This reflects the current European context, where SAVs are not yet publicly available on open roads. As such, the reactions captured in this study are likely representative of how early-stage users might respond when first experiencing SAVs.

All rides were conducted during daylight hours, meaning the effect of low-light or nighttime conditions on NDRT performance was not evaluated. Future research should explore how lighting conditions, particularly the absence of dedicated interior lighting in SAVs, may affect task engagement and user preferences, especially during early morning or evening travel.

It should be noted that the experiment was conducted in late 2022, when residual pandemic-related behavioural adaptations, such as heightened sensitivity to shared spaces, changes in public transport use, and increased familiarity with teleworking, may have influenced participants' baseline attitudes toward SAVs. Future studies could replicate this experiment in post-pandemic conditions to disentangle experience effects from residual COVID-related travel attitudes.

The study's moderate sample size presents another limitation, stemming from the effort to validate user attitudes and preferences for SAVs in a field experiment while operating under time and budget constraints. Furthermore, self-selection bias may have influenced the participant pool, as members of the Delft panel registered within three hours after the study advertisement was released, suggesting that those curious or enthusiastic about AVs were more inclined to participate. These individuals, presumably early adopters, may not fully represent the general population (Feys et al., 2021). To address this, a control group of participants without the incentive to ride in an AV was included.

Participants' awareness of being observed during the test rides could cause the Hawthorne effect, potentially altering their behaviour (Skippon et al., 2016). Finally, since this study provided only a short-term experience, participants' attitudes and preferences may change over time. This underscores the importance of conducting longitudinal studies in real-world application cases and provides a natural transition to sharing potential directions for future research.

Future studies could explore the integration of SAVs into diverse built environments, including rural areas and cities of varying sizes, to assess differences in user attitudes and preferences. Additionally, researchers could examine how the use of travel time for NDRTs differs depending on whether SAVs are used as a primary transport mode or as part of a multimodal journey, particularly for access and egress to transit lines. Understanding which existing travel modes users may switch from when adopting SAVs, as explored by Öztürker et al. (2022), is another crucial area of investigation.

Furthermore, future research should also consider passive activities, such as sleeping or simply observing the surroundings. The extent to which users will choose to spend travel time productively in SAVs remains an open question (Pudāne et al., 2019; Singleton, 2019). Future studies could also extend the assessment of NDRT engagement levels by combining non-intrusive observation of self-selected everyday activities (e.g., reading, emailing) captured by video recordings with more direct validation measures, such as brief post-ride comprehension checks or standardised tasks during the test rides (e.g., n-Back) and gaze-based indicators like eye-tracking or blink rate.

Future research could also explore more advanced model specifications to better capture heterogeneity in unobserved utility variance. In particular, random scale mixed logit models or latent class models (Hess & Train, 2017) allow for more flexible treatment of scale by accounting for individual- or subgroup-level variation in error structures. While such approaches introduce greater model complexity and require larger sample sizes, they offer valuable opportunities to uncover latent heterogeneity that may be masked in fixed-scale formulations. These extensions would be especially relevant for studies aiming to segment user preferences or test responses to SAV exposure across diverse population groups.

Addressing these limitations and pursuing the suggested research directions will provide a deeper understanding of user preferences, behavioural shifts, and the long-term impact of travel time use in SAVs across various environments and use cases, ultimately aiding in the successful integration of AVs into future public transport systems.

5.6 Conclusions

Shared automated vehicles (SAVs) operating in urban areas have the potential to transform travel by enabling users to engage in non-driving-related tasks (NDRTs), enhancing productivity and travel satisfaction. When integrated with public transport systems, SAVs can offer a more sustainable alternative to privately owned AVs, while maintaining similar levels of privacy and comfort in a less crowded environment.

In the present study, we explored how the possibility of using travel time for work and leisure NDRTs in SAVs within urban environments influences users' attitudes and preferences for these vehicles when compared to traditional travel modes such as conventional cars, urban PT (buses or trams), and bicycles. We also looked at the important economic indicator of the perceived value of travel time (VoTT). To understand users’ attitudes and preferences for an

SAV service, we conducted a field study using a Wizard-of-Oz (WoZ) simulator-on-wheels vehicle to emulate such a service being available on the streets of Delft (Netherlands). A total of 104 participants completed two test rides, engaging in work- and leisure-related NDRTs while their engagement levels were measured via video recordings.

Results of a mixed panel logit model estimated jointly on pre- and post-test data revealed several key findings that deepen the understanding of behavioural and experiential aspects of travel time use in SAVs. SAVs were perceived as less sensitive to travel costs than PT and cars, while preference for work-related NDRTs reduced the negative perception of travel time in SAVs post-test, aligning with prior findings that productive use of travel time enhances travel satisfaction. Moreover, engagement levels during SAV rides further influenced preferences, as participants who fully concentrated on both work and leisure activities perceived travel time in conventional cars more negatively. These results reflect how direct exposure to work and leisure NDRTs reshapes preferences across modes.

The shifts in the perceptions of travel time were reflected in changes to VoTTs. Before the test rides, SAVs had higher VoTTs than cars and PT. After the rides, VoTTs for SAVs decreased when used for work-related activities, underscoring their advantage for productivity-focused travel. By contrast, the ability to fully concentrate on NDRTs during test rides raised VoTTs for conventional cars to match SAVs' levels for leisure-oriented participants. PT VoTTs remained unchanged.

The results also revealed changes in participants' attitudes toward SAVs after their firsthand experiences. Initial participants' preferences shifted from the PT pre-test to the SAVs post-test, driven by the perception of using travel time for work activity, which includes the comfort of conducting work tasks and the ability to concentrate on them. While PT was initially preferred due to participants' familiarity with working during commutes, the experience of NDRTs during the test rides enhanced their perception of SAVs as a productive and comfortable environment for work.

Based on the perception of using travel time for leisure activities, both SAVs and conventional cars were equally favoured post-test, highlighting their comfort and privacy for more relaxing activities. For those sceptical of AV technology, trust and safety concerns led to a preference for PT as a more familiar and safer alternative. Additionally, participants who initially intended to use SAVs for time savings tended to avoid PT, but after the rides, no longer showed interest in SAVs as their preferred mode of transport.

Lastly, the WoZ experiment proved to be a relevant method for simulating realistic SAV experiences, with 74% of participants believing they were riding in an AV. This approach provided participants with the opportunity to experience work- and leisure-related NDRTs while travelling, offering a practical framework for future behavioural research in urban contexts.

In summary, this study demonstrates how an immersive WoZ experimental framework can advance our understanding of travel behaviour in SAVs. Compared to hypothetical stated-preference surveys, this exposure captured behavioural responses that aligned more closely with revealed-preference evidence (Kouwenhoven & de Jong, 2018; Molin et al., 2020) and showed shifts in preferences, attitudes, and VoTTs tied to real NDRT engagement. By capturing these experiential factors, the study provides a nuanced perspective on how user expectations are formed and highlights SAVs' potential to redefine productive travel time use while paving the way for their integration into urban transport systems.

Beyond immediate impacts on user attitudes and preferences, the findings underscore the broader societal and environmental implications of SAV adoption. The ability of SAVs to promote productive use of travel time could lead to shifts in urban mobility patterns, encouraging fewer private car trips and enhancing the efficiency of shared mobility systems.

Although the findings of this study provide preliminary evidence based on short-term experiences with SAVs in experimental settings, they highlight the importance of accounting for the use of travel time in this travel mode to accurately capture user attitudes and preferences. This consideration is particularly relevant for public transport operators, urban policymakers, and private mobility providers when making investment decisions aimed at improving travel comfort and facilitating productive use of travel time.

Chapter 6

Conclusions

Drawing together the conceptual and empirical insights from Chapters 2 through 5, this final chapter synthesises the main findings of the thesis and reflects on their implications for both research and practice. The overarching aim has been to understand how service quality improvements and ride experience influence users' preferences for automated public transport modes, specifically automated minibuses and shared automated vehicles. Building upon the conceptual foundation developed in Chapter 2 and the empirical analyses in Chapters 3 to 5, this chapter integrates the key insights to provide a comprehensive understanding of how vehicle automation may enhance the quality and user preferences for public transport.

The chapter is organised as follows: Section 6.1 summarises the main findings across the conceptual and empirical studies; Section 6.2 discusses the implications for practice, outlining how transport planners, policymakers, and service operators can apply these insights to guide the responsible deployment of automated mobility; and Section 6.3 presents directions for future research, highlighting areas where further investigation could strengthen the behavioural and policy foundations for automated public transport.

6.1 Main findings

In this section, we respond to the research questions introduced in Section 1.2 and highlight the main findings:

RQ 1: In which aspects could the service quality of public transport be improved through the introduction of automated public transport modes such as shared automated vehicles and automated minibuses?

The first research question, addressed in Chapter 2, explored how automated public transport modes, namely shared automated vehicles (SAVs) and automated minibuses (AmBs), may influence the service quality of public transport. The aim was to understand in which dimensions automation could offer improvements, such as availability, accessibility, or comfort, and in which areas it could raise concerns, including security, customer care, or digital exclusion. To answer this question, a structured literature review was conducted, guided by the EN 13816:2002 framework that defines eight key dimensions of PT service quality. This framework was complemented with insights from Maslow's hierarchy of needs and the Kano model to capture how users prioritise different aspects of service. The review focused on studies published in the last five years, identifying 23 review papers through database searches and snowballing. By bringing these findings together, the chapter provides an up-to-date overview of where automation may enhance or challenge PT service quality and points to knowledge gaps that future research will need to address.

The analysis revealed that vehicle automation can substantially enhance several dimensions of PT service quality, particularly availability, accessibility, time efficiency, comfort, and environmental impact, by enabling more flexible, reliable, and user-responsive operations. However, it also identified critical risks related to security, customer care, and digital inclusion, as the removal of human staff and reliance on digital interfaces may reduce perceived safety and accessibility for some user groups. Overall, the findings indicate that while automated PT can strengthen both the functional and hedonic layers of service quality, its success depends on inclusive design, effective governance, and sustained user trust. These insights form the foundation for subsequent research in this thesis, which focuses on two key aspects: the type of service for AmBs and the use of travel time in SAVs, both examined through the lens of changing user preferences before and after real ride experiences.

RQ 2: Which type of service, regular or flexible, offered by automated minibuses is preferred, and how do these preferences vary across user groups based on their current travel mode?

This research question, studied in Chapter 3, focused on the deployment potential of automated minibuses (AmBs) for first-mile trips and short (sub)urban commutes in the Netherlands. The study examined preferences for regular services (fixed route, fixed schedule) and flexible services (on-demand, door-to-door), and how these differ across travellers grouped by their current mode of transport: car, public transport (PT), and active modes (AM) (cycling and walking).

To address this question, a stated choice experiment was designed in which respondents compared two AmB alternatives that differed in service type, regular and flexible, to their current travel mode. This approach allowed the two service types to be assessed explicitly and enabled comparisons across user groups. The experiment was conducted with a sample of 833 Dutch travellers, including 520 car users, 153 PT commuters, and 160 AM users, which was substantially representative of the national population in terms of travel mode. To integrate these comparisons, a joint discrete choice model was estimated that combined the three groups within a single framework, allowing their preferences to be compared on a consistent scale.

The analysis revealed distinct patterns across the three segments. PT users showed the highest appreciation for flexible services, valuing the on-demand and door-to-door features that complement conventional transit. They tolerated longer in-vehicle times in exchange for being picked up at home, without the need to walk to or wait at a bus stop. However, their strong cost sensitivity underscores the importance of affordable pricing if AmBs are to be attractive. Car users showed relatively greater acceptance of regular services, perceiving travel costs less negatively in this configuration. Their weaker interest in flexible services suggests that AmBs offer limited added value beyond the flexibility they already enjoy with private cars. For this group, seamless multimodal connections and cost advantages over car use appear crucial to enable modal shift. AM users, by contrast, displayed no strong preference between the two service types. While large-scale shifts from active to automated modes are undesirable from a sustainability perspective, AM users could nevertheless become occasional AmB passengers, especially when supported by positive attitudes.

Across all three segments, trust in AmBs' safety, perceived usefulness, and enjoyment of the service consistently shaped preferences, while prior experience with automated technology could either strengthen or weaken confidence. Taken together, the findings underline that there is no one-size-fits-all solution: the success of AmBs depends on designing services that respond to the distinct needs, expectations, and attitudes of different traveller groups.

RQ 3: How does ride experience affect users' preferences for the type of service provided by automated minibuses?

In Chapter 4, we continue the exploration of AmB deployment potential, shifting the focus from differences across user groups to the role of ride experience. The case study in Helmond, the Netherlands, examined how first-ride and consecutive ride experiences influence choices between regular (fixed route, fixed schedule) and flexible (on-demand, door-to-door) services, in comparison to conventional alternatives, including car, bus, and bicycle. A two-wave stated preference experiment was carried out before and after a test ride, and analysed using a joint hybrid mixed logit model.

The results showed a clear preference for flexible-service AmBs, especially in relation to travel time and costs. Participants perceived the travel time of flexible services as comparable to that of cars, while their willingness to pay resembled the valuation of bus trips. This suggests that flexible AmBs can combine attributes of both private and public transport in the perception of potential users.

Regular-service AmBs were less favoured overall but showed important shifts in perception after the test ride. Travel time disutility became more salient, while the importance of travel costs decreased. Following the ride, participants perceived the travel time of regular services as similar to buses and bicycles, but their travel costs as equally unfavourable as those of cars. Moreover, inconveniences related to waiting and walking time became more pronounced after the ride experience, pointing to greater sensitivity to access and egress conditions once users had tried the service.

Participants with prior AmB experience in other pilots responded differently from first-time riders. They were more willing to walk to the stop for regular-service AmBs, and in doing so, they even preferred this option over conventional buses. The perception of the ride as enjoyable in this pilot further reinforced the preference for regular services. In addition, preferences for supervision shifted: before the ride, participants leaned towards remote operator control, but afterwards they expressed a stronger preference for onboard steward supervision.

Overall, the findings show that even a single pilot ride can meaningfully reshape perceptions of automated minibuses, altering how users evaluate travel time, costs, and access conditions relative to conventional modes. These dynamics highlight the importance of panel studies for capturing how attitudes and preferences evolve with growing experience and provide an early indication of how ride experience may shape the adoption of this emerging transport mode.

RQ 4: How does the possibility of using travel time influence users' preferences for shared automated vehicles?
RQ 5: How does ride experience shape users' preferences for shared automated vehicles, particularly in relation to the potential use of travel time?

These research questions, studied in Chapter 5, investigated how the possibility of using travel time for non-driving related tasks (NDRTs), together with firsthand ride experience, shapes potential users' preferences for SAVs compared to conventional transport modes, namely cars, public transport (PT) (bus or tram), and bicycles. The study focused on the potential of SAVs to turn travel time from lost time into productive or enjoyable time, and to do so in a more sustainable way than if automated vehicles were adopted primarily as private cars. To study this, a field experiment was conducted in Delft, the Netherlands, using a Wizard-of-Oz (WoZ) simulator-on-wheels that emulated SAV operations in urban traffic. A total of 104 participants completed two test rides while engaging in work- and leisure-related NDRTs. Their engagement levels were captured via video recordings, and their preferences were measured through pre- and post-ride stated choice surveys analysed with a joint mixed panel logit model.

The results showed that the disutility of travel time for SAVs was initially similar to that of cars and PT, but ride experience altered this assessment. When participants used SAV time for work, the disutility of travel time decreased in comparison to leisure activities. Participants who were able to concentrate fully on both work and leisure activities during SAV rides subsequently evaluated car travel time more negatively, likely because the burden of driving became more apparent in contrast to the multitasking opportunities provided by SAVs. In terms of travel costs, SAVs were consistently favoured over PT and cars, likely reflecting expectations of lower fixed expenses such as ownership, parking, and maintenance.

The calculation of values of travel time (VoTTs) reflected these findings. Before the rides, SAVs were associated with higher VoTTs than cars and PT. After the rides, VoTTs for SAVs decreased in the context of work activities, reflecting their potential for productivity-oriented travel. Conversely, participants who concentrated fully on tasks during SAV rides reported higher VoTTs for cars, suggesting that their expectations of productivity and comfort were not met in conventional vehicles. PT VoTTs remained broadly stable.

Psychological factors also shaped preferences. Before the rides, the perception of work activities supported PT choices, consistent with existing habits of working during public transport trips. After the rides, this perception shifted towards SAVs, as participants recognised their potential for productive travel in a private and flexible setting. In relation to leisure, both SAVs and cars were rated positively after the rides, associated with comfort and privacy. However, some participants remained sceptical of SAVs: low trust, safety concerns, and negative attitudes toward automation maintained their preference for PT. Some participants who initially believed SAVs would save travel time revised their view after the ride, recognising that actual time savings were limited or that other aspects of the service, such as comfort or convenience, were less attractive than anticipated.

Bringing these results together, we see that both the opportunity to use travel time productively and direct ride experience significantly reshape how SAVs are perceived relative to conventional modes. The results demonstrate that experiential exposure reveals differences in attitudes, preferences, and associated VoTTs that hypothetical surveys alone cannot capture, underscoring the role of productive travel time in the potential integration of SAVs into future urban mobility systems.

6.2 Implications for practice

The results of this thesis provide practical insights for policymakers, planners, and operators considering the deployment of automated public transport modes. Across the chapters, different perspectives converge on the importance of user segmentation, service design, and experiential exposure in shaping preferences for both AmBs and SAVs.

Vehicle automation and public transport service quality

The structured literature review in Chapter 2 not only identifies the research areas addressed in this thesis in Chapters 3-5 but also provides a strategic lens through which to understand how vehicle automation may reshape the service quality of public transport. While conceptual in nature, it highlights several considerations and implications:

Frameworks for evaluation: Practitioners should use established service quality dimensions (EN 13816) and interpret them through user-centred models such as Maslow's hierarchy of needs and the Kano model. This combination clarifies not only what aspects of service automation may affect, but also how travellers prioritise them.

Opportunities and risks: Automated modes may enhance availability, accessibility, and comfort, but could also weaken service quality through digital exclusion, loss of human support, or safety concerns. Planners should therefore balance the "bright side" and "dark side" of vehicle automation when designing policies and services.

Equity and inclusion: Vehicle automation strategies must explicitly address affordability, accessibility, and digital barriers to ensure that future PT systems remain equitable.

Designing AmB services for diverse traveller segments

The findings of Chapters 3 and 4 show that travellers' current mode of transport strongly influences their preferences for AmB services, and that even short ride experiences can reshape these preferences. For practice, this implies that service design should be differentiated and supported by staged deployment strategies:

Targeting public transport (PT) users with flexible services: PT users were most receptive to flexible, on-demand AmBs, valuing door-to-door convenience and showing tolerance for in-vehicle time. Operators should prioritise this group when introducing flexible feeders, while ensuring fare affordability.

Positioning regular services for car users: Car users expressed greater acceptance of regular services, perceiving them as predictable and less costly than flexible alternatives. Such services could attract car users to multimodal commutes if combined with seamless transfers and reliable schedules.

Complementing active modes (AM): AM users may occasionally use AmBs, particularly flexible ones, in adverse conditions. Strategies should emphasise complementarity rather than substitution of sustainable travel.

Pilot trials as trust-building tools: Direct experience, even in short trials, substantially shifted perceptions of both flexible and regular services, highlighting the need for demonstration projects in deployment strategies.

Supervision models: Early users felt more reassured by onboard stewards than remote operators, suggesting that visible human presence may be required in initial deployment phases.

Attention to access and egress: Ride experience heightened sensitivity to walking and waiting times, underscoring the need to minimise transfer frictions through stop design, real-time information, and integrated planning.

Taken together, these results show that AmB deployment requires targeted strategies tailored to distinct traveller groups, reinforced by pilots that build confidence and refine service design.

Shared automated vehicles and the value of travel time

The study on SAVs in Chapter 5 demonstrates that the possibility of using travel time productively or enjoyably is a decisive factor shaping user preferences, and that ride experience is critical for revealing realistic trade-offs. For practice, this leads to several considerations and implications:

Facilitating travel-based multitasking: Vehicle and service design should explicitly support both productive and leisure activities through stable ride quality, comfortable seating, reliable connectivity, and adequate lighting.

Positioning against conventional modes: SAVs were perceived as more attractive than PT for work-related activities and comparable to cars for leisure, indicating opportunities to compete with both modes if comfort and productivity features are emphasised.

Staged deployment to build trust: For sceptical users, visible supervision, transparent communication, and gradual scaling are essential until confidence in automation stabilises.

Pilots as exposure tools: Wizard-of-Oz demonstrations reshaped user preferences and proved valuable for testing service concepts before large-scale rollout. Longer and more consistent trials would better capture daily use.

Managing adoption expectations: Early adopters may not represent mainstream travellers. Operators and policymakers should account for wider population needs when designing services, ensuring that SAVs meet diverse expectations.

Across both AmBs and SAVs, these findings underline that ride experience is not an optional step but a prerequisite for building realistic user expectations and long-term acceptance. While the AmB studies highlighted how service design interacts with user segments, the SAV study showed how experiential exposure reshapes the perceived value of travel time. Together, they emphasise that automation should be developed and deployed not only as a technological innovation, but as a lived user experience embedded in the broader public transport system.

6.3 Recommendations for future research directions

This section outlines future research directions that stem from the main findings and the limitations discussed in Chapters 3-5.

From a methodological perspective, this thesis demonstrates both the strengths and limitations of using stated preference (SP) methods in combination with experimental exposure to study emerging mobility services. While SP surveys provide flexibility to analyse user responses to novel transport scenarios, they inherently rely on hypothetical choices, which may not fully reflect real-world behaviour. This limitation is partly addressed in this research by incorporating field experiments and Wizard-of-Oz simulations, allowing participants to form preferences based on actual ride experience rather than solely on abstract expectations. Nevertheless, the experimental settings remain simplified representations of real-world conditions, and the sample sizes, constrained by practical considerations, limit the ability to capture more nuanced behavioural differences. The use of advanced discrete choice models with latent variables and panel effects enhances behavioural realism, but also introduces model complexity and assumptions that should be interpreted with care. Future research could build on this approach by combining SP data with revealed preference data as automated services become more widely available, and by expanding sample sizes and experimental realism.

From stated to revealed preferences. Most of the studies relied on stated choice experiments or short pilot rides, which may not fully capture real-world behaviour. Future work should employ revealed preference studies, where travellers use automated minibuses (AmBs) or shared automated vehicles (SAVs) in daily routines, to validate and refine stated preference findings.

Longer-term and repeated exposure. Short trial rides were sufficient to capture first impressions, but they cannot explain how trust, attitudes, and value of travel time (VoTT) evolve over weeks or months. Longitudinal studies that follow the same users across multiple stages of exposure are needed to understand how preferences stabilise or shift with continued experience.

Diverse contexts and user groups. The empirical studies focused on urban settings, limiting generalisability. Future research should examine rural areas, suburban contexts, and different cultural or regulatory environments, while also capturing diverse socio-demographic groups such as older adults, low-income households, or those with accessibility needs.

Segmentation beyond current travel mode. While this thesis focused on traveller segmentation by current mode (car, PT, active modes), future studies should explore additional factors such as age, income, gender, occupation, household structure, and attitudes toward innovation. These factors may influence whether automated services are seen as complements or substitutes for existing travel options.

Integration with wider mobility systems. Future work should investigate how AmBs and SAVs interact with conventional PT and active modes. Research is needed on whether they primarily act as feeders, induce shifts from private cars, or risk drawing users away from sustainable modes like cycling. Understanding system-level effects, including implications for congestion and urban sprawl, is essential for aligning automation with sustainability goals.

Travel time use and service design. While this thesis highlighted differences between work and leisure non-driving-related tasks (NDRTs), future studies should also account for passive activities such as resting or observing the surroundings.

Trust, safety, and supervision models. Trust in automation emerged as a decisive factor, with preferences shifting between remote supervision and onboard stewards. Future research should test how supervision strategies, peer influence, and group travel experiences affect adoption, particularly as technology matures toward fully driverless operation.

Advanced modelling approaches. The models used here provided robust insights but still left substantial unexplained heterogeneity. Future studies could apply more flexible specifications, such as latent class models or random scale mixed logit models, to better capture subgroup differences in attitudes and preferences.

Appendices

Appendix A

Table A.1. Overview of the literature review studies

	Author and year of publication	Type of automated PT	Period	Focus	Selection criteria		Number of included publications
					Search engines	Types of publications	
1	Almaskati et al. (2024)	SAVs	2014 – January 2024	Public transport User perceptions Land use Vehicle ownership Environment	Google Scholar Science Direct Sage Publications ASCE Library	Peer-reviewed journal papers Conference papers	210
2	Axsen and Sovacool (2019)	Three mobility trends: Electric mobility Shared mobility Automated mobility	n/a	User perceptions	Publications included in the Special Issue in Transportation Research Part D	Peer-reviewed journal papers	19
3	Azad et al. (2019)	AmBs	2010 – November 2018	Technology deployment User perceptions Safety Social and economic aspects Regulations, policies, and legal issues	Google Scholar, TRID, Web of Science	Peer-reviewed journal papers Conference papers Technical (project, pilot) reports	40
4	Bala et al. (2023)	SAVs AmBs	2011 - 2021	User perceptions Intention to use Mode choice Willingness constructs	Google Scholar Scopus Web of Science ScienceDirect	Peer-reviewed journal papers Conference papers	76
5	Carrese et al. (2023)	SAVs	Up to March 2023	Integration with public transport systems	Scopus, Web of Science TRID ScienceDirect	Peer-reviewed journal papers Conference papers	27

Table A.1. Overview of the literature review studies *(continued)*

	Author and year of publication	Type of automated PT	Period	Focus	Selection criteria: Search engines	Selection criteria: Types of publications	Number of included publica-tions
6	Chaalal et al. (2023)	AmBs SAVs Automated urban freight transport (robots, drones)	Not specifie d	Combined deployment of SAVs and AmBs for transporting people and goods Operational strategies Connectivity	Not specified	Not specified	Not specified
7	Garus et al. (2022)	AVs (L4, 5) SAVs (additionally, carsharing, dynamic ridesharing, micromobility sharing services)	Not speci-fied	Studies based on activity or trip-based demand models Modelling considering behavioural adaptations	Scopus Google Scholar	Not specified	34
8	Golbabaei et al. (2021)	SAVs	Up to July 2019	Urban mobility Infrastructu-re and land use Travel behavior Environment	Scopus Science Direct Web of Science Wiley Online Library TRID Directory of Open Access Journals	Peer-reviewed journal papers	81
9	Greifenstein (2024)	SAVs AmBs ABs	Up to Decem-ber 2022	User behaviour	Web of Science EBSCO Scopus ScienceDirect	Peer-reviewed journal papers Conference papers, reviews, and conference reviews	77
10	Heikoop et al. (2020)	AmBs	Up to April 2019	User behaviour (acceptance, attitudes)	Scopus	Peer-reviewed journal papers Conference papers	18
11	Iclodean et al. (2020)	AmBs	Not speci-fied	Automated driving technology Legal framework Overview of AmBs pilot trials	Not specified	Not specified	Not specified

Table A.1. Overview of the literature review studies *(continued)*

	Author and year of publication	Type of automated PT	Period	Focus	Selection criteria		Number of included publica-tions
					Search engines	Types of publications	
12	Karolemeas et al. (2024)	SAVs	2013 – not specified	Traffic Travel behaviour Land use Environment	Google Scholar Web of Science ScienceDirect SPRINGER LINK TRID IEEE Xplore Taylor and Francis SAGE Publishing	Peer-reviewed journal papers Conference papers	98
13	La Delfa et al. (preprint)	SAVs AmBs ABs	Up to mid March 2024	Travel behaviour (discrete choice modelling studies): Total travel demand Travel mode choice Use of travel time	Web of Science Scopus EBSCO ScienceDirect China National Knowledge Infrastructure (CNKI)	Peer-reviewed journal papers Conference papers (peer-reviewed)	96
14	Lécureux et al. (2023)	SAVs AmBs ABs	Not specified	AV acceptance SP experiments	Google Scholar Scopus Web of Science	Peer-reviewed journal papers	29
15	Lee & Gim (2024)	SAVs	2015-2023	Accessibility Equity	Web of Science Google Scholar	Peer-reviewed journal papers Conference papers Books	Not specified
16	Narayanan et al. (2020)	SAVs	1950 - 2019	Traffic and safety Travel behavior Economy Transport supply Land use Environment Governance	Scopus	Peer-reviewed journal papers Conference papers Technical reports Policy papers	Not specified

Table A.1. Overview of the literature review studies *(continued)*

	Author and year of publication	Type of automated PT	Period	Focus	Selection criteria		Number of included publica-tions
					Search engines	Types of publications	
17	Naz & Mattingly (Preprint)	SAVs and AVs	2014-2024	VMTs	Not specified (full-text papers)	Google Scholar TRID IEEE Xplore Transporta-tion Research Board Publications Index ACM Digital Library Transporta-tion Research Part A through F Intelligent Transporta-tion Systems PubMed	26
18	Nordhoff et al. (2019)	AVs SAVs AmBs	Up to April 2019	Technology acceptance	Peer-reviewed journal papers Conference papers Grey literature	Scopus Web of Science Google Scholar	124
19	Othman (2022)	AVs SAVs	From 2010	Safety User behaviour Land use Economy Society Environment Public health Benefits of AVs in pandemics AVs in developing countries	Scopus Web of Science Science Direct SPRINGER LINK IEEE Xplore TRID	Not specified	Not specified
20	Pigeon et al. (2021)	AmBs	1999-March 2020	Acceptance and acceptability Willingness to use	Web of Science Scopus PsychInfo Pubmed Springerlink Sage Taylor & Francis Online	Peer-reviewed journal papers Conference papers Thesis Books Book chapters Technical reports	39

Table A.1. Overview of the literature review studies *(continued)*

	Author and year of publication	Type of automated PT	Period	Focus	Selection criteria		Number of included publications
					Search engines	Types of publications	
21	Ribeiro Pimenta et al. (2023)	AVs SAVs	2011-2022	Effects on the built environment: Parking Density Land use diversity Destination accessibility Urban sprawl Street design	Web of Science Scopus	Peer-reviewed journal papers Conference papers Books Technical reports	82
22	Sohrabi et al. (2021)	AVs	Up to October 2020	Safety	Scopus IEEE Xplore Web of Science TRID	Peer-reviewed journal papers Conference papers Thesis Books Book chapters Technical reports	50
23	Zhao and Malikopoulos (2020)	SAVs	Not specified	SAVs system modelling	Not specified	Not specified	Not specified

Appendix B

Example NDRTs provided to participants

Work-related tasks
- Reading and replying to emails
- Reviewing documents or reports
- Scheduling appointments or planning a weekly agenda
- Writing a letter, memo, or text document
- Reading work materials
- Preparing a to-do list or grocery list

Leisure-related tasks
- Reading books, magazines, or news articles
- Watching videos or listening to music/podcasts
- Playing mobile games
- Browsing social media or messaging friends

Participants were free to bring their own materials (e.g., laptop, smartphone, paper documents) or choose from a selection of books and devices provided on-site.

Appendix C

Table C.1. Overview of the sample and control group and comparison with the distribution in the Dutch population

Variable	Category (model)	Category (survey)	Sample, % (104 respondents)	Control group, % (35 respondents)	Population, % (CBS, 2021; CBS 2022a,b; CBS, 2023a,b)
Gender	Male (reference)	Male	65.4	62.9	49.7
	Female	Female	34.6	37.1	50.3
		Prefer not to say	–	–	–
Age	Young (reference)	18-29	12.5	14.2	15.4
		30-39	4.8	34.6	12.6
		40-49	10.6	34.6	12.1
	Old	50-59	21.2	8.6	15.9
		60-69	30.8	–	12.4
		≥70	20.2	–	31.6
		Prefer not to say	–	8.6	–
Education level	Low (reference)	No education	–	–	–
		Primary education	1.0	–	9.0
		Secondary education	16.3	2.9	29.6
		Higher National Diploma	9.6	2.9	26.6
	High	Undergraduate degree (Bachelor's degree)	29.8	17.1	21.2
		Postgraduate degree or higher (Master's degree, PhD, etc.)	43.3	74.2	13.6
		Prefer not to say	–	2.9	–
Income (gross annual per household)	Below 50k (reference)	Less than €9,999	1.9	8.7	4.1
		€10,000 - €19,999	4.8	5.7	11.3
		€20,000 - €29,999	6.7	–	31.5
		€30,000 - €39,999	8.7	11.4	26.1
		€40,000 - €49,999	4.8	–	14.5
	Above 50k	€50,000 - €59,999	16.3	5.7	6.3
		€60,000 - €69,999	5.8	5.7	2.7
		≥ € 70,000	34.6	51.5	3.5
		Prefer not to say	16.3	11.4	–
Occupation	Employed	Employed or self-employed	50.0	94.2	74.2
	Others (reference)	Unemployed or (partially) incapacitated	3.8	–	2.7
		Retired	28.8	–	11.8
		Student or intern	4.8	2.9	2.5
		Housewife/ houseman	1.0	2.9	2.1
		Volunteer	6.7	–	6.7 (2 last categories)
		Others	4.8	–	

Table C.2. Distribution of main transport modes according to the trip purpose in the sample, control group and the Dutch population

Transport mode / Trip purpose*	Category (model)	Work, %	Study, %	Frequently visited destination, %	Sample (control group)[1], %	Population, % (CBS, 2022c)
Car (as a driver)	Car	16.3 (37.1)	– (–)	22.2 (2.9)	38.5 (40.0)	50.0
Car (as a passenger)		1.0 (2.9)	– (–)	0.9 (–)	1.9 (2.9)	18.1
Train	PT	5.8 (2.9)	1.0 (–)	2.8 (–)	9.6 (2.9)	8.7
Bus, tram, or metro		1.0 (8.5)	– (–)	2.8 (–)	3.8 (8.5)	2.6
Bicycle or e-bike	Others (reference)	21.2 (40.0)	2.8 (–)	12.5 (–)	36.5 (40.0)	10.1
Scooter		1.0 (–)	– (–)	– (–)	1.0 (–)	n/a [4]
Walking		1.9 (–)	1.0 (–)	3.8 (–)	6.7 (–)	4.0
Working from home [2]		1.9 (2.9)	– (2.9)	– (–)	1.9 (5.7)	n/a [4]
Other [3]		–	–	–	–	6.5

[1] The data for the control group are given in parentheses

[2] Frequently visited destination was used as the purpose of the trip for this category of respondents

[3] This category is absent from the survey

[4] These categories are missing in the statistics

* The trip purpose of participants is used as the context in the SC experiment

Table C.3. Additional characteristics of the participants in the main experiment and the control group

Variable	Category (model)	Category (survey)	Sample, %	Control group, %
Driving license	Yes	Yes	91.3	91.4
	No (reference)	No	8.7	2.9
		Prefer not to say	–	5.7
PT pass	Yes	Yes	92.3	85.7
	No (reference)	No	7.7	11.4
		Prefer not to say	–	2.9
Traffic accident	Yes	Yes	60.5	51.4
	No (reference)	No	38.5	45.7
		Prefer not to say	1.0	2.9
Use of car- or ride-sharing services (such as Uber and Green Wheels)	Yes	Yes, regularly	1.0	2.9
		Yes, occasionally	17.3	71.3
	No (reference)	No, never used it	76.9	22.9
		No, not familiar with these services	4.8	–
		Prefer not to say	–	2.9
Motion sickness (before test rides)	Yes	Yes	18.3	25.7
	No (reference)	No	81.7	74.3
		Prefer not to say	–	–
Motion sickness (during test rides with work activity)	Yes	Extremely	1.9	n/a
		Moderately	4.8	
		Somewhat	6.7	
		Slightly	12.5	
	No (reference)	Not at all	74.1	
Motion sickness (during test rides with leisure activity)	Yes	Extremely	2.9	n/a
		Moderately	3.8	
		Somewhat	5.8	
		Slightly	18.3	
	No (reference)	Not at all	69.2	
Mobility restrictions	Yes	My mobility is limited (due to age, pregnancy, etc.)	3.8	–
		I am not mobile (due to health problems, age, etc.)	1.0	–
	No (reference)	I am fully mobile (physically)	95.2	100.0
		Prefer not to say	–	–
Total travel time	Long travel	More than 30 min	31.7	17.2
	Short travel (reference)	15-30 min	26.9	25.7
		Less than 15 min	40.4	57.1
Frequency of travel	Frequent	4 or more days per week	40.4	57.1
	Others (reference)	1-3 days per week	45.2	34.3
		1-3 days per month	9.6	-
		1-3 days in the last three months	2.9	-
		I work from home	1.9	8.6
Ride experience in AVs	Yes	Yes, more than once	2.9	2.9
		Yes, once	6.7	8.6
	No (reference)	No, never	90.4	88.5

Appendix D

Table D.1. Scores on attitudinal indicators in the main sample before and after test rides and control group

	Indicators	Scores (mean / standard deviation): Control group	Pre-test	Post-test	Wilcoxon signed-rank test statistics between: Control group – Pre-test	Pre-test – Post-test
Enjoyment of AVs						
S1	I like self-driving cars	4.89 (1.409)	5.16 (1.158)	5.80 (0.907)	Z= -0.052	Z=-4.875**
S2	I think that a ride in a self-driving car is enjoyable (A ride in a self-driving car was enjoyable)	5.29 (1.202)	5.42 (1.103)	6.03 (1.000)	Z= -0.650	Z=-4.381**
S3	I think that a ride in a self-driving car is stressful (A ride in a self-driving car was stressful)	4.17 (1.248)	4.74 (1.386)	5.85 (1.399)	Z= -1.527	Z=-5.730**
Perceived safety and trust						
S4	I trust that a system can drive a self-driving car with no assistance from me	4.57 (1.596)	5.07 (1.457)	5.76 (1.170)	Z= -0.724	Z=-5.079**
S5	I dislike that I don't have control of how the car drives (reversed)	3.83 (1.671)	4.01 (1.721)	4.98 (1.625)	Z= -0.399	Z=-5.157**
S6	I can entrust the safety of a close family member to a self-driving car	4.34 (1.392)	4.63 (1.515)	5.41 (1.319)	Z= -0.217	Z=-5.303**
S7	I think that a ride in a self-driving car is safe (A ride in a self-driving car was safe)	4.40 (1.499)	5.0 (1.231)	6.02 (0.750)	Z= -1.143	Z=-6.702**
Work activity						
S8	It is important for me to use my travel time productively when I'm riding in a self-driving car (I would use my travel time productively when I ride in a self-driving car)	4.94 (1.514)	4.44 (1.717)	5.28 (1.523)	Z= -1.928	Z=-4.098**
S9	I think I will be (I was) able to concentrate on working in a self-driving car	4.09 (1.853)	4.55 (1.461)	5.49 (1.435)	Z= -0.663	Z=-4.864**
S10	I think it will be (It was) comfortable to work in a self-driving car	4.40 (1.701)	4.77 (1.331)	5.05 (1.523)	Z= -0.877	Z=-1.591
S11	I think that a ride in a self-driving car is comfortable (A ride in a self-driving car was comfortable)	5.26 (1.094)	5.13 (1.089)	5.57 (1.197)	Z= -0.915	Z=-2.867**
Leisure activity						
S12	I think I will be (I was) able to concentrate on my leisure activities in a self-driving car	5.11 (1.491)	5.05 (1.361)	5.56 (1.44)	Z= -0.816	Z=-3.297**
S13	I think it will be (It was) comfortable to spend time for leisure activities in a self-driving car	5.23 (1.285)	5.01 (1.296)	5.59 (1.312)	Z= -1.628	Z=-3.549**
S8 and S11		See above				

Table D.1. Scores on attitudinal indicators in the main sample before and after test rides and control group *(continued)*

Indicators		Scores (mean / standard deviation)			Wilcoxon signed-rank test statistics between:	
		Control group	Pre-test	Post-test	Control group – Pre-test	Pre-test – Post-test
Intention to use shared automated vehicles						
S14	I like that an electric self-driving car does not produce pollutant emissions	5.69 (0.963)	6.28 (1.101)	6.28 (1.065)	Z= -1.446	Z=-0.071
S15	In the future, I will use self-driving cars for my daily trips	4.89 (1.676)	4.48 (1.707)	5.08 (1.419)	Z= -2.076*	Z=-3.903**
S16	I think that a ride in a self-driving car saves time (would save my time)	4.83 (1.524)	4.62 (1.382)	5.33 (1.310)	Z= -1.219	Z=-4.956**
Service quality						
S17	I am afraid that there will be no car available when I request one (reversed)	3.71 (1.152)	3.63 (1.436)	3.96 (1.481)	Z= -0.248	Z=-2.325*
S18	I am worried that the car is not clean after its previous use (reversed)	4.26 (1.358)	4.09 (1.596)	4.41 (1.629)	Z= -0.167	Z=-2.846**

The difference between the two scores is significant based on Wilcoxon signed-rank test statistics (IBM, 2017); ** at a 99% level; * at a 95% level

Table D.2. Results of confirmatory factor analysis: model development stages (pre-test)

Stages of model development	First run of the model (hypothesised structure)	Second run	Third run	Final model
Factor 1. Enjoyment of AVs			**Factors 1 and 2 combined**	
S1	0.697	0.749	0.663	0.648
S2	0.633***	0.627***	0.547***	
S3	0.322***			
Factor 2. Perceived safety and trust				
S4	0.853	0.868	0.857***	0.873***
S5	0.492***			
S6	0.802***	0.809***	0.791***	0.798***
S7	0.833***	0.839***	0.836***	0.829***
Factor 3. Work activity				
S8	0.507			
S9	0.685***	0.692	0.702	0.700
S10	0.902***	0.923***	0.912***	0.911***
S11	0.375***			
Factor 4. Leisure activity				
S8	0.532			
S12	0.645***	0.626	0.625	0.620
S13	0.721***	0.713***	0.724***	0.726***
S11	0.807***	0.814***	0.803***	0.801***
Factor 5. Intention to use shared automated vehicles				
S14	0.512			
S15	0.853***	0.841	0.825	0.819
S16	0.622***	0.602***	0.605***	0.610***
Factor 6. Service quality				
S17	0.359	-	-	-
S18	0.967 (p=0.125)	-	-	-
Model fit	RMSEA=0.078 CFI=0.97 TLI=0.951	RMSEA=0.054 CFI=0.983 TLI=0.971	RMSEA=0.086 CFI=0.952 TLI=0.927	RMSEA=0.081 CFI=0.965 TLI=0.942

Table D.3. Assessment of discriminant validity: second-stage CFA model (pre-test)

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1	**0.693**	0.853	0.573	0.658	0.605
Factor 2	0.853	**0.839**	0.681	0.624	0.428
Factor 3	0.573	0.681	**0.819**	0.571	0.357
Factor 4	0.658	0.624	0.571	**0.722**	0.676
Factor 5	0.605	0.428	0.357	0.676	**0.831**

Diagonal values (bold) are the square root of the average variance extracted from the loadings.
Off-diagonal values are latent factor correlations.

Table D.4. Assessment of discriminant validity: final CFA model (pre-test)

	Factor 1 (combined Factors 1 and 2)	**Factor 2** (previously Factor 3)	**Factor 3** (previously Factor 4)	**Factor 4** (previously Factor 5)
Factor 1	**0.794**	0.691	0.701	0.482
Factor 2	0.691	**0.812**	0.581	0.375
Factor 3	0.701	0.581	**0.721**	0.69
Factor 4	0.482	0.375	0.69	**0.721**

Diagonal values (bold) are the square root of the average variance extracted from the loadings.
Off-diagonal values are latent factor correlations.

Table D.5. Results of confirmatory factor analysis: main sample (pre-test)

Factor	Indicators (attitudinal statements)	Factor loadings	Reliability: Internal reliability (Cronbach's alpha)	Reliability: Composite reliability	Convergent validity (average variance extracted)
$RMSEA_{pre\text{-}test} = 0.081$; $CFI_{pre\text{-}test} = 0.965$; $TLI_{pre\text{-}test} = 0.942$					
Factor 1. Perceived safety, trust and enjoyment of AVs	S1. I like self-driving cars	0.65	0.86	0.87	0.63
	S4. I trust that a system can drive a self-driving car with no assistance from me	0.87			
	S6. I can entrust the safety of a close family member to a self-driving car	0.80			
	S7. I think that a ride in a self-driving car is safe (A ride in a self-driving car was safe)	0.83			
Factor 2. Work activity	S9. I think I will be (I was) able to concentrate on working in a self-driving car	0.70	0.76	0.79	0.66
	S10. I think it will be (It was) comfortable to work in a self-driving car	0.91			
Factor 3. Leisure activity	S11. I think that a ride in a self-driving car is comfortable (A ride in a self-driving car was comfortable)	0.80	0.81	0.76	0.52
	S12. I think I will be (I was) able to concentrate on my leisure activities in a self-driving car	0.62			
	S13. I think it will be (It was) comfortable to spend time for leisure activities in a self-driving car	0.73			
Factor 4. Intention to use SAVs	S15. In the future, I will use self-driving cars for my daily trips	0.82	0.66	0.68	0.52
	S16. I think that a ride in a self-driving car saves time (would save my time)	0.61			

Table D.6. Results of confirmatory factor analysis: model development stages (post-test)

Stages of model development	First run of the model (hypothesised structure)	Second run	Third run	Final model
Factor 1. Enjoyment of AVs			**Factors 1 and 2 combined**	
S1	0.896	0.882	0.895	0.728
S2	0.647***	0.626***	0.591***	
S3	0.387***			
Factor 2. Perceived safety and trust				
S4	0.912	0.796	0.660***	0.768***
S5	0.549***			
S6	0.86***	0.689***	0.654***	0.672***
S7	0.71***	0.800***	0.722***	0.776***
Factor 3. Work activity				
S8	0.374			
S9	0.844***	0.847	0.836	0.851
S10	0.939***	0.939***	0.951***	0.932***
S11	0.415***			
Factor 4. Leisure activity				
S8	0.503			
S12	0.873***	0.648	0.609	0.664
S13	0.916***	0.722***	0.716***	0.735***
S11	0.702***	0.769***	0.776***	0.755***
Factor 5. Intention to use shared automated vehicles				
S14	0.42			
S15	0.758***	0.743	0.770	0.740
S16	0.829***	0.839***	0.809***	0.842***
Factor 6. Service quality				
S17	0.391	-	-	-
S18	1.211 (p=0.146)	-	-	-
Model fit	RMSEA=0.097 CFI=0.893 TLI=0.862	RMSEA=0.057 CFI=0.985 TLI=0.974	RMSEA=0.096 CFI=0.952 TLI=0.927	RMSEA=0.075 CFI=0.972 TLI=0.954

Table D.7. Assessment of discriminant validity: second-stage CFA model (post-test)

	Factor 1	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**
Factor 1	**0.765**	0.859	0.451	0.552	0.654
Factor 2	0.859	**0.764**	0.382	0.609	0.708
Factor 3	0.451	0.382	**0.894**	0.665	0.522
Factor 4	0.552	0.609	0.665	**0.716**	0.603
Factor 5	0.654	0.708	0.522	0.603	**0.792**

Diagonal values (bold) are the square root of the average variance extracted from the loadings.
Off-diagonal values are latent factor correlations.

Table D.8. Assessment of discriminant validity: final CFA model (post-test)

	Factor 1 (combined Factors 1 and 2)	**Factor 2** (previously Factor 3)	**Factor 3** (previously Factor 4)	**Factor 4** (previously Factor 5)
Factor 1	**0.735**	0.44	0.638	0.761
Factor 2	0.44	**0.894**	0.658	0.524
Factor 3	0.638	0.658	**0.721**	0.608
Factor 4	0.761	0.524	0.608	**0.794**

Diagonal values (bold) are the square root of the average variance extracted from the loadings.
Off-diagonal values are latent factor correlations.

Table D.9. Results of confirmatory factor analysis: main sample (post-test)

Factor	Indicators (attitudinal statements)	Factor loadings	Reliability: Internal reliability (Cronbach's alpha)	Reliability: Composite reliability	Convergent validity (average variance extracted)
$RMSEA_{post\text{-}test} = 0.075$; $CFI_{post\text{-}test} = 0.972$; $TLI_{post\text{-}test} = 0.954$					
Factor 1. Perceived safety, trust and enjoyment of AVs	S1. I like self-driving cars	0.73	0.84	0.83	0.54
	S4. I trust that a system can drive a self-driving car with no assistance from me	0.77			
	S6. I can entrust the safety of a close family member to a self-driving car	0.67			
	S7. I think that a ride in a self-driving car is safe (A ride in a self-driving car was safe)	0.78			
Factor 2. Work activity	S9. I think I will be (I was) able to concentrate on working in a self-driving car	0.85	0.89	0.89	0.80
	S10. I think it will be (It was) comfortable to work in a self-driving car	0.93			
Factor 3. Leisure activity	S11. I think that a ride in a self-driving car is comfortable (A ride in a self-driving car was comfortable)	0.76	0.82	0.76	0.52
	S12. I think I will be (I was) able to concentrate on my leisure activities in a self-driving car	0.66			
	S13. I think it will be (It was) comfortable to spend time for leisure activities in a self-driving car	0.74			
Factor 4. Intention to use SAVs	S15. In the future, I will use self-driving cars for my daily trips	0.74	0.77	0.77	0.63
	S16. I think that a ride in a self-driving car saves time (would save my time)	0.84			

Table D.10. Results of confirmatory factor analysis: model development stages (control group)

Stages of model development	First run of the model (hypothesised structure)	Second run	Third run	Fourth run	Final model
Factor 1. Enjoyment of AVs				**Factors 1 and 2 combined**	
S1	0.62	0.685	0.701	0.717	0.696
S2	0.817***	0.879***	0.944***	0.908***	0.951***
S3	0.627***	0.536***			
Factor 2. Perceived safety and trust					
S4	0.853	0.889	0.907	0.627***	0.562***
S5	0.602***	0.632***	0.628***	0.46***	
S6	0.149 (p=0.391)				
S7	0.933***	0.886***	0.868***	0.545***	
Factor 3. Work activity					
S8	0.055				
S9	1.975 (p=0.493)				
S10	0.401 (p=0.127)				
S11	0.074 (p=0.162)				
Factor 4. Leisure activity					
S8	0.683	0.684	0.672	0.672	0.672
S12	0.705***	0.707***	0.71***	0.727***	0.709***
S13	0.964***	0.965***	0.968***	0.958***	0.969***
S11	0.703***	0.717***	0.72***	0.721***	0.719***
Factor 5. Intention to use shared automated vehicles					
S14	0.409				
S15	0.56***				
S16	0.556***				
Factor 6. Service quality					
S17	0.435				
S18	0.365***				
Model fit	RMSEA=0.175 CFI=0.761 TLI=0.688	RMSEA=0.133 CFI=0.905 TLI=0.867	RMSEA=0.114 CFI=0.943 TLI=0.914	RMSEA=0.124 CFI=0.948 TLI=0.917	RMSEA=0.122 CFI=0.953 TLI=0.924

Table D.11. Assessment of discriminant validity: third-stage CFA model (control group)

	Factor 1	**Factor 2**	**Factor 4**
Factor 1	**0.831**	0.926	0.59
Factor 2	0.926	**0.811**	0.544
Factor 4	0.59	0.544	**0.777**

Diagonal values (bold) are the square root of the average variance extracted from the loadings.
Off-diagonal values are latent factor correlations.

Table D.12. Assessment of discriminant validity: final CFA model (control group)

	Factor 1 (combined Factors 1 and 2)	**Factor 3** (previously Factor 4)
Factor 1	**0.755**	0.538
Factor 3	0.538	**0.775**

Diagonal values (bold) are the square root of the average variance extracted from the loadings.
Off-diagonal values are latent factor correlations.

Table D.13. Results of confirmatory factor analysis: control group

Factor	Indicators (attitudinal statements)	Factor loadings	Reliability: Internal reliability (Cronbach's alpha)	Reliability: Composite reliability	Convergent validity (average variance extracted)
Control group		RMSEA = 0.122; CFI = 0.953; TLI = 0.924			
Factor 1. Perceived safety, trust and enjoyment of AVs	S1. I like self-driving cars	0.7	0.77	0.79	0.57
	S2. I think that a ride in a self-driving car is enjoyable (A ride in a self-driving car was enjoyable)	0.95			
	S4. I trust that a system can drive a self-driving car with no assistance from me	0.56			
Factor 3. Leisure activity	S8. It is important for me to use my travel time productively when I'm riding in a self-driving car (I would use my travel time productively when I ride in a self-driving car)	0.67	0.84	0.86	0.60
	S11. I think that a ride in a self-driving car is comfortable (A ride in a self-driving car was comfortable)	0.72			
	S12. I think I will be (I was) able to concentrate on my leisure activities in a self-driving car	0.71			
	S13. I think it will be (It was) comfortable to spend time for leisure activities in a self-driving car	0.97			

Table D.14. Results of the latent variables model (pre-test)

Indicators / Predictors	Factor 1. Perceived safety, trust and enjoyment of AVs	Factor 2. Work activity	Factor 3. Leisure activity	Factor 4. Intention to use SAVs
Multiple indicators				
S1. I like self-driving cars	1			
S4. I trust that a system can drive a self-driving car with no assistance from me	-1.58***			
S6. I can entrust the safety of a close family member to a self-driving car	-1.45***			
S7. I think that a ride in a self-driving car is safe (A ride in a self-driving car was safe)	-0.776***			
S9. I think I will be (I was) able to concentrate on working in a self-driving car		1		
S10. I think it will be (It was) comfortable to work in a self-driving car		-0.897***		
S11. I think that a ride in a self-driving car is comfortable (A ride in a self-driving car was comfortable)			0.371***	
S12. I think I will be (I was) able to concentrate on my leisure activities in a self-driving car			1	
S13. I think it will be (It was) comfortable to spend time for leisure activities in a self-driving car			0.943***	
S15. In the future, I will use self-driving cars for my daily trips				1
S16. I think that a ride in a self-driving car saves time (would save my time)				-0.69***
Multiple causes				
Gender: Female (Ref. – Male)	0.441***	0.642***	-0.553***	0.29***
Age: Old (above 50) (Ref. – Young)	-0.356***	-0.365***	-0.287***	-0.065
Education level: High (Ref. – Low)	0.11*	0.039	-0.149*	0.131*
Occupation: Employed (Ref. – Other)	-0.376***	-0.843***	0.841***	-0.62***
Income (gross annual per household): Above 50k (Ref. – Below 50k)	0.344***	0.183**	-0.288***	0.653***

∗∗∗ significant at a 99% confidence interval; ∗∗ at 95%; ∗ at 90%

Table D.15. Results of the latent variables model (post-test)

Indicators / Predictors	Factor 1. Perceived safety, trust and enjoyment of AVs	Factor 2. Work activity	Factor 3. Leisure activity	Factor 4. Intention to use SAVs
Multiple indicators				
S1. I like self-driving cars	1			
S4. I trust that a system can drive a self-driving car with no assistance from me	-0.395***			
S6. I can entrust the safety of a close family member to a self-driving car	-0.343***			
S7. I think that a ride in a self-driving car is safe (A ride in a self-driving car was safe)	-0.505***			
S9. I think I will be (I was) able to concentrate on working in a self-driving car		1		
S10. I think it will be (It was) comfortable to work in a self-driving car		-0.933***		
S11. I think that a ride in a self-driving car is comfortable (A ride in a self-driving car was comfortable)			0.468**	
S12. I think I will be (I was) able to concentrate on my leisure activities in a self-driving car			1	
S13. I think it will be (It was) comfortable to spend time for leisure activities in a self-driving car			0.799***	
S15. In the future, I will use self-driving cars for my daily trips				1
S16. I think that a ride in a self-driving car saves time (would save my time)				0.845***
Multiple causes				
Gender: Female (Ref. – Male)	-0.343***	0.213***	0.14	0.035
Age: Old (above 50) (Ref. – Young)	-0.271**	-0.466***	0.174**	-0.114
Education level: High (Ref. – Low)	0.698***	-0.032	-0.15**	0.131*
Occupation: Employed (Ref. – Other)	-0.049	-0.191***	0.401***	0.446***
Income (gross annual per household): Above 50k (Ref. – Below 50k)	-0.366***	0.0098	0.0468	-0.281***

∗∗∗ significant at a 99% confidence interval; ∗∗ at 95%; ∗ at 90%

References

Abduljabbar, R. L., Liyanage, S., & Dia, H. (2021). The role of micro-mobility in shaping sustainable cities: A systematic literature review. *Transportation Research Part D: Transport and Environment, 92*, 102734. https://doi.org/10.1016/j.trd.2021.102734

Abe, R. (2021). Preferences of urban rail users for first- and last-mile autonomous vehicles: Price and service elasticities of demand in a multimodal environment. *Transportation Research Part C: Emerging Technologies, 126*, 103105. https://doi.org/10.1016/j.trc.2021.103105

Acheampong, R. A., Cugurullo, F., Gueriau, M., & Dusparic, I. (2021). Can autonomous vehicles enable sustainable mobility in future cities? Insights and policy challenges from user preferences over different urban transport options. *Cities, 112,* 103134. https://doi.org/10.1016/j.cities.2021.103134

Alessandrini, A., Alfonsi, R., Delle Site, P., & Stam, D. (2014). Users' preferences towards automated road public transport: results from European surveys. *Transportation Research Procedia, 3,* 139-144. https://doi.org/10.1016/j.trpro.2014.10.099

Allen, J., Muñoz, J. C., & de Dios Ortúzar, J. (2019). Understanding public transport satisfaction: Using Maslow's hierarchy of (transit) needs. *Transport Policy*, *81*, 75-94. https://doi.org/10.1016/j.tranpol.2019.06.005

Almaskati, D., Kermanshachi, S., & Pamidimukkala, A. (2024). Convergence of emerging transportation trends: A comprehensive review of shared autonomous vehicles. *Journal of Intelligent and Connected Vehicles*, *7*(3), 177-189. https://doi.org/10.26599/JICV.2023.9210043

Almlöf, E. (2022). *Exploring societal impacts of self-driving public transport using four-step transport models* (Doctoral dissertation, KTH Royal Institute of Technology). Accessed from https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1658722&dswid=-9295

Ashkrof, P., Homem de Almeida Correia, G., Cats, O., & van Arem, B. (2019). Impact of automated vehicles on travel mode preference for different trip purposes and distances.

Transportation Research Record, 2673(5), 607-616. https://doi.org/10.1177%2F0361198119841032

Atasoy, B., Caesar, H., Ellerbroek, J., Hiemstra-van Mastrigt, S., Maknoon, M.Y., van Oort, N., Psyllidis, A., van der Spek, S.C., Snelder, M., Triggianese, M., Veeneman, W. & Swarte, M. P. (2025). Mobility Futures: Four scenarios for the Dutch mobility system in 2050. (Report). Delft University of Technology. https://research.tudelft.nl/en/publications/mobility-futures-four-scenarios-for-the-dutch-mobility-system-in-

Axsen, J., & Sovacool, B. K. (2019). The roles of users in electric, shared and automated mobility transitions. *Transportation Research Part D: Transport and Environment*, *71*, 1-21. https://doi.org/10.1016/j.trd.2019.02.012

Azad, M., Hoseinzadeh, N., Brakewood, C., Cherry, C. R., & Han, L. D. (2019). Fully autonomous buses: A literature review and future research directions. *Journal of Advanced Transportation*, *2019*(1), 4603548. https://doi.org/10.1155/2019/4603548

Badia, H., & Jenelius, E. (2020). Feeder transit services in different development stages of automated buses: comparing fixed routes versus door-to-door trips. *Transportation Research Procedia, 47*, 521-528. https://doi.org/10.1016/j.trpro.2020.03.127

Bahamonde-Birke, F., & de Dios Ortúzar, J. (2014). Is sequential estimation a suitable second best for estimation of hybrid choice models?. *Transportation Research Record*, *2429*(1), 51-58. https://doi.org/10.3141/2429-06

Bala, H., Anowar, S., Chng, S., & Cheah, L. (2023). Review of studies on public acceptability and acceptance of shared autonomous mobility services: Past, present and future. *Transport Reviews,* 1-27. https://doi.org/10.1080/01441647.2023.2188619

Baltodano, S., Sibi, S., Martelaro, N., Gowda, N., & Ju, W. (2015). The RRADS platform: a real road autonomous driving simulator. In *Proceedings of the 7th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (pp. 281-288). https://doi.org/10.1145/2799250.2799288

Bansal, P., Kockelman, K. M., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies, 67*, 1-14. https://doi.org/10.1016/j.trc.2016.01.019

Barabino, B., Cabras, N. A., Conversano, C., & Olivo, A. (2020). An integrated approach to select key quality indicators in transit services. *Social Indicators Research, 149*, 1045-1080. https://doi.org/10.1007/s11205-020-02284-0

Barreto, R. A., Kellett, J., Pierce, J. C., & Van den Hengel, A. (2022). I'm in love with my car psychological attachment to cars, automated vehicles and the driverless future. *Journal of Transport Economics and Policy, 56(1),* 28-55.

Bellem, H., Thiel, B., Schrauf, M., & Krems, J. F. (2018). Comfort in automated driving: An analysis of preferences for different automated driving styles and their dependence on personality traits. *Transportation Research Part F: Traffic Psychology and Behaviour, 55,* 90-100. https://doi.org/10.1016/j.trf.2018.02.036

Bellet, T., & Banet, A. (2023). UTAUT4-AV: An extension of the UTAUT model to study intention to use automated shuttles and the societal acceptance of different types of automated vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *99*, 239-261. https://doi.org/10.1016/j.trf.2023.10.007

Ben-Akiva, M., Walker, J., Bernardino, A. T., Gopinath, D. A., Morikawa, T., & Polydoropoulou, A. (2002). Integration of choice and latent variable models. *Perpetual motion: Travel behaviour research opportunities and application challenges*, *2002*, 431-470.

Beretta, L., & Santaniello, A. (2016). Nearest neighbor imputation algorithms: a critical evaluation. *BMC Medical Informatics and Decision Making, 16*(3), 197-208. https://doi.org/10.1186/s12911-016-0318-z

Bierlaire, M. (2016). *PythonBiogeme: A short introduction* (Report TRANSP-OR 160706, Series on Biogeme). Transport and Mobility Laboratory, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fédérale de Lausanne, Switzerland.

Bierlaire, M. (2023). *A short introduction to Biogeme* (Technical report TRANSP-OR 230620). Transport and Mobility Laboratory, ENAC, EPFL.

Blais, A. R., & Weber, E. U. (2009). *The domain-specific risk taking scale for adult populations: Item selection and preliminary psychometric properties* (No. DRDC-TORONTO-TR-2009-203). DEFENCE RESEARCH AND DEVELOPMENT TORONTO (CANADA).

Bos, P. (2017). *Self-driving bus to improve accessibility of rural areas in the Netherlands. Peoplemover as a first- and last-mile solution*. MSc Thesis for Environment and Society Studies programme, Nijmegen School of Management, Radboud University Nijmegen. https://theses.ubn.ru.nl/bitstream/handle/123456789/5436/Masterthesis%20Pieter%20Bos%20s4371887%20final%20version%207aug17.pdf?sequence=1

Britten, N. (2021). *An on-road assessment of driver secondary task engagement and performance during Assisted & Automated Driving* (Doctoral dissertation, Virginia Tech). https://vtechworks.lib.vt.edu/items/9777e580-093a-41dd-9b6b-517f827e205d

Brown, G. T., Harris, L. R., O'Quin, C., & Lane, K. E. (2017). Using multi-group confirmatory factor analysis to evaluate cross-cultural research: identifying and understanding non-invariance. *International Journal of Research & Method in Education, 40(1)*, 66-90. https://doi.org/10.1080/1743727X.2015.1070823

Brown, T. A. (2015). *Confirmatory Factor Analysis for Applied Research* (2nd ed.). New York: The Guilford Press.

Calabrò, G., Le Pira, M., Giuffrida, N., Inturri, G., Ignaccolo, M., & Correia, G. H. D. A. (2022). Fixed-route vs. demand-responsive transport feeder services: An exploratory study using an agent-based model. *Journal of Advanced Transportation, 2022*(1), 8382754. https://doi.org/10.1155/2022/8382754

Carrese, F., Sportiello, S., Zhaksylykov, T., Colombaroni, C., Carrese, S., Papaveri, M., & Patella, S. M. (2023). The integration of shared autonomous vehicles in public transportation services: a systematic review. *Sustainability, 15(17),* 13023. https://doi.org/10.3390/su151713023

Centraal Bureau voor de Statistiek [Central Bureau of Statistics (CBS)]. (2018). *Income distribution*. https://www.cbs.nl/en-gb/visualisaties/income-distribution (accessed in September 2020).

Centraal Bureau voor de Statistiek [Central Bureau of Statistics (CBS)]. (2019). *Hoeveel reisden inwoners van Nederland en hoe?* https://www.cbs.nl/nl-nl/visualisaties/verkeer-en-vervoer/personen/mobiliteit (accessed in September 2020)

Centraal Bureau voor de Statistiek [Central Bureau of Statistics (CBS)] Statline. (2020a). *Population: education level, gender, age and migration background.* https://opendata.cbs.nl/statline/#/CBS/nl/dataset/82275NED/table?fromstatweb (accessed in September 2020).

Centraal Bureau voor de Statistiek [Central Bureau of Statistics (CBS)] Statline. (2020b). *Population: gender, age and marital status.* https://opendata.cbs.nl/statline/#/CBS/nl/dataset/7461BEV/table?fromstatweb (accessed in September 2020).

Centraal Bureau voor de Statistiek [Central Bureau of Statistics (CBS)] Statline. (2020c). *Population: region by month.* https://opendata.cbs.nl/statline/#/CBS/nl/dataset/37230ned/table (accessed in September 2020).

Centraal Bureau voor de Statistiek (CBS) [Central Bureau of Statistics] (2021). Verdeling gestandaardiseerd inkomen [Income distribution (standardised income)]. Retrieved from https://www.cbs.nl/nl-nl/visualisaties/inkomensverdeling

Centraal Bureau voor de Statistiek (CBS) [Central Bureau of Statistics] (2022a). Bevolking; hoogstbehaald onderwijsniveau en onderwijsrichting, 2003-2022 [Population; highest level of education and direction of education achieved, 2003-2022]. Retrieved from https://www.cbs.nl/nl-nl/cijfers/detail/85184NED?dl=6B41D

Centraal Bureau voor de Statistiek (CBS) [Central Bureau of Statistics] (2022b). Bevolking op 1 januari en gemiddeld; geslacht, leeftijd en regio [Population on January 1 and average; gender, age and region]. Retrieved from https://www.cbs.nl/nl-nl/cijfers/detail/03759ned?dl=39E0B

Centraal Bureau voor de Statistiek (CBS) [Central Bureau of Statistics] (2022c). Hoeveel wordt er met het openbaar vervoer gereisd? [How much travel is done by public transport?]. Retrieved from https://www.cbs.nl/nl-nl/visualisaties/verkeer-en-vervoer/personen/openbaar-vervoer

Centraal Bureau voor de Statistiek (CBS) [Central Bureau of Statistics] (2023a). Aantal mensen buiten beroepsbevolking in 2022 snel geslonken [Number of people outside the labor force will shrink rapidly in 2022]. Retrieved from https://www.cbs.nl/nl-nl/nieuws/2023/18/aantal-mensen-buiten-beroepsbevolking-in-2022-snel-geslonken

Centraal Bureau voor de Statistiek (CBS) [Central Bureau of Statistics] (2023b). Bevolking, 15 tot 75 jaar. Samenstelling beroepsbevolking [Population, 15 to 75 years. Composition of the labour force]. Retrieved from https://www.cbs.nl/nl-nl/visualisaties/dashboard-beroepsbevolking/bevolking-15-tot-75-jaar

Centraal Bureau voor de Statistiek (CBS) [Central Bureau of Statistics] (2023c). Mobility; per trip, trip characteristics, modes of travel and regions. Retrieved from https://opendata.cbs.nl/#/CBS/en/dataset/85056ENG/table

Chaalal, E., Guerlain, C., Pardo, E., & Faye, S. (2023). Integrating connected and automated shuttles with other mobility systems: challenges and future directions. *IEEE Access*, *11*, 83081-83106. https://doi.org/10.1109/ACCESS.2023.3294110

Chee, E. P., Susilo, Y. O., Brenden, A. P., & Wong, Y. D. (2018). Investigating the willingness of use autonomous bus as a last-mile travel mode: First evidence from public trial in Kista, Stockholm. In *hEART 2018–7th Symposium of the European Association for Research in Transportation*. https://transp-or.epfl.ch/heart/2018/abstracts/5469.pdf

Chee, P. N., Susilo, Y. O., & Wong, Y. D. (2020). Determinants of intention-to-use first-/last-mile automated bus service. *Transportation Research Part A: Policy and Practice, 139*, 350-375. https://doi.org/10.1016/j.tra.2020.06.001

Chee, P. N., Susilo, Y. O., & Wong, Y. D. (2021). Longitudinal interactions between experienced users' service valuations and willingness-to-use a first-/last-mile automated bus service. *Travel Behaviour and Society, 22*, 252-261. https://doi.org/10.1016/j.tbs.2020.10.004

Chen, R., Arief, M., Zhang, W., & Zhao, D. (2020). How to evaluate proving grounds for self-driving? A quantitative approach. *IEEE Transactions on Intelligent Transportation Systems, 22(9)*, 5737-5748. https://doi.org/10.1109/TITS.2020.2991757

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management, 41(2),* 745-783. https://doi.org/10.1007/s10490-023-09871-y

ChoiceMetrics (2018). *Ngene 1.2. User Manual & Reference Guide. The Cutting Edge in Experimental Design*. ChoiceMetrics Pty Ltd.

Chowdhury, S., Ceder, A. A., & Schwalger, B. (2015). The effects of travel time and cost savings on commuters' decision to travel on public transport routes involving transfers. *Journal of Transport Geography*, *43*, 151-159. https://doi.org/10.1016/j.jtrangeo.2015.01.009

Cirillo, C., & Hetrakul, P. (2010). Continuous random coefficient logit models: a comparison of parametric and non-parametric methods to estimate individual preferences over Cybernetic Transportation Systems. *Transportation Research Board 89th Annual Meeting.* Washington, DC.

Classen, S., Mason, J., Hwangbo, S. W., Wersal, J., Rogers, J., & Sisiopiku, V. (2021). Older drivers' experience with automated vehicle technology. *Journal of Transport & Health, 22*, 101107. https://doi.org/10.1016/j.jth.2021.101107

Cornet, Y., Lugano, G., Georgouli, C., & Milakis, D. (2022). Worthwhile travel time: a conceptual framework of the perceived value of enjoyment, productivity and fitness while travelling. *Transport Reviews, 42(5),* 580-603. https://doi.org/10.1080/01441647.2021.1983067

Correia, G. H., Looff, E., van Cranenburgh, S., Snelder, M., & van Arem, B. (2019). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. *Transportation Research Part A: Policy and Practice, 119,* 359-382. https://doi.org/10.1016/j.tra.2018.11.016

Correia, G., & Viegas, J. M. (2011). Carpooling and carpool clubs: Clarifying concepts and assessing value enhancement possibilities through a Stated Preference web survey in Lisbon, Portugal. *Transportation Research Part A: Policy and Practice, 45(2),* 81-90. https://doi.org/10.1016/j.tra.2010.11.001

de Dios Ortúzar, J., & Willumsen, L. G. (2011). *Modelling transport*. John Wiley & Sons.

De Winter, J., van Leeuwen, P. M., & Happee, R. (2012). Advantages and disadvantages of driving simulators: A discussion. In *Proceedings of measuring behavior* (Vol. 2012, pp. 28-31). Utrecht: sn.

De Winter, J. C., Happee, R., Martens, M. H., & Stanton, N. A. (2014). Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence. Transportation Research Part F: Traffic Psychology and Behaviour, 27, 196-217. https://doi.org/10.1016/j.trf.2014.06.016

Dekker, M. J. (2017). *Riding a self-driving bus to work: Investigating how travellers perceive ADS-DVs on the last mile* (Master's thesis). TU Delft, Delft, Netherlands. https://repository.tudelft.nl/islandora/object/uuid%3Ac9773355-d4a3-4063-9799-11343c625c01?collection=education

Delle Site, P., Filippi, F., & Giustiniani, G. (2011). Users' preferences towards innovative and conventional public transport. *Procedia-Social and Behavioral Sciences, 20*, 906-915. https://doi.org/10.1016/j.sbspro.2011.08.099

Detjen, H., Pfleging, B., & Schneegass, S. (2020). A Wizard of Oz field study to understand non-driving-related activities, trust, and acceptance of automated vehicles. In *12th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (pp. 19-29). https://doi.org/10.1145/3409120.3410662

Diba, D. S., Gore, N., & Pulugurtha, S. S. (2025). Integrating autonomous shuttles: insights, challenges, and strategic solutions from practitioners and industry experts' perceptions. *Future Transportation*, *5*(1), 9. https://doi.org/10.3390/futuretransp5010009

Dillmann, J., Den Hartigh, R. J. R., Kurpiers, C. M., Raisch, F. K., Kadrileev, N., Cox, R. F. A., & De Waard, D. (2023). Repeated conditionally automated driving on the road: How do drivers leave the loop over time? *Accident Analysis & Prevention, 181,* 106927. https://doi.org/10.1016/j.aap.2022.106927

Distler, V., Lallemand, C., & Bellet, T. (2018). Acceptability and acceptance of autonomous mobility on demand: the impact of an immersive experience. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (p. 612). ACM. https://doi.org/10.1145/3173574.3174186

Dong, X., DiScenna, M., & Guerra, E. (2019). Transit user perceptions of driverless buses. *Transportation, 46*, 35–50. https://doi.org/10.1007/s11116-017-9786-y

Dubielzig, M., Reisch, M. & Panou, M. (2018). *D2.4 First Passenger needs analysis and specifications*. *AVENUE. Autonomous vehicles to evolve to a new urban experience.* Project deliverable. https://h2020-avenue.eu/wp-content/uploads/2020/07/D2-4-First-Passenger-needs-analysis-and-specifications.pdf

Eden, G., Nanchen, B., Ramseyer, R., & Evéquoz, F. (2017). On the road with an autonomous passenger shuttle: integration in public spaces. In *Proceedings of the 2017 CHI conference extended abstracts on human factors in computing systems* (pp. 1569-1576).

Ejichukwu, E., Tong, L., Hazime, G., & Jia, B. (2024). Enhancing autonomous vehicle design and testing: a comprehensive review of AR and VR integration. arXiv preprint arXiv:2404.19021. Accessed https://arxiv.org/pdf/2404.19021

Ekman, F., Johansson, M., Bligård, L. O., Karlsson, M., & Strömberg, H. (2019). Exploring automated vehicle driving styles as a source of trust information. *Transportation Research Part F: Traffic Psychology and Behaviour, 65,* 268-279. https://doi.org/10.1016/j.trf.2019.07.026

Elbanhawi, M., Simic, M., & Jazar, R. (2015). In the passenger seat: investigating ride comfort measures in autonomous cars. *IEEE Intelligent Transportation Systems Magazine, 7(3),* 4-17. https://doi.org/10.1109/MITS.2015.2405571

Elo, S., & Kyngäs, H. (2008). The qualitative content analysis process. *Journal of Advanced Nursing, 62*(1), 107-115. https://doi.org/10.1111/j.1365-2648.2007.04569.x

Eriksson, A., Banks, V. A., & Stanton, N. A. (2017). Transition to manual: Comparing simulator with on-road control transitions. *Accident Analysis & Prevention, 102*, 227-234. https://doi.org/10.1016/j.aap.2017.03.011

Eriksson, P. E., Swenberg, T., Zhao, X., & Eriksson, Y. (2018). How gaze time on screen impacts the efficacy of visual instructions. *Heliyon*, *4*(6). https://doi.org/10.1016/j.heliyon.2018.e00660

Etzioni, S., Daziano, R. A., Ben-Elia, E., & Shiftan, Y. (2021). Preferences for shared automated vehicles: A hybrid latent class modeling approach. *Transportation Research Part C: Emerging Technologies, 125,* 103013. https://doi.org/10.1016/j.trc.2021.103013

European Commission. (2015). *Driver distraction*. European Road Safety Observatory. Directorate-General for Mobility and Transport. https://road-safety.transport.ec.europa.eu/document/download/ef6ce711-f91e-49a6-b4ae-de2e133f2000_en?filename=ersosynthesis2015-driverdistraction25_en.pdf

European Commission. (2022). *Driver distraction: Road safety thematic report*. European Road Safety Observatory. Directorate-General for Transport. https://road-safety.transport.ec.europa.eu/document/download/662f244a-b3ad-442a-aa60-50f8437c86f2_en?filename=Road_Safety_Thematic_Report_Driver_Distraction_2022.pdf

European Committee for Standardization. (2002). *EN 13816:2002 - Transportation - Logistics and services - Public passenger transport - Service quality definition, targeting and measurement*. Brussels, Belgium: CEN.

European Committee for Standardization. (2006). *EN 15140:2006 - Public passenger transport - Basic requirements and recommendations for systems that measure delivered service quality*. Brussels, Belgium: CEN.

European Court of Auditors. (2023). *Intermodal freight transport: EU still far from getting freight off the road* (Special Report No. 08/2023). Publications Office of the European Union. https://op.europa.eu/webpub/eca/special-reports/intermodal-freight-transport-08-2023/en/

Faisal, A., Kamruzzaman, M., Yigitcanlar, T., & Currie, G. (2019). Understanding autonomous vehicles. *Journal of Transport and Land Use*, *12*(1), 45-72. https://www.jstor.org/stable/26911258

Fan, Q., van Essen, J. T., & Correia, G. H. (2023). Optimising fleet sizing and management of shared automated vehicle (SAV) services: A mixed-integer programming approach integrating endogenous demand, congestion effects, and accept/reject mechanism impacts. *Transportation Research Part C: Emerging Technologies, 157,* 104398. https://doi.org/10.1016/j.trc.2023.104398

Farooq, B., Cherchi, E., & Sobhani, A. (2018). Virtual immersive reality for stated preference travel behavior experiments: A case study of autonomous vehicles on urban roads. *Transportation Research Record, 2672(50),* 35-45. https://doi.org/10.1177/0361198118776810

Feys, M., Rombaut, E., & Vanhaverbeke, L. (2021). Does a test ride influence attitude towards autonomous vehicles? A field experiment with pretest and posttest measurement. *Sustainability, 13(10),* 5387. https://doi.org/10.3390/su13105387

Garus, A., Alonso, B., Alonso Raposo, M., Ciuffo, B., & dell'Olio, L. (2022). Impact of new mobility solutions on travel behaviour and its incorporation into travel demand models. *Journal of Advanced Transportation*, *2022*(1), 7293909. https://doi.org/10.1155/2022/7293909

Gerber, M. A., Schroeter, R., Xiaomeng, L., & Elhenawy, M. (2020). Self-interruptions of non-driving related tasks in automated vehicles: Mobile vs head-up display. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1-9). https://doi.org/10.1145/3313831.3376751

Ghotge, R., Nijssen, K. P., Annema, J. A., & Lukszo, Z. (2022). Use before you choose: What do EV drivers think about V2G after experiencing it? *Energies, 15*(13), 4907. https://doi.org/10.3390/en15134907

Golbabaei, F., Yigitcanlar, T., & Bunker, J. (2021). The role of shared autonomous vehicle systems in delivering smart urban mobility: A systematic review of the literature. *International Journal of Sustainable Transportation*, *15*(10), 731-748. https://doi.org/10.1080/15568318.2020.1798571

Golbabaei, F., Yigitcanlar, T., Paz, A., & Bunker, J. (2023). Perceived opportunities and challenges of autonomous demand-responsive transit use: what are the socio-demographic predictors? *Sustainability*, *15*(15), 11839. https://doi.org/10.3390/su151511839

González, R. M., Marrero, A. S., & Marrero, G. A. (2016). How the values of travel time change when a panel data around a new tram implementation is used. *European Journal of Transport and Infrastructure Research, 16*(4), 554–572. https://doi.org/10.18757/ejtir.2016.16.4.3158

Google Maps. (n.d.). *[Helmond, the Netherlands]*. Retrieved June 20, 2023, from https://www.google.com/maps/@51.4676075,5.6170233,15z?entry=ttu

Greifenstein, M. (2024). Factors influencing the user behaviour of shared autonomous vehicles (SAVs): a systematic literature review. *Transportation Research Part F: Traffic Psychology and Behaviour, 100,* 323-345. https://doi.org/10.1016/j.trf.2023.10.027

Guo, J., Susilo, Y., Antoniou, C., & Pernestål, A. (2021). When and why do people choose automated buses over conventional buses? Results of a context-dependent stated choice experiment. *Sustainable Cities and Society, 69*, 102842. https://doi.org/10.1016/j.scs.2021.102842

Guo, J., Susilo, Y., Antoniou, C., & Pernestål, A. (2022). Word of mouth and behavioural intentions of the automated bus service. *Cities, 126*, 103668. https://doi.org/10.1016/j.cities.2022.103668

Gurumurthy, K. M., & Kockelman, K. M. (2018). Analyzing the dynamic ride-sharing potential for shared autonomous vehicle fleets using cellphone data from Orlando, Florida. *Computers, Environment and Urban Systems*, *71*, 177-185. https://doi.org/10.1016/j.compenvurbsys.2018.05.008

Haghani, M., Bliemer, M. C., Rose, J. M., Oppewal, H., & Lancsar, E. (2021). Hypothetical bias in stated choice experiments: Part I. Macro-scale analysis of literature and integrative synthesis of empirical evidence from applied economics, experimental psychology and neuroimaging. *Journal of Choice Modelling, 41*, 100309. https://doi.org/10.1016/j.jocm.2021.100309

Hagenzieker, M., Boersma, R., Nuñez Velasco, J. P., Öztürker, M., Zubin, I., & Heikoop, D. (2021). *Automated buses in Europe: An inventory of pilots: Final report*. https://www.researchgate.net/publication/356604869_Hagenzieker_et_al_2021_Automated_Buses_in_Europe_An_Inventory_of_Pilots_-_Final_Report

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2009). *Multivariate Data Analysis*. 7th Edition Pearson Prentice Hall.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* (p. 197). Springer Nature.

Hamadneh, J., & Esztergár-Kiss, D. (2022). The preference of onboard activities in a new age of automated driving. *European Transport Research Review, 14(1),* 15. https://doi.org/10.1186/s12544-022-00540-7

Harrell F.E. (2015) *Missing Data*. In: Regression Modeling Strategies. Springer Series in Statistics. Springer, Cham. https://doi.org/10.1007/978-3-319-19425-7_3

Hartwich, F., Witzlack, C., Beggiato, M., & Krems, J. F. (2019). The first impression counts: A combined driving simulator and test track study on the development of trust and acceptance of highly automated driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 65*, 522–535. https://doi.org/10.1016/j.trf.2018.05.012

Hasan, U., Whyte, A., & AlJassmi, H. (2022). A microsimulation modelling approach to quantify environmental footprint of autonomous buses. *Sustainability*, *14*(23), 15657. https://doi.org/10.3390/su142315657

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: data mining, inference, and prediction*. Springer Science & Business Media.

Heikoop, D. D., Velasco, J. P. N., Boersma, R., Bjørnskau, T., & Hagenzieker, M. P. (2020). Automated bus systems in Europe: A systematic review of passenger experience and road user interaction. *Advances in Transport Policy and Planning*, *5*, 51-71. https://doi.org/10.1016/bs.atpp.2020.02.001

Hensher, D. A. (1994). Stated preference analysis of travel choices: the state of practice. *Transportation, 21*(2), 107-133. https://doi.org/10.1007/BF01098788

Hensher, D. A. (2006). How do respondents process stated choice experiments? Attribute consideration under varying information load. *Journal of Applied Econometrics, 21*(6), 861-878. https://doi.org/10.1002/jae.877

Hensher, D. A., Rose, J. M., Rose, J. M., & Greene, W. H. (2005). *Applied choice analysis: a primer*. Cambridge University Press.

Hernandez, J., Liu, Z., Hulten, G., DeBarr, D., Krum, K., & Zhang, Z. (2013, April). Measuring the engagement level of TV viewers. In *2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)* (pp. 1-7). IEEE. https://doi.org/10.1109/FG.2013.6553742

Herrenkind, B., Brendel, A. B., Nastjuk, I., Greve, M., & Kolbe, L. M. (2019). Investigating end-user acceptance of autonomous electric buses to accelerate diffusion. *Transportation Research Part D: Transport and Environment, 74*, 255-276. https://doi.org/10.1016/j.trd.2019.08.003

Hess, S., Rose, J. M., & Polak, J. (2010). Non-trading, lexicographic and inconsistent behaviour in stated choice data. *Transportation Research Part D: Transport and Environment, 15*(7), 405-417. https://doi.org/10.1016/j.trd.2010.04.008

Hess, S., & Train, K. (2017). Correlation and scale in mixed logit models. *Journal of Choice Modelling*, *23*, 1-8. https://doi.org/10.1016/j.jocm.2017.03.001

Hinnüber, F., Szarucki, M., & Szopik-Depczyńska, K. (2019). The effects of a first-time experience on the evaluation of battery electric vehicles by potential consumers. *Sustainability, 11*(24), 7034. https://doi.org/10.3390/su11247034

Hoogendoorn-Lanser, S., Van Nes, R., Hoogendoorn, S. P., & Bovy, P. (2006). Home–activity approach to multimodal travel choice modeling. *Transportation Research Record, 1985*(1), 180-187. https://doi.org/10.1177/0361198106198500120

IBM Corp. (2017). *IBM SPSS Statistics for Windows, Version 25.0*. Armonk, NY: IBM Corp.

Iclodean, C., Cordos, N., & Varga, B. O. (2020). Autonomous shuttle bus for public transportation: A review. *Energies*, *13*(11), 2917. https://doi.org/10.3390/en13112917

Innocenti, A., Lattarulo, P., & Pazienza, M. G. (2013). Car stickiness: Heuristics and biases in travel choice. *Transport Policy*, *25*, 158-168. https://doi.org/10.1016/j.tranpol.2012.11.004

Intertraffic. (2025, March 25). *Enhancing liveability: How the Netherlands is leading the way in sustainable mobility*. https://www.intertraffic.com/news/sustainability/netherlands-leading-the-way

Jensen, A. F., Cherchi, E., & de Dios Ortúzar, J. (2014). A long panel survey to elicit variation in preferences and attitudes in the choice of electric vehicles. *Transportation, 41*, 973–993. https://doi.org/10.1007/s11116-014-9517-6

Jensen, A. F., Cherchi, E., & Mabit, S. L. (2013). On the stability of preferences and attitudes before and after experiencing an electric vehicle. *Transportation Research Part D: Transport and Environment, 25*, 24–32. https://doi.org/10.1016/j.trd.2013.07.006

Jian, J. Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International Journal of Cognitive Ergonomics, 4*(1), 53-71. https://doi.org/10.1207/S15327566IJCE0401_04

Johansson, M. V., Heldt, T., & Johansson, P. (2006). The effects of attitudes and personality traits on mode choice. *Transportation Research Part A: Policy and Practice*, *40*(6), 507-525. https://doi.org/10.1016/j.tra.2005.09.001

Karolemeas, C., Tsigdinos, S., Moschou, E., & Kepaptsoglou, K. (2024). Shared autonomous vehicles and agent based models: a review of methods and impacts. *European Transport Research Review*, *16*(1), 25. https://doi.org/10.1186/s12544-024-00644-2

Keseru, I., & Macharis, C. (2018). Travel-based multitasking: review of the empirical evidence. *Transport Reviews, 38(2)*, 162-183. https://doi.org/10.1080/01441647.2017.1317048

Keseru, I., Heyndels, E., Ton, T. D., & Macharis, C. (2020). Multitasking on the go: An observation study on local public transport in Brussels. *Travel Behaviour and Society, 18*, 106-116. https://doi.org/10.1016/j.tbs.2019.10.003

Kettle, L., & Lee, Y. C. (2022). Augmented reality for vehicle-driver communication: a systematic review. *Safety, 8(4)*, 84. https://doi.org/10.3390/safety8040084

Kircher, K., Ahlstrom, C., & Kircher, A. (2009, June). Comparison of two eye-gaze based real-time driver distraction detection algorithms in a small-scale field operational test. In *Driving Assessment Conference* (Vol. 5, No. 2009). University of Iowa. https://pubs.lib.uiowa.edu/driving/article/id/28100/

Klingegård, M., Andersson, J., Habibovic, A., Nilsson, E., & Rydström, A. (2020). Drivers' ability to engage in a non-driving related task while in automated driving mode in real traffic. *IEEE Access, 8,* 221654-221668. https://doi.org/10.1109/ACCESS.2020.3043428

Ko, S. M., & Ji, Y. G. (2018). How we can measure the non-driving-task engagement in automated driving: Comparing flow experience and workload. *Applied Ergonomics, 67,* 237-245. https://doi.org/10.1016/j.apergo.2017.10.009

Kouwenhoven, M., & de Jong, G. (2018). Value of travel time as a function of comfort. *Journal of Choice Modelling, 28*, 97-107. https://doi.org/10.1016/j.jocm.2018.04.002

Kouwenhoven, M., Muller, J., Thoen, S., Willigers, J. & de Jong, G. (2023). *Values of time, reliability and comfort in the Netherlands 2022. New values for passenger travel and freight transport.* (Technical report. Project number 19022). https://english.kimnet.nl/publications/publications/2024/04/03/new-values-of-travel-time-reliability-and-comfort-in-the-netherlands

König, M., & Neumayr, L. (2017). Users' resistance towards radical innovations: The case of the self-driving car. *Transportation Research Part F: Traffic Psychology and Behaviour*, *44*, 42-52. https://doi.org/10.1016/j.trf.2016.10.013

Kroesen, M., Milakis, D., & Van Wee, B. (2023). Automated Vehicles: Changes in expert opinions over time. *Transport Policy*, *136*, 1-10. https://doi.org/10.1016/j.tranpol.2023.03.005

Kyriakidis, M., Happee, R., & de Winter, J. C. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F: Traffic Psychology and Behaviour, 32*, 127-140. https://doi.org/10.1016/j.trf.2015.04.014

La Delfa, A., Greifenstein, M., & Han, Z. Impact of Shared Autonomous Vehicles (SAVs) on Travel Behaviour: A Systematic Literature Review. *Preprint.* Available at SSRN: https://ssrn.com/abstract=4840055

Launonen, P., Salonen, A. O., & Liimatainen, H. (2021). Icy roads and urban environments. Passenger experiences in autonomous vehicles in Finland. *Transportation Research Part F: Traffic Psychology and Behaviour, 80*, 34-48. https://doi.org/10.1016/j.trf.2021.03.015

Lee, J., & Gim, T. H. T. (2024). Reconsidering AVs future: A socio-spatial perspective. *Technology in Society*, *78*, 102618. https://doi.org/10.1016/j.techsoc.2024.102618

Lee, J., Lee, E., Yun, J., Chung, J. H., & Kim, J. (2021). Latent heterogeneity in autonomous driving preferences and in-vehicle activities by travel distance. *Journal of Transport Geography, 94,* 103089. https://doi.org/10.1016/j.jtrangeo.2021.103089

Lécureux, B., Bonnet, A., Manout, O., Berrada, J., & Bouzouina, L. (2023). Acceptance of shared autonomous vehicles: A literature review of stated choice experiments. *Transportation Research Procedia*, *72*, 2738-2745. https://doi.org/10.1016/j.trpro.2023.11.815

Levordashka, A., Stanton Fraser, D., & Gilchrist, I. D. (2023). Measuring real-time cognitive engagement in remote audiences. *Scientific Reports*, *13*(1), 10516. https://doi.org/10.1038/s41598-023-37209-7

Li, X., Schroeter, R., Rakotonirainy, A., Kuo, J., & Lenné, M. G. (2020). Effects of different non-driving-related-task display modes on drivers' eye-movement patterns during take-over in an automated vehicle. *Transportation Research Part F: Traffic Psychology and Behaviour, 70*, 135-148. https://doi.org/10.1016/j.trf.2020.03.001

Liao, F., & Correia, G. (2022). Electric carsharing and micromobility: A literature review on their usage pattern, demand, and potential impacts. *International Journal of Sustainable Transportation, 16*(3), 269-286. https://doi.org/10.1080/15568318.2020.1861394

Liu, T., Cats, O., & Gkiotsalitis, K. (2021). A review of public transport transfer coordination at the tactical planning phase. *Transportation Research Part C: Emerging Technologies*, *133*, 103450. https://doi.org/10.1016/j.trc.2021.103450

Liu, P., Jiang, Z., Li, T., Wang, G., Wang, R., & Xu, Z. (2021). User experience and usability when the automated driving system fails: Findings from a field experiment. *Accident Analysis & Prevention, 161*, 106383. https://doi.org/10.1016/j.aap.2021.106383

Liu, P., Xu, Z., & Zhao, X. (2019). Road tests of self-driving vehicles: Affective and cognitive pathways in acceptance formation. *Transportation Research Part A: Policy and Practice, 124,* 354-369. https://doi.org/10.1016/j.tra.2019.04.004

López-Lambas, M. E., & Alonso, A. (2019). The driverless bus: An analysis of public perceptions and acceptability. *Sustainability, 11*(18), 4986. https://doi.org/10.3390/su11184986

Loria Rebolledo, L. E., Watson, V., Kiso, T., & Phimister, E. C. (2019). Investigating users' preferences for low emission buses: Experiences from Europe's largest hydrogen bus fleet. *Journal of Choice Modelling, 32*, 100169. https://doi.org/10.1016/j.jocm.2019.05.001

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: analysis and applications*. Cambridge University Press.

Lu, Y., Kimpton, A., Prato, C. G., Sipe, N., & Corcoran, J. (2024). First and last mile travel mode choice: A systematic review of the empirical literature. *International Journal of Sustainable Transportation*, *18*(1), 1-14. https://doi.org/10.1080/15568318.2023.2218285

Lukovics, M., Prónay, S., Majó-Petri, Z., Kovács, P., Ujházi, T., Volosin, M., Palatinus, Z. & Keszey, T. (2023). Combining survey-based and neuroscience measurements in customer acceptance of self-driving technology. *Transportation Research Part F: Traffic Psychology and Behaviour, 95,* 46-58. https://doi.org/10.1016/j.trf.2023.03.016

Lundquist, M. (2018). *Autonomous bus passenger experience*. http://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1218637&dswid=-8784

Madigan, R., Louw, T., Dziennus, M., Graindorge, T., Ortega, E., Graindorge, M., & Merat, N. (2016). Acceptance of Automated Road Transport Systems (ARTS): an adaptation of the UTAUT model. *Transportation Research Procedia, 14*, 2217-2226. https://doi.org/10.1016/j.trpro.2016.05.237

Madigan, R., Louw, T., Wilbrink, M., Schieben, A., & Merat, N. (2017). What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems. *Transportation Research Part F: Traffic Psychology and Behaviour, 50*, 55-64. https://doi.org/10.1016/j.trf.2017.07.007

Malokin, A., Circella, G., & Mokhtarian, P. L. (2021). Do millennials value travel time differently because of productive multitasking? A revealed-preference study of Northern California commuters. *Transportation, 48*, 2787–2823. https://doi.org/10.1007/s11116-020-10148-2

Meyer, J., Becker, H., Bösch, P. M., & Axhausen, K. W. (2017). Autonomous vehicles: The next jump in accessibilities? *Research in Transport Economics, 62,* 80–91. https://doi.org/10.1016/j.retrec.2017.03.005

Milakis, D., & Müller, S. (2021). The societal dimension of the automated vehicles transition: Towards a research agenda. *Cities*, *113*, 103144. https://doi.org/10.1016/j.cities.2021.103144

Milakis, D., Van Arem, B., & Van Wee, B. (2017). Policy and society related implications of automated driving: A review of literature and directions for future research. *Journal of Intelligent Transportation Systems, 21(4)*, 324-348. https://doi.org/10.1080/15472450.2017.1291351

Milakis, D., & van Wee, B. (2020). Implications of vehicle automation for accessibility and social inclusion of people on low income, people with physical and sensory disabilities, and older people. In *Demand for emerging transportation systems* (pp. 61-73). Elsevier. https://doi.org/10.1016/B978-0-12-815018-4.00004-8

Millonig, A., & Fröhlich, P. (2018, September). Where autonomous buses might and might not bridge the gaps in the 4 A's of public transport passenger needs: a review. In *Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (pp. 291-297). https://doi.org/10.1145/3239060.3239079

Minhas, S., Hernández-Sabaté, A., Ehsan, S., & McDonald-Maier, K. D. (2020). Effects of non-driving related tasks during self-driving mode. *IEEE Transactions on Intelligent Transportation Systems, 23(2),* 1391-1399. https://doi.org/10.1109/TITS.2020.3025542

Mobility Innovation Centre Delft (MICD) (2022). Autonomous Driving. Retrieved from https://micd.tudelftcampus.nl/projects/autonomous-driving-passenger-experience/

Molin, E., Adjenughwure, K., de Bruyn, M., Cats, O., & Warffemius, P. (2020). Does conducting activities while traveling reduce the value of time? Evidence from a within-subjects choice experiment. *Transportation Research Part A: Policy and Practice, 132*, 18-29. https://doi.org/10.1016/j.tra.2019.10.017

Moták, L., Neuville, E., Chambres, P., Marmoiton, F., Monéger, F., Coutarel, F., & Izaute, M. (2017). Antecedent variables of intentions to use an autonomous shuttle: Moving beyond TAM and TPB? *European Review of Applied Psychology, 67*(5), 269-278. https://doi.org/10.1016/j.erap.2017.06.001

Mouratidis, K., & Serrano, V. C. (2021). Autonomous buses: Intentions to use, passenger experiences, and suggestions for improvement. *Transportation Research Part F: Traffic Psychology and Behaviour, 76*, 321-335. https://doi.org/10.1016/j.trf.2020.12.007

Narayanan, S., Chaniotakis, E., & Antoniou, C. (2020). Shared autonomous vehicle services: A comprehensive review. *Transportation Research Part C: Emerging Technologies*, *111*, 255-293. https://doi.org/10.1016/j.trc.2019.12.008

National Highway Traffic Safety Administration. (2012). *Visual-Manual NHTSA Driver Distraction Guidelines for In-Vehicle Electronic Devices* (Report No. DOT HS 811 541). https://www.nhtsa.gov/sites/nhtsa.gov/files/811541.pdf

Naujoks, F., Befelein, D., Wiedemann, K., & Neukum, A. (2018). A review of non-driving-related tasks used in studies on automated driving. In *Advances in Human Aspects of Transportation: Proceedings of the AHFE 2017 International Conference on Human Factors in Transportation*, July 17−21, 2017, The Westin Bonaventure Hotel, Los Angeles, California, USA 8 (pp. 525-537). Springer International Publishing. https://doi.org/10.1007/978-3-319-60441-1_52

Naujoks, F., Purucker, C., & Neukum, A. (2016). Secondary task engagement and vehicle automation–Comparing the effects of different automation levels in an on-road experiment. *Transportation Research Part F: Traffic Psychology and Behaviour, 38,* 67-82. https://doi.org/10.1016/j.trf.2016.01.011

Naujoks, F., Purucker, C., Wiedemann, K., & Marberger, C. (2019). Noncritical state transitions during conditionally automated driving on German freeways: Effects of non-driving related tasks on takeover time and takeover quality. *Human Factors, 61(4)*, 596-613. https://doi.org/10.1177/0018720818824002

Naz, F., & Mattingly, D. S. P. Assessing automated vehicle induced VMT: Meta analysis of current research. *Preprint.* Available at SSRN: https://ssrn.com/abstract=5030045

Nazari, F., Noruzoliaee, M., & Mohammadian, A. K. (2018). Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes. *Transportation Research Part C: Emerging Technologies*, *97*, 456-477. https://doi.org/10.1016/j.trc.2018.11.005

Nibud (2020). *Wat kost een auto?*. https://www.nibud.nl/consumenten/wat-kost-een-auto/ (accessed in September 2020).

Nibud (2023). *Autokosten* [Car expenses] Retrieved from https://www.nibud.nl/onderwerpen/uitgaven/autokosten/

Nielsen, N. H. (2021). *Head Pose Estimation* [Source code]. https://github.com/niconielsen32/ComputerVision/blob/master/headPoseEstimation.py

Noble, A. M., Miles, M., Perez, M. A., Guo, F., & Klauer, S. G. (2021). Evaluating driver eye glance behavior and secondary task engagement while using driving automation systems. *Accident Analysis & Prevention, 151,* 105959. https://doi.org/10.1016/j.aap.2020.105959

Nordhoff, S., De Winter, J., Kyriakidis, M., Van Arem, B., & Happee, R. (2018a). Acceptance of driverless vehicles: Results from a large cross-national questionnaire study. *Journal of Advanced Transportation, 2018*. https://doi.org/10.1155/2018/5382192

Nordhoff, S., de Winter, J., Madigan, R., Merat, N., van Arem, B., & Happee, R. (2018b). User acceptance of automated shuttles in Berlin-Schöneberg: A questionnaire study. *Transportation Research Part F: Traffic Psychology and Behaviour, 58*, 843-854. https://doi.org/10.1016/j.trf.2018.06.024

Nordhoff, S., Kyriakidis, M., Van Arem, B., & Happee, R. (2019). A multi-level model on automated vehicle acceptance (MAVA): A review-based study. *Theoretical Issues in Ergonomics Science*, *20*(6), 682-710. https://doi.org/10.1080/1463922X.2019.1621406

Osz, K., Rydström, A., Fors, V., Pink, S., & Brostrom, R. (2018). Building Collaborative Test Practices: Design Ethnography and WOz in Autonomous Driving Research. *Interaction Design and Architecture(s) Journal – IxD&A, 37,* 12-20. https://doi.org/10.55612/s-5002-037-001

Othman, K. (2022). Exploring the implications of autonomous vehicles: A comprehensive review. *Innovative Infrastructure Solutions*, *7*(2), 165. https://doi.org/10.1007/s41062-022-00763-6

Öztürker, M., Homem de Almeida Correia, G., Scheltes, A., Olde Kalter, M. J., & van Arem, B. (2022). Exploring users' preferences for automated minibuses and their service type: A stated choice experiment in the Netherlands. *Journal of Advanced Transportation, 2022*, 4614848. https://doi.org/10.1155/2022/4614848

Öztürker, M., de Almeida Correia, G. H., & van Arem, B. (2024). Ride experience in automated minibuses: measuring users' transport mode preferences before and after a test ride. *Transportation Research Procedia*, *78*, 335-344. https://doi.org/10.1016/j.trpro.2024.02.043

Pakusch, C., & Bossauer, P. (2017). User acceptance of fully autonomous public transport. In *Proceedings of the 14th International Joint Conference on e-Business and*

Telecommunications (ICETE 2017), 2 (pp. 52-60). ICE-B. https://doi.org/10.5220/0006472900520060

Pakusch, C., Stevens, G., Boden, A., & Bossauer, P. (2018). Unintended effects of autonomous driving: A study on mobility preferences in the future. Sustainability, 10(7), 2404. https://doi.org/10.3390/su10072404

Pech, T., Enhuber, S., Wandtner, B., Schmidt, G., & Wanielik, G. (2019). Real time recognition of non-driving related tasks in the context of highly automated driving. In *Advanced Microsystems for Automotive Applications 2018: Smart Systems for Clean, Safe and Shared Road Vehicles 22nd* (pp. 43-55). Springer International Publishing. https://doi.org/10.1007/978-3-319-99762-9_4

Pernestål, A., Darwish, R., Susilo, Y., Chee, P. N. E., Jenelius, E., Hatzenbühler, J., & Hafmar, P. (2018). *Shared Automated Vehicles-Research & Assessment in a 1st pilot: SARA1 Results report*. KTH Royal Institute of Technology. https://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1786205&dswid=146

Piao, J., McDonald, M., Hounsell, N., Graindorge, M., Graindorge, T., & Malhene, N. (2016). Public views towards implementation of automated vehicles in urban areas. *Transportation Research Procedia, 14* (pp. 2168-2177). Elsevier. https://doi.org/10.1016/j.trpro.2016.05.232

Pigeon, C., Alauzet, A., & Paire-Ficout, L. (2021). Factors of acceptability, acceptance and usage for non-rail autonomous public transport vehicles: A systematic literature review. *Transportation Research Part F: Traffic Psychology and Behaviour*, *81*, 251-270. https://doi.org/10.1016/j.trf.2021.06.008

Portouli, E., Karaseitanidis, G., Lytrivis, P., Amditis, A., Raptis, O., & Karaberi, C. (2017). Public attitudes towards autonomous mini buses operating in real conditions in a Hellenic city. *2017 IEEE Intelligent Vehicles Symposium (IV)* (pp. 571-576). Redondo Beach, CA, USA: IEEE. https://doi.org/10.1109/IVS.2017.7995779

Prioni, P., & Hensher, D. A. (2000). Measuring service quality in scheduled bus services. *Journal of Public Transportation, 3*(2), 51-74. https://doi.org/10.5038/2375-0901.3.2.4

Pudāne, B., Molin, E. J., Arentze, T. A., Maknoon, Y., & Chorus, C. G. (2018). A time-use model for the automated vehicle-era. *Transportation Research Part C: Emerging Technologies, 93,* 102-114. https://doi.org/10.1016/j.trc.2018.05.022

Pudāne, B., Rataj, M., Molin, E. J., Mouter, N., van Cranenburgh, S., & Chorus, C. G. (2019). How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands. *Transportation Research Part D: Transport and Environment, 71,* 222-235. https://doi.org/10.1016/j.trd.2018.11.014

Pudāne, B., Van Cranenburgh, S., & Chorus, C. G. (2021). A day in the life with an automated vehicle: Empirical analysis of data from an interactive stated activity-travel survey. *Journal of Choice Modelling, 39,* 100286. https://doi.org/10.1016/j.jocm.2021.100286

RailJournal. (2022, November 25). *Netherlands to spend €4bn on public transport infrastructure*. https://www.railjournal.com/policy/netherlands-to-spend-e4bn-on-public-transport-infrastructure/

Ramseyer, R., Cimmino, F., Emery, L., Grèzes, S., Grèzes, V., Nanchen, B., Simon, E. & Fragnière, E. (2018, November). Using phenomenology to assess risk perception of a new technology in public transportation the case of the autonomous vehicles as mobility as a service (MaaS) in Switzerland. In *2018 3rd International Conference on System Reliability and Safety (ICSRS)* (pp. 289-293). IEEE. https://doi.org/10.1109/ICSRS.2018.8688840

Razmi Rad, S., de Almeida Correia, G. H., & Hagenzieker, M. (2020). Pedestrians' road crossing behaviour in front of automated vehicles: Results from a pedestrian simulation experiment using agent-based modelling. *Transportation Research Part F: Traffic Psychology and Behaviour, 69*, 101-119. https://doi.org/10.1016/j.trf.2020.01.014

Ribeiro Pimenta, A., Kamruzzaman, M., & Currie, G. (2023). Long-term effects of autonomous vehicles on the built environment: a systematic scoping review towards conceptual frameworks. *Transport Reviews*, *43*(6), 1083-1117. https://doi.org/10.1080/01441647.2023.2189325

Riegler, A., Riener, A., & Holzmann, C. (2021). A systematic review of virtual reality applications for automated driving: 2009–2020. *Frontiers in Human Dynamics, 3*, 689856. https://doi.org/10.3389/fhumd.2021.689856

Rizki, M., Joewono, T. B., Dharmowijoyo, D. B., & Belgiawan, P. F. (2021). Does multitasking improve the travel experience of public transport users? Investigating the activities during commuter travels in the Bandung Metropolitan Area, Indonesia. *Public Transport*, *13*, 429-454. https://doi.org/10.1007/s12469-021-00263-3

Roche-Cerasi, I. (2019). Public acceptance of driverless shuttles in Norway. *Transportation Research Part F: Traffic Psychology and Behaviour, 66*, 162-183. https://doi.org/10.1016/j.trf.2019.09.002

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). The Free Press.

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2), 1–36. http://www.jstatsoft.org/v48/i02/

SAE International (2021). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. Retrieved from https://www.sae.org/standards/content/j3016_202104/

Salonen, A. O., & Haavisto, N. (2019). Towards autonomous transportation. Passengers' experiences, perceptions and feelings in a driverless shuttle bus in Finland. *Sustainability, 11*(3), 588. https://doi.org/10.3390/su11030588

Sanguinetti, A., Ferguson, B., Oka, J., Alston-Stepnitz, E., & Kurani, K. (2021). Designing robo-taxis to promote ride-pooling. In T. Ahram, R. Taiar, K. Langlois, & A. Choplin (Eds.), *Human interaction, emerging technologies and future applications III* (Vol. 1253, pp. 11–17). Springer. https://doi.org/10.1007/978-3-030-55307-4_2

Scikit-Learn. (n.d.). *KNNImputer*. https://scikit-learn.org/stable/modules/generated/sklearn.impute.KNNImputer.html?highlight=knn+imputer#sklearn.impute.KNNImputer

Seaman, S., Gershon, P., Angell, L., Mehler, B., & Reimer, B. (2022). Non-driving-related task engagement: the role of speed. *Safety, 8(2),* 34. http://doi.org/10.3390/safety8020034

Shaheen, S., & Bouzaghrane, M. A. (2019). Mobility and energy impacts of shared automated vehicles: A review of recent literature. *Current Sustainable/Renewable Energy Reports*, *6*, 193-200. https://doi.org/10.1007/s40518-019-00135-2

Shaheen, S., Cohen, A., Chan, N., & Bansal, A. (2020). Sharing strategies: carsharing, shared micromobility (bikesharing and scooter sharing), transportation network companies, microtransit, and other innovative mobility modes. In *Transportation, land use, and environmental planning* (pp. 237-262). Elsevier. https://doi.org/10.1016/B978-0-12-815167-9.00013-X

Shahini, F., & Zahabi, M. (2022). Effects of levels of automation and non-driving related tasks on driver performance and workload: A review of literature and meta-analysis. *Applied Ergonomics, 104*, 103824. https://doi.org/10.1016/j.apergo.2022.103824

Shi, E., & Bengler, K. (2022). Non-driving related tasks' effects on takeover and manual driving behavior in a real driving setting: A differentiation approach based on task switching and modality shifting. *Accident Analysis & Prevention, 178,* 106844. https://doi.org/10.1016/j.aap.2022.106844

Shladover, S. E. (2018). Connected and automated vehicle systems: Introduction and overview. *Journal of Intelligent Transportation Systems*, *22*(3), 190-200. https://doi.org/10.1080/15472450.2017.1336053

Singleton, P. A. (2019). Discussing the "positive utilities" of autonomous vehicles: Will travellers really use their time productively? *Transport Reviews, 39(1)*, 50-65. https://doi.org/10.1080/01441647.2018.1470584

Singleton, P. A. (2020). Multimodal travel-based multitasking during the commute: Who does what? *International Journal of Sustainable Transportation, 14(2),* 150-162. https://doi.org/10.1080/15568318.2018.1536237

Skippon, S. M., Kinnear, N., Lloyd, L., & Stannard, J. (2016). How experience of use influences mass-market drivers' willingness to consider a battery electric vehicle: A randomised controlled trial. *Transportation Research Part A: Policy and Practice, 92*, 26-42. https://doi.org/10.1016/j.tra.2016.06.034

Smolnicki, P. M., & Sołtys, J. (2016). Driverless mobility: The impact on metropolitan spatial structures. *Procedia Engineering, 161*, 2184-2190. https://doi.org/10.1016/j.proeng.2016.08.813

Sohrabi, S., Khodadadi, A., Mousavi, S. M., Dadashova, B., & Lord, D. (2021). Quantifying the automated vehicle safety performance: A scoping review of the literature, evaluation of methods, and directions for future research. *Accident Analysis & Prevention*, *152*, 106003. https://doi.org/10.1016/j.aap.2021.106003

Solís-Marcos, I., Ahlström, C., & Kircher, K. (2018). Performance of an additional task during Level 2 automated driving: An on-road study comparing drivers with and without experience with partial automation. *Human Factors, 60(6),* 778-792. https://doi.org/10.1177/0018720818773636

Sperling, D. (2018). *Three revolutions: Steering automated, shared, and electric vehicles to a better future*. Island Press. https://doi.org/10.5822/978-1-61091-906-7

Statista. (2025a). Distribution of carbon dioxide emissions worldwide in 2023, by sector. Statista. https://www.statista.com/statistics/1129656/global-share-of-co2-emissions-from-fossil-fuel-and-cement/

Statista. (2025b). Distribution of carbon dioxide emissions produced by the transportation sector worldwide in 2023, by sub sector. Statista. https://www.statista.com/statistics/1185535/transport-carbon-dioxide-emissions-breakdown/

Steg, L. (2003). Can public transport compete with the private car? *IATSS research*, *27*(2), 27-35. https://doi.org/10.1016/S0386-1112(14)60141-2

Sullman, M. J., & Taylor, J. E. (2010). Social desirability and self-reported driving behaviours: Should we be worried? *Transportation Research Part F: Traffic Psychology and Behaviour*, *13*(3), 215-221. https://doi.org/10.1016/j.trf.2010.04.004

Sun, S., & Wong, Y. D. (2022). Travel-based multitasking behaviour in Singapore: Determinants and impacts on money-time-seat trade-offs. *Travel Behaviour and Society*, *26*, 84-95. https://doi.org/10.1016/j.tbs.2021.09.005

Susilo, Y. O., Lyons, G., Jain, J., & Atkins, S. (2012). Rail passengers' time use and utility assessment: 2010 findings from Great Britain with multivariate analysis. *Transportation Research Record, 2323(1),* 99-109. https://doi.org/10.3141/2323-12

Swait, J., & Bernardino, A. (2000). Distinguishing taste variation from error structure in discrete choice data. *Transportation Research Part B: Methodological, 34*(1), 1-15. https://doi-org/10.1016/S0191-2615(99)00009-0

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge University Press. https://eml.berkeley.edu/books/choice2.html

Urry, J. (2004). The 'system' of automobility. *Theory, Culture & Society, 21*(4-5), 25-39. https://doi.org/10.1177/0263276404046059

van Gent, P., Farah, H., Nes, N. V., & van Arem, B. (2017). Towards Real-Time, Nonintrusive Estimation of Driver Workload in a Simulated Environment. In *Proceedings of the 6th International Conference on Road Safety & Simulation (RSS): 17-19 October 2017, The Hague, Netherlands.* Article 283. https://research.tudelft.nl/files/31672191/Towards_Real_Time_Nonintrusive2.pdf

Varghese, V., & Jana, A. (2018). Impact of ICT on multitasking during travel and the value of travel time savings: Empirical evidences from Mumbai, India. *Travel Behaviour and Society, 12*, 11-22. https://doi.org/10.1016/j.tbs.2018.03.003

Wadud, Z., & Huda, F. Y. (2019, February). Fully automated vehicles: the use of travel time and its association with intention to use. In *Proceedings of the Institution of Civil Engineers-Transport* (Vol. 176, No. 3, pp. 127-141). Thomas Telford Ltd. https://doi.org/10.1680/jtran.18.00134

Wardman, M. (2004). Public transport values of time. *Transport Policy*, *11*(4), 363-377. https://doi.org/10.1016/j.tranpol.2004.05.001

Wardman, M., Chintakayala, P., & Heywood, C. (2020). The valuation and demand impacts of the worthwhile use of travel time with specific reference to the digital revolution and endogeneity. *Transportation, 47(3),* 1515-1540. https://doi.org/10.1007/s11116-019-10059-x

Weidner, F., Hoesch, A., Poeschl, S., & Broll, W. (2017). Comparing VR and non-VR driving simulations: An experimental user study. In *2017 IEEE Virtual Reality (VR)* (pp. 281-282). https://doi.org/10.1109/VR.2017.7892286

Wicki, M., Guidon, S., Becker, F., Axhausen, K. W., & Bernauer, T. (2019). How technology commitment affects willingness to use AVs: Results from realistic mode choice experiment for a self-driving shuttle service. *19th Swiss Transport Research Conference. STRC.*

Winter, K., Wien, J., Molin, E., Cats, O., Morsink, P., & van Arem, B. (2019). Taking The Self-Driving Bus: A Passenger Choice Experiment. In *2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)* (pp. 1-8). IEEE. https://doi.org/10.1109/MTITS.2019.8883310

World Health Organization. (2023). Global status report on road safety 2023. World Health Organization. https://www.who.int/publications/i/item/9789240086517

World Health Organization (WHO). (2024). Ambient (outdoor) air quality and health. https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health

Xu, Z., & Zheng, N. (2024). Integrating connected autonomous shuttle buses as an alternative for public transport – A simulation-based study. *Multimodal Transportation*, *3*(2), 100133. https://doi.org/10.1016/j.multra.2024.100133

Yan, X., Levine, J., & Zhao, X. (2019). Integrating ridesourcing services with public transit: An evaluation of traveler responses combining revealed and stated preference data. *Transportation Research Part C: Emerging Technologies*, *105*, 683-696. https://doi.org/10.1016/j.trc.2018.07.029

Yan, X., Zhao, X., Han, Y., Van Hentenryck, P., & Dillahunt, T. (2021). Mobility-on-demand versus fixed-route transit systems: An evaluation of traveler preferences in low-income communities. *Transportation Research Part A: Policy and Practice*, *148*, 481-495. https://doi.org/10.1016/j.tra.2021.03.019

Yang, L., Wang, R., Zhao, X., Xu, Z., & Yang, Y. (2021). CAVTest: A closed connected and automated vehicles test field of Chang'an University in China. *SAE International Journal of Connected and Automated Vehicles, 4(12-04-04-0032),* 423-435. https://doi.org/10.4271/12-04-04-0032

Yap, M. D., Correia, G., & Van Arem, B. (2016). Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. *Transportation Research Part A: Policy and Practice, 94*, 1-16. https://doi.org/10.1016/j.tra.2016.09.003

Yu, H., Gupta, A., Lee, W., Arroyo, I., Betke, M., Allesio, D., ... & Woolf, B. P. (2021, July). Measuring and integrating facial expressions and head pose as indicators of engagement and affect in tutoring systems. In *International Conference on Human-Computer Interaction* (pp. 219-233). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-77873-6_16

Zhao, L., & Malikopoulos, A. A. (2022). Enhanced mobility with connectivity and automation: A review of shared autonomous vehicle systems. *IEEE Intelligent Transportation Systems Magazine, 14*(1), 87–102. https://doi.org/10.1109/MITS.2019.2953526

Zhao, X., Susilo, Y. O., & Pernestål, A. (2022). The dynamic and long-term changes of automated bus service adoption. *Transportation Research Part A: Policy and Practice*, *155*, 450-463. https://doi.org/10.1016/j.tra.2021.10.021

Zou, X., O'Hern, S., Ens, B., Coxon, S., Mater, P., Chow, R., Neylan, M. & Vu, H. L. (2021). On-road virtual reality autonomous vehicle (VRAV) simulator: An empirical study on user experience. *Transportation Research Part C: Emerging Technologies, 126,* 103090. https://doi.org/10.1016/j.trc.2021.103090

Zubin, I., Van Oort, N., Van Binsbergen, A., & Van Arem, B. (2021). Deployment scenarios for first/last-mile operations with driverless shuttles based on literature review and stakeholder survey. *IEEE Open Journal of Intelligent Transportation Systems*, *2*, 322-337. https://doi.org/10.1109/OJITS.2021.3106164

About the Author

Maryna Öztürker was born in Lutsk, Ukraine. From an early age, she developed a keen interest in cities and how people move within them, which inspired her to study Urban Development and Management at Lutsk State Technical University (Lutsk, Ukraine). She obtained both her Bachelor's and Master's degrees with distinction, specialising in Public Transport and Communication Lines.

After graduation, she joined Lutsk National Technical University as a lecturer, teaching courses and supervising master's theses. Alongside her academic work, she gained professional experience as an architect and urban planner, contributing to several urban development projects in Lutsk, Ukraine.

In 2013, Maryna moved to the Netherlands and in 2015 joined the Department of Transport and Planning in Delft University of Technology as a guest researcher. Three years later, she began her PhD studies here, exploring how automated public transport may reshape people's travel experiences and choices. Her research combines survey design, stated preference experiments, discrete choice modelling, and empirical ride studies.

Throughout her academic journey, Maryna has presented her work at webinars, workshops and an international conference and published in peer-reviewed journals. Her paper "Ride experience in automated minibuses: measuring users' transport mode preferences before and after a test ride" received the Best Paper Award of the session Innovate and Sustainable Solutions at the Euro Working Group Transportation (EWGT 2023) conference in Santander, Spain.

Beyond research, she enjoys playing piano, dancing, travelling, and exploring the psychological and philosophical aspects of human behaviour.

List of Publications

Journal papers

- Öztürker, M., Homem de Almeida Correia, G., Scheltes, A., Olde Kalter, M. J., & van Arem, B. (2022). Exploring users' preferences for automated minibuses and their service type: A stated choice experiment in the Netherlands. *Journal of Advanced Transportation, 2022*, 4614848. https://doi.org/10.1155/2022/4614848

- Öztürker, M., Nordhoff, S., Hoogendoorn-Lanser, S., van Arem, B., & Homem de Almeida Correia, G. (2026). Use of travel time in a shared automated vehicle for work and leisure: Results from a field experiment with a Wizard-of-Oz simulator-on-wheels vehicle. *Transportation Research Part C: Emerging Technologies*, *188*, 105646. https://doi.org/10.1016/j.trc.2026.105646

Peer-Reviewed Conference Papers

- Öztürker, M., de Almeida Correia, G. H., & van Arem, B. (2024). Ride experience in automated minibuses: measuring users' transport mode preferences before and after a test ride. *Transportation Research Procedia*, *78*, 335-344. https://doi.org/10.1016/j.trpro.2024.02.043

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Summary

This thesis explores how automated public transport, including automated minibuses and shared automated vehicles, can improve service quality and influence user preferences. Combining literature review, stated-preference experiments, pilot rides and a Wizard-of-Oz study, it shows that service design, user segmentation and real ride experience are crucial for building trust, supporting adoption and integrating automated mobility into sustainable public transport systems.

About the Author

Maryna Öztürker is a transport researcher from Ukraine. She holds Bachelor's and Master's degrees in Urban Development and Management and completed her PhD at TU Delft, studying user preferences for automated public transport.

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