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UNDERSTANDING CHANGES IN DECISION-MAKING PROCESSES
TO ADOPT FIRST-/LAST-MILE AUTOMATED BUS SERVICE

CHEE PEI NEN (ESTHER)

School of Civil and Environmental Engineering, NTU
School of Architecture and the Built Environment, KTH

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School of Architecture and the Built Environment, KTH

A thesis submitted to
the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy
2020

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I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

18 August 2020

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Date

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Prof. Yusak O. Susilo

AUTHORSHIP ATTRIBUTION STATEMENT

This thesis contains material from three papers published in the following peer-reviewed journals in which I am listed as an author.

Chapter 2 section 2.1.1 and Chapter 4 are published as

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The contributions of the co-authors are as follows:

- Prof. Yusak O. Susilo provided the initial project direction.
- I prepared the manuscript drafts. The manuscript was revised by Prof. Yusak O. Susilo, A/Prof. Wong Yiik Diew, and Dr. Anna Pernestål.
- I co-designed the survey study with Prof. Yusak O. Susilo and Dr. Anna Pernestål.
- I conceptualised the methodology and analysed the data.

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- I co-designed the survey study with Prof. Yusak O. Susilo.
- I conceptualised the methodology and analysed the data.

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- I conceptualised the methodology and analysed the data.

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SUMMARY

This research investigates the changes in the interactions of objective factors (factors which are independent of perception e.g. socio-demographic characteristics), subjective factors (psychological factors which are inherent in individual), and user's behavioural responses towards a new technology/service in response to actual experience with the technology/service. In specific, this research investigates the changes in decision-making parameters to adopt first-/last-mile automated bus service over three important adoption stages, as specified in diffusion of innovations theory: 1. decision (before any actual ride experiences), 2. implementation (first trial) and 3. continuation (after the first trial).

Findings show that objective factors have both direct and indirect influences on users' behavioural responses towards a new technology. There are dominant perceptions towards the technology among the same group of people with same socio-demographic characteristics/ travel characteristics / familiarity with the technology. However, the relationships between the objective factors with the associated perceptions are not stable when the users have gathered incomplete information about the technology. Decision made without complete information about the technology is subjected to logical fallacy. Consequently, the decision made is irrational and subject to changes after an individual gains complete information about the new technology/service through actual experience with the new technology/service.

Actual ride experiences provide users complete information about the technology. As compared to the behavioural responses of first-time users, the behavioural responses of the adopters (users who continued with the service after first trial) is stable and consistent. Also, reinforcement learning process was found exist in the adopters of the first-/last mile automated bus service. The findings give a strong evidence that users' level of information about a

new technology/service has significant impact on the stability of the representation of both the objective and subjective factors.

As a conclusion, users' level of information about a new technology/service has crucial impact on the reliability of the representation of the objective factors and subjective factors identified from the travel behaviour studies of new technology/service like automated vehicle/bus. The decision made when users have incomplete information of a new technology is irrational and subject to changes. Hence, the representation of the objective factors and subjective factors identified from hypothetical studies which the respondents lack real experience with automated vehicle/bus technology is unreliable. On the other hand, actual experience provides users with complete information about the new technology/service and allow users to learn about the technology/service. As a result, users can make a more rational decision hence the representation of the identified objective factors and subjective factors is reliable.

As another contribution of this research, a systematic approach to obtain objective measurements from real-world pedestrian-automated bus interactions using Light Detection and Ranging (LiDAR) data is also demonstrated in this thesis. The key parameters obtained from the analysis can be used to check against the existing road design principles to anticipate the implementation of ABs on the road. The approach developed can also be used as the fundamental framework to measure the safety risk between a crossing pedestrian with an automated vehicle/bus.

SAMMANFATTNING

Denna forskning undersöker förändringarna i interaktionen mellan objektiva faktorer (faktorer som är oberoende av uppfattningen, t.ex. sociodemografiska egenskaper), subjektiva faktorer (psykologiska faktorer som är inneboende i individen) och användarens beteendemässiga svar gentemot en ny teknik / tjänst som svar på verklig erfarenhet av tekniken / tjänsten. I synnerhet undersöker denna forskning förändringarna i beslutsfattande parametrar för att anta första / sista mils självkörande busstjänst över tre viktiga antagningssteg, som specificeras i spridning av innovationsteorin: 1. beslut (före några faktiska självkörande bussresaupplevelser), 2 genomförande (första försöket) och 3. fortsättning (efter första försöket).

Resultaten visar att objektiva faktorer har både direkt och indirekt påverkan på användarnas beteendemässiga svar mot en ny teknik. Det finns dominerande uppfattningar om tekniken bland samma grupp människor med samma sociodemografiska egenskaper / reseegenskaper / förtrogenhet med tekniken. Relationerna mellan de objektiva faktorerna med tillhörande uppfattningar är dock inte stabila när användarna har samlat in ofullständig information om tekniken. Beslut som fattas utan fullständig information om tekniken utsätts för logisk felaktighet. Följaktligen är beslutet irrationellt och föremål för förändringar efter att en individ fått fullständig information om den nya tekniken / tjänsten genom faktisk erfarenhet av den nya tekniken / tjänsten.

Faktiska självkörande bussresaupplevelser ger användarna fullständig information om tekniken. Jämfört med beteendemässiga svar från förstagångsanvändare är adopterarnas (användare som fortsatte med tjänsten efter första försöket) beteendemässiga svar stabila och konsekventa. Det fanns också inlärningsprocesser för förstärkning i antagarna av den första / sista mils självkörande busstjänsten. Resultaten ger ett starkt bevis för att

användarnas informationsnivå om en ny teknik / tjänst har en betydande inverkan på stabiliteten i representationen av både de objektiva och subjektiva faktorerna.

Som en slutsats har användarnas informationsnivå om en ny teknik / tjänst avgörande inverkan på tillförlitligheten i representationen av de objektiva faktorerna och subjektiva faktorer som identifierats från resebeteendestudierna med ny teknik / tjänst som självkörande fordon / buss. Beslutet som fattas när användare har ofullständig information om en ny teknik är irrationellt och kan komma att ändras. Därför är representationen av de objektiva faktorer och subjektiva faktorer som identifierats från hypotetiska studier som respondenterna saknar verklig erfarenhet av självkörande fordons- / bussteknik opålitlig. Å andra sidan ger den faktiska upplevelsen användarna fullständig information om den nya tekniken / tjänsten och låter användarna lära sig mer om tekniken / tjänsten. Som ett resultat kan användare fatta ett mer rationellt beslut, varför representationen av de identifierade objektiva faktorerna och subjektiva faktorerna är tillförlitliga.

Som ytterligare ett bidrag från denna forskning demonstreras också ett systematiskt tillvägagångssätt för att erhålla objektiva mätningar från verkliga fotgängar-automatiserade bussinteraktioner med Light Detection and Ranging (LiDAR)-data i denna avhandling. De viktigaste parametrarna som erhållits från analysen kan användas för att kontrollera mot befintliga principer för vägkonstruktion för att förutse implementeringen av AB på vägen. Det utvecklade tillvägagångssättet kan också användas som den grundläggande ramen för att mäta säkerhetsrisken mellan en korsande fotgängare med ett självkörande fordon / buss.

LIST OF PUBLICATIONS

The following publications, papers or articles are sorted by type and are in chronological order of publication and the contribution of the thesis author in each paper is specified.

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1. Chee, P.N.E., Susilo, Y.O., Pernestål, A., & Wong, Y.D. (2020). "Which factors affect willingness-to-pay for automated vehicle services? Evidence from public road deployment in Stockholm, Sweden." *European Transport Research Review* 12(20), DOI: [10.1186/s12544-020-00404-y](https://doi.org/10.1186/s12544-020-00404-y) (Study 1 of this thesis is adapted from this paper)
(Contributions: Conceptualization, Methodology, Formal analysis, Investigation, Writing - Original Draft)
2. Chee, P.N.E., Susilo, Y.O., Wong, Y.D. (2020). "Determinants of intention-to-use first-/last-mile automated bus service." *Transportation Research Part: A*, 139 (Sep), 350-375. DOI: 10.1016/j.tra.2020.06.001 (Study 3 of this thesis is adapted from this paper)
(Contributions: Conceptualization, Methodology, Formal analysis, Investigation, Writing - Original Draft)
3. Chee, P.N.E., 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 (Jan), 252-261. DOI: 10.1016/j.tbs.2020.10.004 (Study 2 of this thesis is adapted from this paper)
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Research Articles

1. Chee, P.N.E., Susilo, Y. O., Pernestål, A., & Wong, Y. D. (2020). "Assessing pedestrian midblock road-crossing risk when interacting with automated bus" (*Under revision*) (Study 4 of this thesis is adapted from this paper)
(Contributions: Conceptualization, Methodology, Formal analysis, Investigation, Writing - Original Draft)

2. Susilo, Y. O., Darwish, R., Pernestål, A., & Chee, P. N. E. (2020). Book chapter “Lessons from the Deployment of the World First Automated Bus Service on a Mixed Public Road in Stockholm”. In *Nectar Book: Transport in Human Scale Cities. (Ready for publication)*
(Contributions: Writing - Review & Editing, Knowledge Sharing based on early findings from Study 1 to Study 4 of this thesis)

Research Project Report

1. Pernestål, A., Darwish, R., Susilo, Y.O., Chee, P.N.E., Jenelius, E., Hatzenbuehler, J., & Hafmar, P. (2018). *SARA1 Results Report: Shared Automated Vehicles - Research & Assessment in a 1st pilot*. Retrieved from
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(Contributions: Writing - Review & Editing, Knowledge Sharing based on early findings from Study 1 and Study 3 of this thesis)

GLOSSARY

Accessibility (public transport) – Having access to public transport services.

Demand responsive – One type of shared private transport service which vehicles (can be taxis, buses, automated buses or other vehicles) alter their routes based on particular transport demand rather than using a fixed route or timetable.

Cluster analysis – A multivariate method to classify a sample of subjects into a number of different groups based on the similarity in the measured variables.

Cross-sectional study – A type of observational study which looks at data only at one specific point in time.

Factor analysis – A statistical method to reduce a large number of variables into fewer numbers of factors.

First-mile – Travel trip from workplace, school or home to a metro station / a train station.

Hedonic attribute – Attribute which is associated to emotional or sensory experiences of a consumer of a product/service (Batra & Ahtola, 1991).

Integrated Choice and Latent Variable model – A hybrid model of a multinomial discrete choice model and a latent variable model.

Intention-to-use – The strength of one's intention to perform a specified behaviour.

Last-mile – Travel trip from a metro station / a train station to workplace, school or home.

Latent variable – Variable which is not directly observed but is inferred from other observed variables.

Midblock crossing – Cross a road in the middle of a building block without using crossing facilities e.g. zebra crossing.

Objective factors – Factors which are independent of perception or an individual's conceptions.

On-demand transport service – It is designed to provide passengers with flexibility around the route they take and the time they travel.

Panel study – A longitudinal study design in which repeated measures are collected from the same sample at different points in time.

Personal car – Car for personal use.

Principal component analysis – An orthogonal linear transformation which transforms data to a new coordinate system such that the greatest variance by some scalar projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on.

Provision – The action of supplying or providing something for use.

Service quality attribute perception – In the context of public transports, it means perception about the attributes of the service quality of a public transport services such as safety and security, accessibility, cleanliness, and frequency.

Stated choice experiment – A type of experiment which the relative importance of attributes to individuals is elicited by presenting a series of

choice sets where the levels of the attributes are changed across the sets to the respondent.

Structural equation modelling – A multivariate statistical analysis technique which combines factor analysis and multiple regression analysis to analyse the structural relationship between measured variables and latent constructs.

Subjective factors – Psychological factors which are inherent in individual e.g. perceptions, motives and habits.

Unsignalised midblock crossing – Pedestrian crosses a road between two intersections without using any crossing-facilities e.g. zebra-crossing.

Willingness-to-pay – The maximum price at or below which a consumer will definitely pay for a service.

LIST OF ABBREVIATIONS

AB – Automated bus	LiDAR – Light Detection and Ranging
AV – Automated vehicle	LOS – Level of service
AVE – Average variance extracted	PAV – Personalized automated vehicle
ASR – Adjusted Standardised Residuals	PCA – Principal component analysis
CAV – Connected automated vehicle	PET – Post-Encroachment Time
CFI – Comparative fit index	PICUD – Potential Index for Collision with Urgent Deceleration
CIF – Criticality Index Function	PMD – Personal mobility devices
CMIN/df – Minimum discrepancy	PSD – Proportion of Stopping Distance
CMV – Common method variance	RMSEA – Root Mean Square Error of Approximation
CR – Composite reliability	SAV – Shared automated vehicle
CFA – Confirmatory factor analysis	SEM – Structural equation modelling
CPI – Crash Potential Index	SRMR – Standardised Root Mean Square Residual
DOI – Diffusion of Innovations Theory	TAM – Technology Acceptance Model
DRAC – Deceleration Rate to Avoid a Crash	TDPI – Time difference to the point of intersection
DSPP – Distance between Stop Position and Pedestrian	TET – Time-Exposed Time-to-Collision
DSS – Difference of Space distance and Stopping Distance	TIB – Theory of Interpersonal Behaviour
GFI – Goodness of Fit	TIT – Time-Integrated Time-to-Collision
H – Headway	TPB – Theory of Planned Behaviour
ICLV – Integrated Choice and Latent Variable	TRA – Theory of Reasoned Action
IM – Igbaria's Model	TTC – Time-to-collision
IPA – Importance-performance analysis	
ITU – Intention-to-use	

TTM – Transtheoretical Model of Change

U&G – Uses and Gratification Theory

UTAUT – Unified Theory of Acceptance and Use of Technology

VIF – Variance inflation factor

WTP – Willingness-to-pay

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1 INTRODUCTION

This chapter begins with *Background* which explains the context of this research, followed by *Research problems* which highlights the research gaps identified with regard to the individual's decision-making parameters and behavioural responses towards first-/last-mile automated bus (AB) service. This chapter also covers the framework adopted in this research and the thesis outline.

1.1 Background

Public transportation can offer a time- and cost-effective mobility service for people moving around in urban areas. However, people prefer driving their own vehicle rather than taking public transport when they experience dissatisfactory service with first-/last-mile access to main public transport stations (Wang & Odoni, 2016). Small ABs such as the EZ10 and the Autonom Shuttle may be effectively implemented to improve first-/last-mile connections, which, in turn, increases the overall effectiveness and attractiveness of public transport.

ABs may be deployed as an on-demand service within the public bus system. An AB has a larger capacity than an automated car, increasing accessibility to the service (Meyer et al., 2017). The on-demand aspect of their availability plausibly retains some of the flexibility of driving a personal car. Prospective riders, instead of having to walk some distance to a nearby bus stop and/or endure lengthy waiting times for a bus during non-peak periods, can instead request for AB service through a smartphone application, and, in return, they are provided with a shared-ride service at their doorstep within a shorter waiting time, potentially resulting in a quicker journey time overall. Such an on-demand AB service is especially valuable during non-peak periods when the frequency of bus services tends to be low.

In addition, AB services can also contribute to reducing road congestion during peak periods. Ride-sharing has been found to be beneficial towards reducing vehicular traffic flow: at least 50% of single-person trips (based on the trip data collected from smartphone applications) across 1267 zones over 30 days in the Orlando metropolitan area can be rendered into shared-trip service with only a maximum five minute increase in travel time, without changing the passengers' travel patterns (Gurumurthy

& Kockelman, 2018). Furthermore, replacing low-demand bus lines with a smaller size AB shuttle service can potentially enhance overall bus service quality by reducing passenger-vehicle-kilometres for passengers, while accruing higher profit per kilometre for the service's operators (Shen et al., 2018).

Moreover, ABs have the added benefit of being environmentally sustainable. One AB can replace about eleven conventional vehicles with at least 5% adoption rate, resulting in a reduction in air pollutants emission and energy consumption (Fagnant & Kockelman, 2014). ABs also reduce parking demand, hence reducing the necessity of space for parking facilities (Zhang et al., 2015). The reclaimed space can be used to serve the communities' need for a more sustainable and liveable environment.

Every coin has two sides. Although ABs have been successfully programmed and tested, there remain possible safety risks caused by faulty code from the software, sensor failures in drastic weather, or insufficient knowledge and/or ability to react to in complex scenarios. On top of that, AVs/ABs are subject to hacking due to their reliance on software and wireless connectivity. Also, some existing jobs (e.g. bus drivers) will be replaced with the implementation of AB services. However, the impact on the employment market can be moderated through helping the existing workforce upgrade their skills.

Nevertheless, integrating ABs into the public transport system remains an option for reducing reliance on private car use by providing people more attractive and sustainable transport alternatives with better first-mile and last-mile travel experience. However, the successful implementation of an AB service depends on users' actual uptake of the service, which is greatly influenced by their acceptance of the service.

1.2 Research problems

Travellers' decisions to move from one place to another, including both choice of route and choice of transport mode, are an important aspect of travel behaviour. Other than the built environment (e.g. land use and travel distance, etc.) and weather conditions, the traveller's decision to use any given transport mode is affected by their perceptions

(Gao et al., 2019; Jen et al., 2011; Mokhtarian & Salomon, 2010; Panter et al., 2010; Rojas López & Wong, 2019; Şimşekoğlu et al., 2015; Susilo et al., 2010).

People demonstrate different level of readiness to adopt a new innovation (Rogers, 2002). Likewise, people respond differently to a newly introduced transport service over time (Termida, 2017). Such dynamic changes in individuals' perceptions contribute to the variability in the decision to use the transport service. Understanding the decision-making process at the individual level is especially important to the provision of a new transport service. Using the example of a first-/last-mile AB service, variability among and within each of the users' behavioural responses to the AB service would impact both short-term and long-term demands of the service and thus the viability of operating the AB service.

Individuals' behavioural responses to automated vehicles (AVs) (of which the AB is one) were first investigated from a microeconomic perspective, considering objective factors, including 1. socio-demographic variables e.g. age (Rödel et al., 2014; Bansal et al., 2016), gender (Schoettle & Sivak, 2014; Payre et al., 2014; Rödel et al., 2014; Salonen, 2018), income (Sanbonmatsu et al., 2018), and use of multiple modes (Krueger et al., 2016); 2. travel time using ABs (Scheltes & de Almeida Correia, 2017; Bansal et al., 2016); 3. waiting time for ABs (Scheltes & de Almeida Correia, 2017); and 4. travel fare (Piao et al., 2016). Studies which focus on the objective factors were built according to the utility maximisation theory, which assumes that individuals choose the transport mode which maximises their utility. However, such an assumption and approach is scrutinised due to the decontextualisation of the choice behaviour from an individual's learning process of a new innovation through experiencing, intending, attuning, and acting (Dijst et al., 2008). This is the first research gap identified in this study. This research shall look at how subjective factors used to measure user experience in terms of service quality perceptions affect behavioural responses towards AV services, given the potential users had been exposed to AV technology to address the research gap.

Besides, subjective factors, including onboard safety (Piao et al., 2016; Salonen, 2018), seat comfort, noise from hydraulic compress, AB capacity, service route,

operation hours, availability of the information about AB (Eden et al., 2017), and existence of an on-board steward (Piao et al., 2016), were also explored in the studies investigating individuals' behavioural responses towards AB service. However, not only are the interactions of attitudinal variables with an individual's decision to use the AB service important, but the interactions between the objective factors (e.g. socio-demographic variables) and the subjective factors (e.g. user perceptions of the service attributes) are also important to understand individuals' behavioural responses to AV or AB service. The interactions contain important information to explain the decision-making criteria of various groups of users, each with unique characteristics. For example, the inclusion of attitudinal latent variables in the Integrated Choice and Latent Variable (ICLV) model provides information about the service requirements of the early adopters. This is the second research gap identified in this study. In order to address this gap, this research shall investigate the interactions between the objective and subjective factors which contribute to intention-to-use (ITU) a new transport service.

Psychological theories, including the Theory of Planned Behaviour (TPB) (Buckley et al., 2018) and the extended Technology Acceptance Model (TAM); (Buckley et al., 2018; Choi & Ji, 2015; Jiang et al., 2019; Panagiotopoulos & Dimitrakopoulos, 2018; Xu et al., 2018), were applied to identify the psychological constructs affecting acceptance of AV, given that the users were exposed to virtual experiences with AV through simulations. Perceived usefulness, trust, and perceived ease of use are significant latent variables influencing people's acceptance of AV technology (Panagiotopoulos & Dimitrakopoulos, 2018). Other than the TPB and extended TAM models, the Unified Theory of Acceptance and Use of Technology (UTAUT) model was applied, and the changes in the UTAUT psychological constructs of 14 participants who experienced a simulated on-demand automated shuttle service were investigated (Distler et al., 2018). However, the results obtained from the simulations have the limitation of being distant from the actual experience with the AV technology/service. This is the third research gap identified in this study, and in order to address this gap, this research shall examine the decision-making parameters of ITU a new transport service from users who have actual experiences with the new transport service.

Behavioural responses towards a product/service are related to or inherent in the use of a product (Jensen, 2002). User experience was found to affect perceived usefulness, trust, and perceived ease of use of a private-use AV (Xu et al., 2018), and behavioural responses and decision-making criteria to use a service (e.g. first-/last-mile AB service) change over time with further experiences (Mick & Fournier, 1996; Youn & Lee, 2019). Behavioural change such as adoption of first-/last-mile AB service does not happen as a single event but in several stages. According to the diffusion of innovations (DOI) theory (Rogers, 2002), a user's adoption of a new innovation involves five stages: 1. knowledge¹, 2. persuasion², 3. decision³, 4. implementation⁴, and 5. continuation⁵; experience is one of the five main factors that affect an individual's adoption of a new innovation (Rogers, 2002).

Besides the DOI model, the Transtheoretical Model of Change (TTM) Prochaska, 2008) was adopted by Langbroek et al. (2017) to investigate the changing of behaviour from a conventional vehicle to an electric vehicle in Stockholm. There are five stages of behavioural changes in TTM: 1. pre-contemplation⁶, 2. contemplation⁷, 3. preparation⁸, 4. action⁹, and 5. maintenance¹⁰. Applications of TTM on health psychology and in Langbroek et al. (2017) were built on the assumption that the existing behaviour is problematic, which requires a change to new behaviour (e.g. unhealthy behaviour/not being environmentally friendly). Self-efficacy (the perceived ability to perform a new behaviour) and knowledge about EVs increased from the earlier to the later stages, and the attitude towards EVs became more positive over the stages; these two

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¹ During *knowledge* stage, an individual is first exposed to an innovation, but lacks information about the innovation.

² During *persuasion* stage, an individual is interested in the innovation and actively seeks related information.

³ During *decision* stage, an individual takes the concept of the change and weighs the advantages/disadvantages of using the innovation and decides whether to adopt or reject the innovation.

⁴ During *implementation* stage, an individual employs the innovation to a varying degree depending on the situation. During this stage the individual also determines the usefulness of the innovation and may search for further information about it.

⁵ During *continuation* stage, an individual finalizes his/her decision to continue using the innovation.

⁶ During *pre-contemplation* stage, an individual has no intention to change behaviour. Also, the individual has very little awareness of the negative effects of the existing behaviour.

⁷ During *contemplation* stage, intention to change behaviour starts to develop but at quite an abstract level.

⁸ During *preparation* stage, an individual starts a concrete plan to change the behaviour.

⁹ During *action* stage, changing of behaviour occurs.

¹⁰ During *maintenance* stage, an individual gets used to new behaviour after gaining experience with the new behaviour.

evidences support the presence of the individual's learning process in the adoption of new behaviour/transport model (Langbroek et al., 2017).

Many cross-sectional studies have investigated behavioural responses towards AV/AB technology or service. Since people take time to learn about a new innovation and respond to the innovation in different stages as demonstrated (Langbroek, 2018; Termida, 2017), having a cross-sectional study may not be sufficient because user acceptance of AV/AB technology or service is a dynamic process. The recent studies investigating adoption behaviour of AV/AB service focused on capturing the behavioural determinants towards acceptance of the technology (Acheampong & Cugurullo, 2019a; Hilgarter & Granig, 2020; Hutchins et al., 2019; Lijarcio et al., 2019; Paddeu et al., 2020; Papadima et al., 2020; Rahimi et al., 2020; Salonen & Haavisto, 2019; S. Wang et al., 2020; Jingwen Wu et al., 2020). However, other than Hilgarter and Granig (2020), Hutchins et al. (2019), Paddeu et al. (2020), Papadima et al. (2020), and Salonen and Haavisto (2019), the rest of the studies investigated the adoption behaviour of AV/AB hypothetically, meaning the respondents did not have real experiences with the technology.

Hutchins et al. (2019) and Paddeu et al. (2020) recognised the possible fallacy in the representation of behavioural determinants drawn from the hypothetical studies when the respondents had no actual experiences with the technology. However, the two studies did not examine the changes in the behavioural determinants given that users gain actual experience with the technology/service. Hutchins et al. (2019) investigated the impact of service experience delivered through virtual reality (VR) on the respondents' decision-making parameters to use safety-critical vehicle systems. Paddeu et al. (2020) focused on investigating the impact of social influence on acceptance of shared AV services through a qualitative survey and a co-design process of the service.

Through qualitative surveys, Hilgarter and Granig (2020), Papadima et al. (2020), and Salonen and Haavisto (2019) did investigate users' perceptions towards AB services after the users had actual experience with the service. Still, the studies were cross-

sectional studies for which the changes in the decision-making parameters to use the service in response to users' actual experience with the technology were not explored. This is the fourth research gap identified in this study, and to address this gap, this research shall investigate the interactions of decision-making parameters of ITU a new transport service with increasing actual ride experiences. A longitudinal panel study can be used to capture the behavioural changes overtime, with a level of detail which is necessary to unravel true causality, minimising the ecological correlation attributable to the aggregation of information.

According to the Kano model (Kano et al., 1984), the relationships of individuals' decision-making criteria with behavioural responses towards a transport service may not always be linear. Extended from Kano's alternative models, the three-factor theory (Matzler et al., 2004) categorises individuals' decision-making criteria as follows: 1. basic factor, 2. performance factor, and 3. exciting factor. The basic factor influences the behavioural response towards a transport service most visibly when the service is underperforming, and there is no impact on behavioural response towards a transport service when it is performing adequately. The performance factor impacts the behavioural response towards a transport service when the service is either underperforming or overperforming, and the exciting factor influences behavioural response towards a transport service most visibly when the service is overperforming, but there is no influence on behavioural response towards a transport service when it is underperforming.

Allen et al., (2019) adapted Kano's theory to understand an individual's requirements from a transport service within the framework of Maslow's hierarchy of (transit) needs. Users' transit needs are hierarchical. The basic level of need is relevant in affecting users' behavioural response towards a transport service when it is not at a satisfactory level. Once the basic level of need is fulfilled, it becomes irrelevant, and the next level of need e.g. safety, becomes relevant. Understanding the dynamic changes in the relationships of users' decision-making criteria with their behavioural responses towards first-/last-mile AB gives useful guidelines for the design, maintenance, and improvement of the service. This is the fifth research gap identified in this study, and to fill this gap, this research shall investigate the interactions of decision-making

parameters of ITU a new transport service in relation to the dynamic relationships of users' service quality needs with ITU a new transport service.

Not only are individuals' behavioural responses an important factor to the successful implementation of first-/last-mile AB service, but so too is having good road infrastructure to support this implementation. In order to anticipate the changes of road design principle in light of the incoming travel mode, it is important to analyse real-world on-the-road interactions between road users with AV/AB to derive important operational parameters to aid the understanding of road users' responses to the AV/AB and to improve the road design, with safety concerns in mind. This is the sixth research gap identified in this study, and to address this gap, this research shall identify and analyse the important operational parameters to aid understanding of road users' responses to the AV/AB. This research focuses on the interaction between crossing pedestrians and an oncoming AB when pedestrians cross at midblock without using any crossing facility.

With the identified research gaps in mind, this thesis reflects upon the investigation of the changes in an individual's decision-making parameters to adopt first-/last-mile AB service, driven by 1. actual exposure to the service, 2. actual experiences with the service, and 3. the relativity of an individual's decision-making parameters with ITU the service. Moreover, this research ventures into an analysis of real-world pedestrians' interaction with an AB to derive important operational parameters to aid road design in light of the incoming travel mode. The following five research questions are formulated to address the identified research gaps:

Research question 1 (RQ1) – How do subjective factors (e.g. perceptions of service quality) used to measure user experience affect behavioural responses towards AV services?

Research question 2 (RQ2) – How do objectives factors interact with the subjective factors which affect intention-to-use a new transport service?

Research question 3 (RQ3) – What are the changes in the decision-making parameters of intention-to-use a new transport service in response to actual ride experiences?

Research question 4 (RQ4) – How do decision-making parameters of intention-to-use a new transport service vary in relation to the dynamic relationships of users' service quality needs with intention-to-use a new transport service?

Research question 5 (RQ5) – What are the important indicators which govern the interactions between crossing pedestrians and ABs when the pedestrians cross at unsignalised midblock points?

1.3 Research framework

This research investigates the changes in decision-making parameters to adopt a new transport service/innovation (first-/last-mile AB service) in three stages through *study 1*, *study 2*, and *study 3*. Additionally, this research ventures into the analysis of real-world pedestrians' interaction with an AB in *study 4*.

In order to address RQ1 and RQ2, *study 1* investigates behavioural responses in terms of the willingness-to-pay (WTP) of the potential users given the service being delivered in three different ways (1. on-demand personalised AV service, 2. demand-responsive shared AV service, and 3. first-/last-mile AB service). *Study 1* not only investigates the effects of objective factors (e.g. socio-demographic variables, travel characteristics, etc.) but also the effects of subjective factors (e.g. service attributes expectations) on WTP, as well as the interactions between the objective and subjective factors. Moreover, the behavioural responses were investigated given that the users had been exposed to the technology daily, compared with most previous studies which heavily depended on stated preferences studies.

In order to address RQ3, *study 2* examines the changes in the interactions of decision-making parameters, due to an increase in experience after the first usage and the subsequent usage of a first-/last mile AB service through a 2-wave longitudinal panel study. Panel data has the advantage to explain the types of shifts in attitudes between

time periods. Furthermore, the factors which drive the shifts in attitudes can be explained.

Subsequently, to address RQ4, *study 3* investigates the changes in the interactions of decision-making parameters driven by the user's relativity value of service quality provision. Such interactions highlight the hierarchical impacts of attitudinal factors on users' ITU the first-/last-mile AB service. This information helps the service operators to prioritise the areas to improve.

The first three studies (*study 1* to *study 3*) form the main pillar of this research. As a small pillar, this research also ventures into investigating the objective measurement of acceptance of AB technology in terms of pedestrians' perceived safety risk when the pedestrians interact with an AB operating on the road using real-world pedestrian-AB interactions data, as reflected in *study 4*, which aims to address RQ5. The objective is to understand how pedestrians' speed changing strategies are affected by the safety risk when interacting with an AB at the midblock using real-world pedestrian-AB interaction data. Figure 1.1 illustrates how the studies address the research questions at hand.

Figure 1.1 Illustration of how each study addresses the identified research questions

1.4 Thesis outline

Figure 1.2 shows the outline of this thesis. This thesis is organised into eight chapters. *Chapter 1* is the introductory chapter in which research problems, research gaps, research questions, research framework, and thesis outline are discussed. *Chapter 2* gives the literature review on 1. *decision-making parameters to adopt first-/last-mile AB service*, 2. *effects of actual experiences on the relationships of users' perceived values with ITU*, 3. *the asymmetric relationships of user perceptions with ITU*, and 4. *pedestrian interactions with AV/AB*. The research gaps identified from *Chapter 1* and *Chapter 2* are addressed by four studies, *study 1* to *study 4*, which are presented in *Chapter 4* to *Chapter 7*.

Chapter 3 describes the data sets used in this research. Two types of data – survey data and Light Detection and Ranging (LiDAR) data – are collected and analysed in this research. Survey data set 1 and survey data set 2 are data collected from a two rounds panel survey, in conjunction with a trial operation of first-/last mile AB service in Kista, Stockholm. The respondents of the panel survey are the people who were truly exposed to the new transport service in the trial operation area of a first-/last mile AB service (the areas near Helenelund commuter train station and Kista Science City). LiDAR data, which captures the real-world interactions between pedestrians and an oncoming AB when crossing at the unsignalised midblock, is collected using a LiDAR device mounted on the front of an AB operated in Kista and Barkarby, Stockholm. Survey data set 1 is used in *study 1* and *study 3*; both survey data set 1 and data set 2 are used in *study 2*; LiDAR data is used in *study 4*.

Lastly, this thesis ends with *Chapter 8*, in which conclusions, research contributions, limitations, and recommendations for future research and practical implications of the findings are presented.

Figure 1. 2 Thesis outline

2 LITERATURE REVIEW

Literature review is carried out to understand the subject areas connected to each research question. First, this chapter investigates connections of objective factors (e.g. socio-demographic variables and travel characteristics) and subjective factors (e.g. service quality attributes perceptions) with behavioural responses towards AV services in terms of WTP and ITU first-/last-mile AB service. Then, literature review is performed to understand the changes in decision-making parameters to adopt a new transport service in response to increasing ride experiences. Continuously, literature review is conducted to study the dynamic relationships between users' service quality attribute perceptions with users' ITU a transport service. Lastly, it ends with a review of the past research methods used to analyse pedestrian's interactions with an AV.

2.1 Understanding decision-making parameters to adopt first-/last-mile AB service

This sub-section aims to understand the individual's decision-making parameters of WTP and ITU AV/AB services. This sub-section first looks at WTP then ITU. Both indicators are important clues to understand the possible implementation of AV/AB services.

2.1.1 Decision-making parameters of willingness-to-pay for AV services

Understanding willingness-to-pay

WTP is defined as the highest price an individual is willing to pay for a product or service (Breidert et al., 2015). Pricing for a service can be operationalised in two ways: cost-based pricing and value-based pricing. Cost-based pricing is a pricing method that sets a selling price of goods or services by adding a fixed sum or a percentage of the total cost as profit to the cost of the product. Value-based pricing prices goods or services according to their perceived value to customers. When value-based pricing is used, the perceived values which influence one's WTP for a service must be identified (Kotler et al., 2008). In the case of operating an AV service, the expected service quality attributes influence one's WTP for the service. Furthermore, perceptions vary according to social-demographics and familiarity with the content and context of a service (Vinson et al., 1977). Considering valid estimates of WTP for the type of AV service with inclusion of the relevant perceptions are indeed vital for sensible pricing strategy of the AV service (Balderjahn, 2003).

Existing studies to understand decision-making parameters of WTP for AV/AV technology

Asgari & Jin, (2019), Bansal et al., (2016), Bansal & Daziano, (2018), Jiang et al., (2019), Kyriakidis et al., (2015), Liu et al., (2019), and Talebian & Mishra, (2018) investigated WTP for AV or AV technology. (Jiang et al., 2019), (Bansal et al., and (Kyriakidis et al, 2015) examined WTP itself only, without investigating the factors affecting WTP.

On the other hand, several studies looked into the factors influencing WTP for AV or AV technology. (Daziano et al., 2017) used mixed logit models to estimate WTP for private AV with different levels of automation for various socio-demographics. The results showed that the preferences for automation are diverse. Households who are not aware of driverless car technology are not willing to pay extra money for the technology. Out of the 1260 respondents with good representation of U.S. population, those who drive long distance, being aware of driverless car technology, own car, and with higher education have the most desire towards the technology and are willing to pay USD2784 for a privately owned automated car with partial automation (level-3 and level-4 automation) and USD6580 for a privately owned automated car with full automation.

(Talebian & Mishra, 2018) included WTP in the simulation model of the adoption of connected automated vehicle (CAV) and found that WTP is affected by peer-to-peer communication about the technology. (Bansal & Kockelman, 2018) regressed socio-demographic predictors, location-based predictors, travel-based predictors, tech-based predictors and safety-based predictors with WTP for private AV with different automation levels, and found that older people and experienced drivers have lower WTP for the technologies. (Liu et al., 2019) tested a psychological model to explain WTP for fully automated driving technology; social trust is identified to impact WTP directly rather than through perceived risk and perceived benefit.

Lastly, other than including socio-demographic variables like in the afore-mentioned studies, (Asgari & Jin, 2019) included respondent attitudes towards driving, factors affecting mode choice selection, shared transportation, multi-tasking and new

technology in the structural equation model to study their effects on WTP for four levels of automation (basic vehicles, adding advanced features, partial automation and full automation). They concluded people are willing to pay more when they believe that using the automated features/services will provide them with better utility in terms of time and cost savings, stress reduction, convenience, and quality of life. This highlights the importance of understanding WTP from user perceptions point of view, particularly their level of expectation or satisfaction with the service quality attributes of an AV service.

The understanding of user expectation, perceptions and satisfaction about a product or service attributes/characteristics is crucial towards deploying a successful product and/or service delivery (Netemeyer et al., 2004; Ligas & Chaudhuri, 2012). Such knowledge is essential to operators and stakeholders who are interested in providing market-driven AV services, and fosters more realistic estimation of the long-term demands and impacts from the implementations of the AV services. As highlighted by (Abenoza et al., 2017) operational and service quality attributes especially service frequency, length of trip time, and service provider's responsiveness in public transport services, play a more crucial role in influencing the travel demand and travel satisfaction than the physical design and technology of the vehicle itself.

Herein, user expectation, perceptions, and acceptance towards such operational characteristics should not be disregarded when investigating factors that influence user WTP for AV services. Moreover, the results from (Shin et al., 2015) who evaluated WTP of South Koreans for private vehicles with different smart options (automated driving, connectivity, voice command, wireless internet and availability of software application) at different option prices showed that consumers are homogenously sensitive to price but vary in their preferences of the smart options. This shows the importance of understanding the effects of the associated perceptions of the AV services at individual service quality attributes instead of the services as a whole bundle.

WTP values for various AV services in past studies except (Asgari & Jin, 2019) explored mainly the effects of socio-demographic characteristics, commuting behaviours and other non-attitudinal variables on WTP for AV or AV technology. There

is hardly any study that determines the impacts of service quality attributes of AV deployment towards one's WTP for these services. Also, knowledge is still very sparse about WTP for AV services, particularly factors associated with user WTP for first-/last mile AB service as compared to on-demand personalised AV service and demand responsive shared AV service.

2.1.2 Decision-making parameters of intention-to-use first-/last-mile AB service

Understanding intention-to-use

ITU, is an essential proxy indicator of people's actual usage of a product, service, or technology. Various theories and models have long been applied in diverse fields to forecast people's usage of a product, service, or technology, or to study the factors that influence people's usage of a product, service, or technology. In transportation planning, theories and models of user acceptance of technology have been applied to forecast people's decision-making among different modes of transport. Results from a meta-analysis of the theoretical models used in the study of travel mode selection by (Lanzini & Khan, 2017) show that intentions, together with habits and past usage experience, are the most significant predictors of people's actual selection of a travel mode.

Relationships between individual's perception with ITU

User perceptions of a product/service/technology are not only important to WTP, but also ITU of a product/service/technology. This is demonstrated by the following technology acceptance models:

1. Theory of Reasoned Action (TRA) (Hill et al., 1977)
2. Theory of Planned Behaviour (TPB) (Ajzen, 1991)
3. Technology Acceptance Model (TAM) (Davis, 1989)
4. TAM 2 (Venkatesh & Davis, 2000)
5. Igbaria's Model (IM) (Igbaria et al., 1994)
6. Theory of Interpersonal Behaviour (TIB) (Triandis, 1979)
7. Diffusion of Innovations Theory (DOI) (Rogers, 2003)
8. Social Cognitive Theory (Rana & Dwivedi, 2015)
9. Motivational Model (Davis et al., 1992)
10. Uses and Gratification Theory (U&G) (Grellhesl & Punyanunt-Carter, 2012)

11. Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh & Zhang, 2010)

These models all highlight the necessity of considering users' perceptions of service quality when investigating ITU. As such, these models offer a useful framework for research evaluating ITU of first-/last-mile AB services.

The UTAUT model was used by (Madigan et al., 2016) to identify factors affecting the acceptance of automated road transport systems in La Rochelle, France and Lausanne, Switzerland. Performance expectancy (people's belief of the ability of the system to work well when compared with other public transport systems) was identified as the most reliable predictor to people's acceptance of the service, followed by social influence and effort expectancy (Madigan et al., 2016). Also, users' perceptions of the product/service attributes contribute to an effect of diffusion to the emerging technology such as electrical vehicle (Jensen et al., 2017). The perceptions shall not be missed in modelling the demand of an emerging technology like AB service.

In summary, people's perceptions of the expected level of quality delivered by the operator of an AB service, as well as their satisfaction with the service's actual quality, are essential factors that affect people's ITU an AB service.

Understanding individual's perceptions towards AV

Technology awareness, familiarity with AVs, safety concerns, trust, influences of prevailing social norms, environmental concerns, perceived behavioural control and the perceived benefit of using AVs are the perceived criteria that influence people's ITU of AVs, as identified from a review conducted by (Gkartzonikas & Gkritza, 2019). Perceptions are parts of latent psychological constructs. They are inferred from the direct measurement of theoretically relevant variables. Such measurements are commonly realised using survey instruments with an attitudinal scale score. These scales are based on the assumption that it is possible to uncover a person's internal thoughts such as perceptions, motivation or beliefs through a scale (Fraenkel et al., 2012). In these scales, there are three response formats used to express individuals'

preferences: dichotomous (agree/disagree), semantic-differential, and Likert (Fraenkel et al., 2012).

Survey using a Likert scale is commonly applied in studies investigating the perceptions affecting ITU of AV (including AB in transit service) or automated driving technology. The analytical methods used are descriptive analysis (Brell et al., 2018; Buckley et al., 2018; Kyriakidis et al., 2015; Nordhoff et al., 2018; Panagiotopoulos & Dimitrakopoulos, 2018; Payre et al., 2014; Schoettle & Sivak, 2014), statistical analysis (Bansal & Kockelman, 2017; Buckley et al., 2018; Hulsén et al., 2018; Liljamo et al., 2018), factor analysis (Acheampong & Cugurullo, 2019; Haboucha et al., 2017; Hudson et al., 2019; Kaur & Rampersad, 2018), and structural equation modelling (SEM) (Liu et al., 2018; Nwachukwu, 2014; Xu et al., 2018; Zhang et al., 2019).

The stated choice experiment was applied by (Howard, 2014; Krueger et al., 2015) to predict the likelihood to adopt AV/automated driving technologies. (Nielsen & Haustein, 2018), in contrast, used cluster analysis. Their respondents were categorised into subgroups based on attitudinal variables after performing principal component analysis (PCA). Their results showed that those who are enthusiastic about using a self-driving car include males, young people, people with a high level of education, and people who live in cities. Those who are sceptical about AV use are elderly people, car-reliant people, and those who live in suburban areas. This analysis method was useful in identifying early adopters of AV.

Profile-case best-worst scaling was used by (Sanbonmatsu et al., 2018) to model adoption decisions under the influences of the attributes associated with AV. In their survey, the respondent was asked to select the most and the least attractive attributes. Their results showed that purchase price and incentive policies are influential regarding people's willingness to adopt AV. In addition, the authors highlighted other significant explanatory variables influencing the acceptance of AV, including socio-demographic variables, gender, age, educational background, living environment (urban or suburban), and car reliance. Income was also found to be significant when the data were analysed using the best-worst analysis method (Sanbonmatsu et al.,

2018). Finally, (Nazari et al., 2018) found that the number of family members in a household also contributes to the acceptance of AV.

Extended applications of the TAM have been used to investigate psychological constructs affecting the acceptance of AV (Buckley et al., 2018; Choi & Ji, 2015; Jiang et al., 2019; Panagiotopoulos & Dimitrakopoulos, 2018; Xu et al., 2018). The TPB was also used by (Buckley et al., 2018) to identify drivers' ITU of AVs after experiencing a simulation driving experience in an AV. Perceived usefulness, trust and perceived ease of use are significant latent variables influencing peoples' acceptance of AV technology (Panagiotopoulos & Dimitrakopoulos, 2018). Prior experience was also found to affect perceived usefulness, trust and perceived ease of use (Xu et al., 2018).

Understanding individual's perceptions towards first-/last-mile AB service

Perceived value is the most essential determinant of commuters' behavioural ITU a transport service (Jen et al., 2011). In the context of a first-/last-mile AB service, users' perceived value can be assessed from the perspective of quality of service as demonstrated by Citymobil2 project (McDonald et al., 2018). The service quality was assessed through the availability of information, users' satisfaction of the ticketing methods, perceived cleanliness, perceived comfort, perceived level of privacy and perception of safety, which are in-line with the service quality attributes used to assess customers' satisfaction of public transport service. Service quality attributes found to be significant in past acceptance studies of AB are reliability, on-board safety (Piao et al., 2016; Salonen, 2018), comfort (Eden et al., 2017), and travel time (Bansal et al., 2016; Scheltes & de Almeida Correia, 2017).

2.2 Changes in the relationships of users' perceived values with intention-to-use due to experience

There were studies which investigated the effect of experience on ITU personal use AV/AB including Hilgarter and Granig (2020), Hutchins et al. (2019), Paddeu et al. (2020), Papadima et al. (2020), Salonen and Haavisto (2019), Xu et al., (2018) and Distler et al., (2018). However, there is yet a study that investigates changes in the ITU of a first-/last-mile AB service due to increasing actual ride experiences.

(Xu et al., 2018) extended the TAM to model ITU and willingness to ride private-use AV. Two factors, i.e. trust in automated driving technologies and perceived safety when taking the AV ride, were added into the extended TAM model. The results found ride experience increases riders' perceived usefulness, perceived ease-of-use and trust in the AV service by a little amount. (Distler et al., 2018) asked participants to rank the needs from an on-demand automated mobility service. Competence of the on-demand service, security and relatedness (being connected and having a sense of social interactions) from using the service were considered more important after the experience. However, domain-specific attitudes such as users' perceived value of AB services were yet to be explored. Such objective measures were argued as being stronger predictors of acceptance of AB than socio-demographic variables (Nordhoff et al., 2018).

Within the field of consumer research, consumers' pre-purchase values and post-purchase values are different (Jensen, 2002). The perceived value of a first-time buyer towards a product is mainly based on his expectations of the product (Diamantopoulos et al., 1997); post-use valuation is an important indicator of the continuous use of a service (Yu & Lee, 2019). Repeat buying is associated with the post-purchase value which is realised through actual use of a product (Boztepe, 2007).

Users' satisfaction evolves over repeated consumption experiences (Homburg et al., 2006). Habit gives a positive emotional association to a specific behaviour and increases the intention to maintain the behaviour (Phua et al., 2017). Expectations before the adoption of a service shape the post-adoption perceptions (Zhou, 2011). Also, satisfaction is generated from users' interactions with service up to the present time and is used to predict future experiences (Crosby et al., 1990). This means post-use satisfaction after initial usage can be used as a reference point to shape the valuation for further usage. Also, initial valuation affects continuous usage in terms of difference between the expectations and reality with experiences of a product/service (Bhattacharjee & Premkumar, 2004; Venkatesh et al., 2011).

Experience influences the variables which contribute to the acceptance of a new technological product such as an electric vehicle (Peters & Dötschke, 2014). People's

evaluation of a new technological product such as electric vehicle changes after using it (Burgess et al., 2013). The variables which contribute to acceptance before experiencing a service can change after the experience. When users have no prior experience or information, their expectations are uncertain and tentative, due to the absence of usage information (Crompton & Love, 1995). Under these circumstances, using the expectations as firm criteria against which to make evaluative judgments is likely to be fallacious (Crompton & Love, 1995).

2.3 Dynamic relationships in user perceptions and intention-to-use

People's perceptions in terms of the expected level of service (LOS) quality delivered by the operator of an AB service, and their satisfaction level with the service quality itself, are two significant predictors of people's ITU an AB service. However, how can these perceptions be measured, assessed quantitatively, and translated into a useful rubric for use by operators and policymakers to determine the minimum standard of service quality and the optimal parameters of quality that their service should deliver in order to be successfully adopted by the target user? The following discussion aims to answer this question.

Within the field of public transport, people's perception of a public transport service is quantified as their level of satisfaction or expectations of the service's quality (Redman et al., 2013). People's acceptance is measured as their overall satisfaction with the public transport service (Transportation Research Board, 1999). Perceived value, which is affected by service quality (Cronin et al., 2000; Zeithaml, 1988) was found to be a predictor of satisfaction with public transport (Cronin et al., 2000; Petrick, 2004; Woodruff, 1997). Commonly-used statistical techniques to identify the key factors affecting people's perceptions of the transport service include: exploratory factor analysis (Hu et al., 2015; Jomnonkwao & Ratanavaraha, 2016; Nwachukwu, 2014; Popuri et al., 2011; Efthymiou et al., 2018), confirmatory factor analysis (CFA) (Hu et al., 2015; Jomnonkwao & Ratanavaraha, 2016; Ratanavaraha et al., 2016), and SEM (De Oña et al., 2013; Machado et al., 2016; Lai & Chen, 2011; Eboli & Mazzulla, 2008; Jen & Hu, 2003). Also, the relative weight of the list of tested factors is analysed using regression analysis (Chang & Yeh, 2005; Nwachukwu, 2014), ordered logit models

(Rojo et al., 2013), ordered probit models (Bordagaray et al., 2014; Rojo et al., 2013), and multinomial logit models (Dell’Olio et al., 2011; Eboli & Mazzulla, 2008).

In practice, in order to find which service quality attributes are to be prioritised to enhance users' overall satisfaction, importance-performance analysis (IPA), also known as quadrant analysis, is commonly used (Figler et al., 2011; Weinstein, 2000; Shen et al., 2016; Abenoza et al., 2017). An IPA is built assuming that the perceptions of service quality attributes and their influences on overall satisfaction have a linear or symmetric relationship. This poses a significant limitation to IPA since overall satisfaction does not always respond linearly to every kind of service attribute perception. Hence, three-factor theory (Matzler et al., 2004), which is built in reference to the Kano model and the extended Kano model, is proposed to overcome the limitations of IPA in addressing the topic of this study.

Unlike IPA in which the relationship between service quality and overall satisfaction is assumed to be linear, the Kano model (Kano et al., 1984) recognises the fact that some relationships between service quality and overall satisfaction are nonlinear. In addition, the Kano model only classifies the service’s qualities into different groups and explains the relationships qualitatively. Furthermore, following the original Kano model, quantitative Kano alternative models such as the Fuzzy Kano model (FKM), Analytical Kano model, and Kano Regression model have been proposed to classify a service’s qualities differently.

Applications of Kano’s alternative models are developed into the three-factor theory that classifies service quality attributes into three groups of factors: (1) basic factor, (2) performance factor, and (3) exciting factor. Figure 2.1 maps their relations to each other with regards to their capacity for influence, and service performance. Basic factors are the service quality attributes influencing overall satisfaction most visibly when they are underperforming, and with no impact on overall satisfaction when performing adequately. The performance factor is a service quality attribute with significant impacts on overall satisfaction when either underperforming or overperforming, in accordance with the assumptions of IPA. Exciting factor is the

service quality attribute influencing overall satisfaction most visibly when overperforming but has no influence on overall satisfaction when underperforming.

However, the application of the three-factor theory in the field of transport is limited. (Zhang et al., 2015) first applied Kano's three-factor theory using an importance grid, followed by (Wu et al., 2018) who applied three-factor theory using regression with dummy variables for the identification of the three groups of factors, as presented on Figure 1. (Abenzoza et al., 2019) applied three-factor theory to characterise public transport service quality attributes based on their levels of influence on travel satisfaction. Allen et al., (2019) adapted Kano's theory to understand public transport satisfaction within the framework of Maslow's hierarchy of (transit) needs.

Figure 2.1 Three-factor theory of satisfaction (Wu et al., 2018)

Users' transit needs are hierarchical and can be arranged into a hierarchy of transit needs as shown in Figure 2.2 (Allen et al., 2019). The basic level of need e.g. reliability is relevant in affecting users' overall satisfaction when it is not at a satisfactory level. Once the basic level of need is fulfilled, it becomes irrelevant while the next level of need e.g. safety becomes relevant. The functional attribute in the hierarchy of transit need shares the similar characteristic with the basic factor in the three-factor theory. Users' dissatisfaction with the functional attribute will result in dissatisfaction with the

service. On the other hand, their satisfaction with the functional attribute does not contribute to a higher satisfaction with the service. The security attribute in the hierarchy of transit need shares the similar characteristic with the important performance factor in the three-factor theory whereby satisfaction or dissatisfaction with the security attribute will result in corresponding satisfaction or dissatisfaction with the service. Similarly, the hedonic attribute in the hierarchy of transit need shares the similar characteristic with the exciting factor in the three-factor theory. Users' dissatisfaction with the hedonic attribute does not result in dissatisfaction with the service. However, their satisfaction with the hedonic attribute contributes to a higher satisfaction with the service. Herein, the three-factor theory not only addresses the non-linear relationship between attributes and overall satisfaction, it can also be used to identify the hierarchical needs of the users.

Figure 2.2 Hierarchy of transit needs (adapted from (Allen et al., 2019))

As an alternative to three-factor theory, (Deb & Ali Ahmed, 2018) proposed a method to assign a LOS of the service quality attributes using CFA on perception and expectation, regression analysis for standardisation of the factor scores, and SEM to obtain the effect of perception and expectation on overall satisfaction. However, it has limitations because the LOS and its description of the service quality are assigned by the analyst. (Tyrinopoulos and Antoniou, 2008) and (Efthymiou et al., 2018) used factor analysis, ordered logit models and triangle plots of three identified prevalent

factors to study the impacts of service quality attributes on overall satisfaction across different groups of users.

2.4 Pedestrian interaction with an automated bus

2.4.1 Pedestrian road-crossing behaviour

A pedestrian not only needs to detect objects and their surroundings, but also performs high-level of analysis to obtain situational awareness through interpreting the behaviours of other road users around them. To recognise objects and their behaviours, a pedestrian relies not only on visual cues but also the contextual information (Humphreys & Bruce, 1989). Road-crossing behaviours can be categorised into three levels: operational level, tactical level and strategic level (Gong & Tao, 2011). Operational level models behaviours in which atomic actions are performed by a transport agent to move, such as maintaining safe distance from obstacles and speed control. Tactical level models behaviours in which actions require conscious decision-making of the transport agent to avoid collision in response to different interactions with others. Strategic level models behaviours in which activities such as route planning and route selection require planning before starting the navigation. When it comes to road user's interactive behaviour, safety has always been an essential concern and consideration of all levels of behaviours.

Any behaviour carried out voluntarily by a human subject can be predicted by his (both genders) behavioural intention measured in accordance to the behaviour criteria : context, target, action, time frame and specificity with the assumption that there is no change in intention before performance of the behaviour (Ajzen & Fishbein, 1980). The TPB as shown in Figure 2.3 proposed that one's intention to perform a behaviour is under influence of a person's attitude about the behaviour, subjective norm he holds and a person's perception of the ease or difficulty of performing the behaviour of interest (Ajzen, 1991). Pedestrian's perceived control of the road-crossing behaviour including the gap from the oncoming AB and speed control affect both the pedestrian's decision to cross the road and the actual road-crossing behaviour. This shows the importance to analyse pedestrian midblock road-crossing behaviour not only at tactical level but also at operational level.

Figure 2.3 Theory of Planned Behaviour (Ajzen, 1991)

2.4.2 Pedestrian interaction with an automated vehicle

Three major methods have been used to study pedestrians' interaction with the AV: 1. analysing data from simulators or abstract lab experiments (Michieli & Badia, 2018), 2. experiments in a controlled environment (Clamann et al., 2017; Dey et al., 2017; Lagström & Malmsten Lundgren, 2016; Rodríguez Palmeiro et al., 2018; Rothenbücher et al., 2016), and 3. video analysis of real-life road interactions data (Camara et al., 2018; Madigan et al., 2019).

It is more likely that a pedestrian chooses to cross the road than staying on the sidewalk when seeing an oncoming AV than a normal car (Michieli & Badia, 2018). The highest occurring event is pedestrian crosses the road while the AV is slowing down but not coming to a complete stop (Michieli & Badia, 2018). The disadvantage of using simulation for such analysis is its dependency on assumptions which may not represent real life interactions. Real life data are required to validate the assumptions and improve the analysis.

(Blau, 2015; Fridman et al., 2017; Hagenzieker et al., 2019) investigated pedestrian's interaction with AV through questionnaire. Instead of investigating pedestrian-AV interaction through questionnaire, (Clamann et al., 2017; Dey et al., 2017; Lagström & Malmsten Lundgren, 2016; Rodríguez Palmeiro et al., 2018; Rothenbücher et al., 2016) studied pedestrians' or cyclists' responses to the AV using an AV representative prototype built from non-AV in a controlled environment. (Clamann et al., 2017) asked

the participants about the most influential factor affecting road-crossing decision at the end of the experiment. The result showed pedestrian's spatial distance from a vehicle is the most influential factor affecting a pedestrian's decision to cross in front of the AV representative prototype, followed by speed of the approaching vehicle, and traffic density (Clamann et al., 2017). Experiments in a controlled environment have disadvantages such as participants may have recognised the trickery which the AV representative prototype was not a real AV, and the interactions as demonstrated may be very different from the real-life situations.

Analysing real-life pedestrian-AV interactions data overcomes two limitations from simulation and controlled experiment namely: 1. not having data which represents reality, and 2. having to interpret behaviours through proxies of behaviours. (Camara, et al., 2018) analysed real-world pedestrians crossing data at an unsignalised intersection and generated a decision tree of Pedestrian-Vehicle Interaction through a four-step analysis method: 1. motif selection, 2. logistic regression, 3. manual regression, and 4. decision tree regression. The model was able to predict if the pedestrian is to cross or not cross the road when interacting with an AV but not the level of assertiveness (a single parameter to summarise the entire behavioural preferences of the encountered pedestrian) of the pedestrians (Camara, et al., 2018). (Madigan et al., 2019) investigated the interaction requirements of pedestrians with an AV through analysing video footage collected from two actual demonstrations of automated shuttles, one in La Rochelle (France) and another one in Trikala (Greece). Statistical analyses including Chi-Square analyses, Fisher's exact tests, and Adjusted Standardised Residuals (ASR) were used to analyse the data. Their results show that pedestrians' trajectory decisions when approaching an AV are affected by road width, and the presence or absence of zebra crossings. Also, elderly and females are more likely to show cautionary behaviour around the AVs than younger road users and males.

2.4.3 Pedestrians' choice of speed in response to road-crossing risk

Pedestrians' choice of speed is a function of their capabilities, value of time and the potential risk they are taking (Ishaque & Noland, 2008). Pedestrians' choice of crossing speed is adaptable to the crossing situations and the level of risk they are

taking (Moore, 1953). The 50th percentile of pedestrian walking speed at unsignalized midblock is 1.45 m/s. The average road-crossing speed at unsignalized midblock of young adult is 1.54 m/s, middle age pedestrians at 1.45 m/s, and elderly at 1.04 m/s (Forde & Daniel, 2020). Pedestrians choose to cross a road midblock when they perceive the gap to be sufficient and the road width is not too wide (Chu et al., 2004). Gap acceptance rates suggest that pedestrians tend to choose safe crossing gaps from an oncoming vehicle and that individual gap acceptance levels are strongly mitigated by individual capabilities (Ishaque & Noland, 2008). Female and elderly pedestrians are more cautious when crossing the road (Rastogi et al., 2012). The average observed time gap between pedestrian with a vehicle when performing a 6m wide midblock road-crossing is 10.6s (Rastogi et al., 2012).

(Mahmud et al., 2017) summarised 38 major risk assessment indicators and grouped them into three main types: 1. temporal proximal indicators, 2. distance-based proximal indicators, and 3. deceleration-based indicators. Table 1 lists the three types risk assessment indicators. Most of the indicators were originally developed for near-crash identification between two vehicles, particularly rear-end crashes. However, some of the risk indicators can be applied or modified to assess the near-crash risk between pedestrian and vehicle, given the risk indicators can be calculated from available trajectory data and applicable to all kinds of safety-critical scenarios.

Time-to-collision (TTC) is frequently used for near-crash identification, since it is easy to calculate and to interpret. However, the TTC indicator assumes the objects have constant speeds without considering deceleration/acceleration, which does not reflect the practical scenario. TTC was used by (Madigan et al., 2019) to identify critical incidents between AB with pedestrians and cyclists. The time difference between one vehicle and one pedestrian reaching the same point in their trajectories, TDPI - time difference to the point of intersection was used by (Wu et al., 2018) to classify crash risk between pedestrian and vehicle using real-world interaction data. A shorter TDPI is more dangerous than a longer one.

Table 2.1 Commonly used risk assessment indicators (Mahmud et al., 2017). The table was created by (Wu et al., 2020)

Indicator*	Authors	Description
Temporal proximal indicators		
Time-to-Collision (TTC)	(Hayward, 1971)	The time that remains until a collision between two vehicles would have occurred if the collision course and speed difference were maintained.
Time-Exposed Time-to-Collision (TET)	(Minderhoud & Bovy, 2001)	The duration of exposition to safety-critical time-to-collision values over a specified time duration.
Time-Integrated Time-to-Collision (TIT)	(Minderhoud & Bovy, 2001)	Integral of the TTC-profile during the time below the threshold.
Post-Encroachment Time (PET)	(Allen et al., 1978)	The difference between the time when the leading vehicle last occupied a position and the time when the following vehicle first reached the same position.
Time Difference to the Point of Intersection (TDPI)	(Wu et al., 2018)	The time difference between one vehicle and one pedestrian reaching the same point in their trajectories.
Headway (H)	(Michael et al., 2000)	The time that passes between two vehicles reaching the same location.
Distance-based proximal indicators		
Distance between Stop Position and Pedestrian (DSPP)	(Wu et al., 2018)	The distance between one vehicle and one pedestrian when the vehicle first stopped before reaching the pedestrian.
Potential Index for Collision with Urgent Deceleration (PICUD)	(Lida et al., 2001)	The distance between two vehicles when they completely stop.
Proportion of Stopping Distance (PSD)	(Allen et al., 1978)	The ratio between the remaining distance to the potential point of collision and the minimum acceptable stopping distance.

Table 2.2 Commonly used risk assessment indicators (Mahmud et al., 2017). The table was created by (Wu et al., 2020) (continued)

Distance-based proximal indicators		
Difference of Space distance and Stopping Distance (DSS)	(Okamura et al., 2011)	The difference between the space and the stopping distances.
Deceleration-based indicators		
Deceleration Rate to Avoid a Crash (DRAC)	(Almqvist et al., 1991)	Differential speed between a following vehicle and the leading vehicle divided by their closing time.
Crash Potential Index (CPI)	(Cunto & Saccomanno, 2007)	The probability that a specified vehicle exceeds its maximum available deceleration rate during a specified time interval.
Criticality Index Function (CIF)	(Chan, 2006)	Product of the vehicle speed and the required deceleration.

(Wu et al., 2020) identified near-crash events between vehicle and pedestrian using 2.5s threshold and uncomfortable events with the TDPI range between 2.5s and 3.5s. The events with more than 3.5s TDPI value are classified as normal manoeuvres. The 2.5s value is the standardised brake reaction time for unalerted driver during unexpected events with simple road conditions (American Association of State Highway and Transportation Officials, 2018). Brake reaction time is used to calculate the brake reaction distance of a vehicle at different speed. Together with braking distance, brake reaction distance forms the stopping sight distance of a vehicle. The reaction time of an AV from the moment it detects an obstacle to the moment which brake is applied was found to be 0.5s (Urmson, 2006). As a result, stop sight distance of an AV is shorter than the stop sight distance of a non-AV due to the significant decrease in the brake reaction time. Unlike typical vehicle-vehicle interaction, pedestrian as a human subject needs social space (additional distance away from a stopping vehicle) to feel safe.

In summary, having objective measurements is important to understand In the decision-making process to adopt a new transport service, subjective measurements e.g. attitudinal responses are as important as the objective measurements e.g. socio-demographic variables. However, when it comes to understanding real-world

interaction between a pedestrian with oncoming AB when crossing at the unsignalised midblock, objective measurements provide more important clues to aid the design of road infrastructure or safety rules to ensure safety of the pedestrians.

3 DESCRIPTION OF DATA SETS

Two types of data: survey data and LiDAR data as shown in Figure 3.1 were analysed in this research. Survey data set 1 and survey data set 2 are data collected from a two rounds panel survey. The data sets were collected in conjunction with a trial operation of first-/last mile AB service in Kista, Stockholm. LiDAR data was collected from a LiDAR device attached on the AB in operation from two sites: Kista and Barkarby in Stockholm. This section starts by explaining the experimental design, followed by the description of the survey data sets, followed by description of the LiDAR data. Survey data set 1 was used in study 1 and study 3; both survey data set 1 and data set 2 were used in study 2; LiDAR data was used in study 4.

Figure 3.1 Descriptions of the data used in this research

Experimental Design

Two waves of a panel survey were designed to answer the following four research questions:

- Research question 1 (RQ1) – How do subjective factors (e.g. perceptions of service quality) used to measure user experience affect behavioural responses towards AV services?

- Research question 2 (RQ2) – How do objective factors interact with the subjective factors which affect intention-to-use a new transport service?
- Research question 3 (RQ3) – What are the changes in the decision-making parameters of intention-to-use a new transport service in response to actual ride experiences?
- Research question 4 (RQ4) – How do decision-making parameters of intention-to-use a new transport service vary in relation to the dynamic relationships of users' service quality needs with intention-to-use a new transport service?

Users' behavioural intentions were investigated in two aspects:

WTP for three types of AV services (1. on-demand personalised AV (PAV) service, and 2. demand responsive shared AV (SAV) service, and 3. first-/last-mile AB (AB) service) as if to use the services for a long period of time.

ITU a first-/last-mile shared AB service if the service were made available to the respondents.

These are the dependent variables in the surveys. Same sets of dependent variables (both objective variables and subjective variables) were asked in the two waves of a panel survey.

In order to control the external variables which can potentially affect the research outcomes, the following measures were taken:

1. The respondents were the same respondents in wave 1 and wave 2 of the panel survey.
2. Not only the respondents were recruited randomly, but they were also stratified into different socio-demographic groups to reflect what it would look like if the entire population was asked to do the surveys.
3. The respondents received only one of the possible levels of the experimental treatment (never taken AB ride, have taken the AB ride once and have taken the AB ride more than once).

3.1 Description about survey data set 1 and survey data set 2

Survey data set 1 and survey data set 2 were collected from a survey conducted in conjunction with the Autopiloten project, which involved a test operation of a first-/last mile AB service in the Science City in Stockholm, Kista. First-/last mile service typically serves short distance, bringing passengers to/from travel between the places where they live, work, or study and a transport hub. In the test operation, the service served the first-mile and last-mile of the passengers, transporting the passengers from/to Kista metro station to/from the places where they work, study or live in the area.

The trial operation started in January 2018 and ended in June 2018. Two automated EZ10 buses, which can accommodate up to 11 standing passengers, were used in the project. These ABs drove back and forth along the 750-metre route with a flexible timetable from 6am to 6pm every day. There were designated stops at which the ABs could pick up and drop off passengers. In compliance with the safety regulations of the municipality, the ABs were restricted to an operating speed limit of 20km/h. The service was offered free-of-charge in this trial operation. Under the public transport fare structure in Stockholm, having the first-/last-mile service free-of-charge is sensible because such first-/last mile connection has been accounted for when the commuters pay for the single trip ticket (75 minutes access to all public transport services with a single trip ticket) or monthly pass. Commuters do not need to pay extra to access first-/last-mile services after they have paid for the trip or monthly pass. An image of the AB, the EZ10 bus is shown in Figure 3.2.

An online survey was administrated concurrently with the six-month trial operating period from January to June 2018 by a Swedish survey company recruited by the research team. Survey respondents were recruited by the survey company to take part in two rounds of online surveys throughout the period from February 2018 to May 2018. The participants who completed the surveys were entitled to participate in the contest to win one of ten cash prizes worth 1,500 Swedish Kronor. The survey focused on potential users of the service: people who work, study or live near the trial operation area (the Helenelund commuter train station, and Kista Science City). The area is a science and technology park which hosts many prominent technology companies and a couple of leading national universities. The first round of survey was conducted in

February to March 2018 when the AB service just started. The second round of survey was conducted in April to May 2018 after the service had been in operation for about 4 months.

Figure 3.2 EZ10, the small automated bus used in the trial operation in Kista, Stockholm (SARA 1 Research Team, 2018)

3.1.1 Description of survey data set 1 from the first round of survey (in February to March 2018)

The significant explanatory variables found to affect acceptance of AVs, including ABs were included in the survey. The variables are gender (Acheampong & Cugurullo, 2019; Hulse et al., 2018; Liljamo et al., 2018; Nazari et al., 2018; Nielsen & Haustein, 2018; Payre et al., 2014; Rödel et al., 2014; Salonen, 2018; Schoettle & Sivak, 2014), age (Bansal et al., 2016; Hudson et al., 2019; Nazari et al., 2018; Nielsen & Haustein, 2018; Rödel et al., 2014; Sanbonmatsu et al., 2018; Shin et al., 2015), annual income (Sanbonmatsu et al., 2018), and prior experience with AVs (Xu et al., 2018). Also included were variables commonly used in travel behaviour studies: employment status, current preferred travel modes, a travel attitudinal question (acceptable travel time), and explanatory variables including tech-savviness and familiarity with automated driving technology. Tech-savviness and familiarity with automated driving technology were included to investigate their impacts on prospective users' perceptions and intentions to use the AB service.

The first section of the online survey asked for:

1. personal details, including gender, age range, employment status, and annual income;
2. existing travel modes used in daily commuting;
3. awareness of automated driving technology;
4. tech-savviness;
5. experience using the first-/last-mile AB service trial operated in Kista; and
6. acceptable first-/last-mile travel time for a 750m section of road.

The second section asked for these potential users' perceptions of:

1. the service's frequency, in comparison with the frequency of regular public bus service;
2. onboard safety with a steward on the AB;
3. onboard safety without a steward on the AB;
4. safety perceptions about the ability of an AB to interact safely with other vehicles on the road;
5. ride comfort due to driving speeds and driving patterns of AB;
6. ride comfort due to the facilities of the AB;
7. overall onboard customer service on the AB;
8. time saving/loss travelling with the AB in comparison to taking a (i) regular bus service, (ii) metro, (iii) commuter train, or (iv) car, serving the same distance and route; and
9. travel fare savings/losses due to travelling with the AB, in comparison to using (i) the regular bus service (ii), metro, or (iii) commuter train, serving the same distance and route.

The last section of the survey asked for the ITU a first-/last-mile shared AB service if the service were made available to the respondent. Besides, WTP for three types of AV services: 1. on-demand personalised AV (PAV) service, 2. demand responsive shared AV (SAV) service, and 3. first-/last-mile AB (AB) service as if to use the services for a long period of time. WTP is measured as the amount of money one is willing to pay on top of the public transport monthly pass one was paying at the time

of survey. ITU and WTP were rated on a five-point ordinal scale. The full survey questionnaire is presented in Appendix A.

3.1.2 Description of survey data set 2 from the second round of survey (in April to May 2018)

The respondents who participated in the second round of survey had participated in the first round of survey. In this round of the survey, the following information was collected through the questionnaire from the same respondents:

1. perceptions about various service quality aspects of the service:
  - i. safety perception about the ability of an AB to interact safely with other vehicles on the road
  - ii. on-board safety without a steward on AB
  - iii. ride comfort due to driving speeds and driving patterns of AB
  - iv. ride comfort due to the facilities on AB
  - v. time saving/loss travelling by AB in comparison to taking a regular bus service
  - vi. frequency of AB service in comparison to the frequency of a regular public bus service
2. intention-to-use first-/last mile AB service

The full survey questionnaire is presented in Appendix A.

The longitudinal survey was deployed for which respondents were enlisted by simple random selection, and 604 responses were collected from the first round of survey and 532 responses from the second round of survey while 483 respondents completed both rounds of surveys.

3.2 Description about LiDAR data

The pedestrian-AB interaction data was collected from naturalistic observations at two test-sites of AB service, using a LiDAR device mounted on the front of the AB.

Test sites of first-/last mile AB service

The interaction data was collected from two test sites of first-/last mile AB service in Stockholm, Sweden: Kista and Barkarby test sites. In Kista, a first-/last mile AB service was in trial operation from January 2018 to June 2018. Two ABs which can occupy up to six seated passengers and five standing passengers, EZ10 were used in the

operation. The ABs went back and forth along 750-metre route as shown in Figure 3.3 without fixed frequency from 6am to 6pm. There were designated stops where the ABs can pick-up and drop-off passengers. In compliance with the safety regulations from the municipality, the ABs had an operating speed limit of 20km/h. There was a steward on board. The service was offered free-of-charge.

In Barkarby, a first-/last mile AB service line 549, operated by Nobina for the transport administration Stockholm County Council - SL Public Transport Authority in Stockholm has been in operation since October 2018. Small size AB, EZ10 which can occupy six seated and five standing passengers was used in the operation. The bus operated every 15 minutes along the route as shown in Figure 3.4 from 6:31 to 18:31 on weekdays and 11:46 to 18:16 on Saturdays. There were four stops along a fixed 2.2 km route between Storatorget to Barkarby Handelsplats as shown in Figure 4. The bus operated at the speed of 12 to 15 km per hour with maximum operating speed limit of 20km/h and with a steward on board.

LiDAR device was chosen over conventional video recording to collect movement data because of LiDAR's compliance to the EU privacy protection standard of all road users (European Commission, 2018). A Velodyne VLP-16 LiDAR sensor was installed at the front left of an AB as shown in Figure 3.5. Installation of the LiDAR sensor at this location gave 270 degrees viewing area. LiDAR data contain 3-D representations of the detected objects including nearby road users. Relative distances between pedestrian with AB and the respective time stamps can be retrieved from the LiDAR records.

In Kista, nine sets of LiDAR point clouds data were obtained between the 28 and 29 June 2018, providing 2 hours and 42 minutes of records. In Barkarby, four sets of LiDAR point clouds data were obtained between the 8 and 12 May 2019, providing 4 hours of records. Out of the two sets of LiDAR data, 42 pedestrian's road-crossing interactions at the road midblock were identified, which were analysed in this study.

Figure 3.3 Bus route of first-/last-mile automated bus service in Kista (Google Maps, 2020)

Figure 3.4 Bus route of first-/last-mile automated bus service in Barkarby (Google Maps, 2020)

Figure 3.5 Picture showing the location of the LiDAR sensor installed on automated bus

4 STUDY 1: INTERACTION OF OBJECTIVE FACTORS AND SUBJECTIVE FACTORS WITH WILLINGNESS-TO-PAY FOR THREE AV SERVICES

Study 1 addresses research question 1, and research question 2 through investigating the relationships of service quality attributes perceptions with objective variables (e.g. socio-demographic variables, existing commuting characteristics, tech-savviness, level of familiarity with automated driving technology, etc.) with user's WTP for three AV services. The three types of AV service are 1. on-demand personalised AV (PAV) service, 2. demand responsive shared AV (SAV) service, and 3. first-/last-mile AB service. Herein, SEM with service quality attribute perceptions as latent variables is applied to achieve the objective.

Socio-demographic predictors which are significant to WTP for AVs such as age (Bansal, Kockelman, & Singh, 2016), gender and income level (Bansal, Kockelman, & Singh, 2016; Kyriakidis, Happee, & De Winter, 2015) were included in the model. Additionally, significant factors influencing acceptance of AVs such as technology awareness (Schoettle & Sivak, 2014), use of multiple travel modes (Krueger et al., 2016), and ride experience (Bansal, Kockelman, Singh, 2016) were also included. (Salonen, 2018), (Eden et al., 2017), (Scheltes & de Almeida Correia, 2017) and (Piao et al., 2016) investigated acceptance of using small AB. On-board safety (Piano et al., 2016; Salonen, 2018), comfort (Eden et al., 2017), travel time (Bansal, Kockelman, & Singh, 2016; Scheltes & de Almeida Correia, 2017), travel fare (Piano et al., 2016; Bansal, Kockelman, & Singh, 2016) and presence of steward (Piano et al., 2016) were found to be influential to people's acceptance of AB usage. Hence, service quality attributes including frequency, safety, ride comfort, travel time and travel cost were included as latent variables in the structural equation model applied in this study.

Figure 4.1 shows the constructed structural equation model with service quality attribute perceptions as latent variables. The model was built using the framework of the structural modelling equation part of the Integrated Choice and Latent Variable (ICLV) model (Ben-Akiva et al., 2002). Figure 4.2 illustrates the relationships of structural equation model with ICLV model and confirmatory factor analysis. Together with a choice model, a structural equation model forms an ICLV model. ICLV model provides a greater explanatory power and deeper understanding of the choice

processes taking place in the users' "black box" with the combination of users' decision-making parameters. Confirmatory factor analysis is commonly used to confirm the indicators of the latent variables used in a structural equation model.

The whole ICLV model was not adopted in this study because there was no choice selection involved in this study. This means that, for this study, WTP was not inferred from a stated preference study in which respondents state their preferences through their choices. Instead, the respondents directly stated the amount of money they are willing to pay for the AV services.

Figure 4.1 Conceptual Model of WTP for AV Services

**Illustration of Relationships of Structural Equation Model
with Integrated Choice and Latent Variable & Confirmatory Factor Analysis**

Figure 4.2 Illustration of Relationships of Structural Equation Model with Integrated Choice and Latent Variable & Confirmatory Factor Analysis

4.1 Description of the responses

Data set 1 collected from the first round of survey was analysed in this study.

The individual characteristics included in the model of WTP of AV service are:

1. basic details including gender, age, gross annual income before tax
2. tech-savviness (defined as well informed about or know how to use computers, mobile phones and electronic devices)
3. level of familiarity with automated driving technology
4. AB ride experience
5. existing travel modes for daily commute

Table 4.1 shows the distribution of socio-demographic characteristics of the sample of 584 respondents. There are more male respondents (64.6%) in the survey. Also, most of the respondents (46.1%) are between 45 to 64 years old, working (58.9%), have at least an undergraduate degree (78.6%) and tech savvy (93.8%). 57% of the respondents claimed to be familiar with the technologies used to enable automated road vehicle to drive without human driver. A total of 46.7% of the respondents had taken at least one AB ride.

Table 4.1 Distribution of socio-demographic characteristics of the respondents
(n=584)

Characteristics/ sample group	Total (n=584), %
<u>Gender</u>	
Male	64.6
Female	33.4
<u>Age</u>	
Children (aged under 15 years)	0.0
Young Adult (aged 15-24)	20.7
Adult (aged 25-44)	27.7
Middle-age Adult (aged 45-64)	46.1
Elderly (aged above 65)	5.1
<u>Employment Status</u>	
Working	58.9
Business Owner	3.3
At School	31.0
Permanently Retired from Work	4.1
<u>Education Background</u>	
Undergraduate or above	78.6
<u>Gross Monthly Income (before tax) in Swedish Kronor (SEK)</u>	
Low-income ($\leq 200,000$ SEK $\cong 21386$ USD)	16.6
High-income ($\geq 700,000$ SEK $\cong 74851$ USD)	41.1
<u>Technology Awareness</u>	
Tech-savvy: well informed about or know how to use computers, mobile phones and electronic devices.	93.8
Familiar with the technologies used to enable automated road vehicle to drive without human driver	57.0
<u>Existing Travel Modes</u>	
Walk	26.5
Cycling	13.5
Regular Public Bus	39.6
Metro	48.3
Commuter Train	26.5
Car	26.2
Private Shuttle Service	0.0
<u>Automated Bus Ride Experience (Time Period 1)</u>	
Never	53.3
At least once	46.7

The perceptions included in the model are:

1. safety travelling by AV, with 3 questions
2. cybersecurity, with 2 questions
3. AV ride comfort, with 3 questions
4. travel time, with 4 questions
5. travel fare, with 3 questions

Each service attribute quality perception is a latent variable. Table 4.2 shows the list of indicators of each service attribute quality perception. In general, the respondents had positive perceptions with the safety, ride comfort and travel fare of an AB service. However, they had bad perceptions towards cybersecurity and travel bus of an AB service. Table B1 in Appendix B shows the pattern matrix of the items from factor analysis. The results show that the items have good fit with the respective latent variable. Also, there is no significant correlation between each latent variable, as shown in Table B2 in Appendix B.

WTP for three types of AV services 1. PAV service, 2. SAV service, and 3. AB service that operates in the same way as existing scheduled public bus service) as if to use the service for a long period of time is measured as the amount of money one is willing to pay on top of the public transport monthly pass they were paying at the time of survey.

Table 4.2 Items/indicators for service attribute perception

Service Attribute Perception	Item / Indicator	Question	Mode	Mean
Safety	SafetyWithoutSteward	I feel _____ if there is NO operator/ steward on the automated bus. (1 if Extremely Unsafe; 2 if Unsafe; 3 if Neutral; 4 if Safe; 5 if Extremely Safe)	4	3.2
	Safety_Pedestrian	From the point of view of a pedestrian who wants to cross a road without using pedestrian crossing facilities, I feel _____ when I see an oncoming automated bus on public road.(1 if Extremely Unsafe; 2 if Unsafe; 3 if Neutral; 4 if Safe; 5 if Extremely Safe)	4	3.2
	Safety_CarDriver	From the point of view of a non-automated car driver, I feel _____ when I encounter an automated bus on public road. (1 if Extremely Unsafe; 2 if Unsafe; 3 if Neutral; 4 if Safe; 5 if Extremely Safe)	4	3.2
Cybersecurity	Cybersecurity_Hacked	I feel that the chance of its automated driving system being hacked would be: (1 if Extremely Low; 2 if Low; 3 if Neutral; 4 if High; 5 if Extremely High)	2	2.9
	Cybersecurity_GPS	I feel that the chance of its GPS data being shared with unauthorised parties would be: (1 if Extremely Low; 2 if Low; 3 if Neutral; 4 if High; 5 if Extremely High)	3	2.9
Ride Comfort	RideComfort_Tech	I feel that the level of on-board comfortability due to driving speed and driving patterns of the automated bus would be: (1 if Extremely Uncomfortable; 2 if Uncomfortable; 3 if Neutral; 4 if Comfortable; 5 if Extremely Comfortable)	3	3.4
	RideComfort_Facilities	I feel that the level of on-board comfortability due to the facilities inside the automated bus would be: (1 if Extremely Uncomfortable; 2 if Uncomfortable; 3 if Neutral; 4 if Comfortable; 5 if Extremely Comfortable)	3	3.3

Table 4.2 Items/indicators for service attribute perception (continued)

Service Attribute Perception	Item / Indicator	Question	Mode	Mean
Ride Comfort	OverallRideComfort	I feel that an automated bus ride would be: (1 if Extremely Unpleasant Ride; 2 if Unpleasant Ride ; 3 if Neutral; 4 if Pleasant Ride; 5 if Extremely Pleasant Ride)	3	3.2
Travel Time	Time_RegularPublicBus	Perception about travel time by automated vehicle in comparison to travel time by regular public bus given same distance and route (1 if Much Longer than by regular public bus; 2 if Longer than by regular public bus; 3 if Same; 4 if Shorter than by regular public bus; 5 if Much Shorter than by regular public bus)	3	2.7
	Time_Metro	Perception about travel time by automated vehicle in comparison to travel time by taking metro given same distance and route (1 if Much Longer than by taking metro; 2 if Longer than by taking metro; 3 if Same; 4 if Shorter than by taking metro; 5 if Much Shorter than by taking metro)	2	2.3
	Time_Train	Perception about travel time by automated vehicle in comparison to travel time by train given same distance and route (1 if Much Longer than by train; 2 if Longer than by train; 3 if Same; 4 if Shorter than by train; 5 if Much Shorter than by train)	2	2.3

Table 4.2 Items/indicators for service attribute perception (continued)

Service Attribute Perception	Item / Indicator	Question	Mode	Mean
Travel Time	Time_Car	Perception about travel time by automated vehicle in comparison to travel time by car given same distance and route (1 if Much Longer than by car; 2 if Longer than by car; 3 if Same; 4 if Shorter than by car; 5 if Much Shorter than by car)	2	2.2
Travel Fare	Fare_RegularPublicBus	Perception about travel fare by automated vehicle in comparison to travel fare by regular public bus given same distance and route (1 if Much More Expensive than by regular public bus; 2 if More Expensive than by regular public bus; 3 if Same; 4 if Cheaper than by regular public bus; 5 if Much Cheaper than by regular public bus)	3	3.4
	Fare_Metro	Perception about travel fare by automated vehicle in comparison to travel fare by taking metro given same distance and route (1 if Much More Expensive than by taking metro; 2 if More Expensive than by taking metro; 3 if Same; 4 if Cheaper than by taking metro; 5 if Much Cheaper than by taking metro)	3	3.3
	Fare_Train	Perception about travel fare by automated vehicle in comparison to travel fare by taking train given same distance and route (1 if Much More Expensive than by taking train; 2 if More Expensive than by taking train; 3 if Same; 4 if Cheaper than by taking train; 5 if Much Cheaper than by taking train)	4	3.4

4.2 Data analysis

Structural Equation Model (SEM) that was applied in this study is also called analysis of covariance structures or causal modelling. SEM has a structure that comprises observable variables, latent variables, indicators of the latent variables and utility. In this study, the observable variables are the individual characteristics as shown in Figure 4.1; the latent variables are the service quality attribute perceptions as shown in Figure 4.1; the indicators of the service quality attribute perceptions are listed on Table 4.2; and the utility is the willingness-to-pay for each AV service. The mathematical structure of a SEM model is shown in Figure 4.3.

Figure 4.3 General mathematical function of a SEM model

A structural equation model has the form of:

$$u = \mathbf{B}\mathbf{x} + \mathbf{C}\mathbf{y} + \varepsilon$$

where

K is the number of objective variable

M is the number of latent variable

N is the number of indicator of the respective latent variable

$\mathbf{B} = (1 \times K)$ matrix with the coefficients of objective variables

$\mathbf{x} = (K \times 1)$ vector of objective variables

$\mathbf{C} = (1 \times M)$ matrix with the coefficients of latent variables

ε = normal distributed error term of utility

$$\mathbf{y} = \mathbf{Ax} + \mathbf{v}$$

where

$\mathbf{y} = (M \times 1)$ vector of latent variables

$\mathbf{A} = (M \times K)$ matrix with the coefficients denoting the effects of objective variables on latent variables

$\mathbf{x} = (K \times 1)$ vector of objective variables

$\mathbf{v} = (M \times 1)$ vector composed of M independently and identically normal distributed error terms

The theoretical SEM model as shown in figure 4.1 was analysed using SPSS AMOS. SEM was chosen because it allows estimation of multiple correlated decisions simultaneously, and inclusion of latent variables. Before performing SEM analysis, three assumptions were checked. First, the residuals of the regression must be normally distributed. This assumption can be checked by assessing histogram or normal p-p plot of the residuals of the regression. Secondly, there must not be multicollinearity in the data. This can be checked by assessing Pearson's bivariate correlations matrix, making sure that the correlation coefficients among all independent variables to be less than 0.8. Lastly, the data should be homoscedastic, which can be ascertained by assessing the scatter plot of residuals versus predicted values. These assumptions were duly checked, as presented in Appendix B.

4.3 Results and discussion

Distribution of willingness-to-pay for AV services

Figure 4.4 shows the distribution of the WTP for:

1. on-demand personalised AV (PAV) service
2. demand responsive shared AV (SAV) service
3. first-/last-mile AB service.

Almost half of the respondents (44%) were not willing to pay additional fee for AB service on top of their monthly travel pass. The distribution of WTP for PAV service is more evenly distributed than others. About 16% of the respondents were willing to pay up to 200 Kronor (about 19 euro or USD 21) to gain access to PAV service given the same travel distance. Surprisingly, there were about 12% of the respondents willing to

pay more than 400 Kronor (about 38 euro or USD 42) on top of their monthly travel pass.

Figure 4.4 Distribution of willingness-to-pay for three types of AV services (PAV, SAV and AB services)

Model fit of the model adopted in this study, as shown in Figure 4.1, was examined. Table 4.3 shows the model fit measures of the model. CMIN/df, Root Mean Square Error of Approximation (RMSEA), Standardised Root Mean Square Residual (SRMR), and Goodness of Fit (GFI), were used to examine the model fit of the proposed model. CMIN/df value between 2 to 5 indicates a reasonable fit. RMSEA value which is equal to or less than 0.08 indicates an acceptable error of approximation. SRMR is the square root of the difference between the hypothesised model and the residuals of the sample covariance matrix. A SRMR value which is less than 0.08 indicates good fit. GFI value close to 1 indicates a perfect fit and GFI value more than 0.90 indicates a good model fit. This model has good fit because all the requirements for the indicators are fulfilled.

Table 4.3 Model fit measures of the tested model

	CMIN/df	RMSEA	SRMR	GFI
Model fit indicator	2.780	0.055	0.073	0.924

Significant factors influencing WTP for PAV, SAV and AB services

Figure 4.5 shows the significant factors influencing WTP for respective PAV, SAV, AB services. Values with one decimal place are the regression effects of the service quality attribute variables and individual characteristic variables on WTP for the services. Also, the path coefficients leading from the latent exogenous variables to the indicators are presented, with the coefficients shown by values with two decimal places.

The results show that respondents held different expectations on the AV services. The expected service quality attributes can be treated as the minimum requirements for the respondents to pay for the AV services willingly. Consumers expect PAV service to be safe, with satisfactory ride comfort and be priced competitively; SAV service to be safe and with good ride comfort; AB service to be safe and with acceptable travel time in comparison to travelling by metro, train and car. People would be less willing to pay for the services when the minimum requirements cannot be fulfilled.

Income level, existing travel modes for daily trips, familiarity with automated driving technology and AB ride experience are significant predictors of WTP for the AV services. Respondents who use car for daily trips and existing public bus users are more willing to pay more for on-demand PAV service. Also, similar to the finding by (Asgari & Jin, 2019), those who have taken at least one AB shared ride have greater WTP for PAV service. On the other hand, those who know well about automated driving technology are less willing to pay for PAV service. This observation is contrary with the finding by (Daziano et al., 2017) who found that people who know more about automated driving technology have higher WTP for private AV with full level of automation. This contrary finding signals respondents' distrust of the ability of AV services to operate safely, as demonstrated in the respective result presented in Figure 4.5. High income holders are less willing to pay for demand responsive SAV service. There is one highlight in the results: people who travel by commuter train for daily trips have less WTP for any of the AV services. This may be associated to the

context of this study in which the trial-operated AV service was not connected to the train station in the area.

Figure 4.6 shows the factors contributing to respondents' perceived safety, ride comfort and fare affordability in using an AV service. The values are the regression effects of the individual characteristic variables on the service quality perceptions. The results provide a quick glance into the perceptions of different user groups. Respondents who are tech-savvy perceive AV ride to be comfortable, safe and with acceptable travel time in comparison to travelling by metro, train and car. Also, those who ride bicycle for daily trips find that using AV service is comfortable. Male respondents are more confident with the safety of AV. Car users perceive AV services to be a more affordable travel option than driving a car.

On the other hand, respondents who walk for daily trips perceive AV ride to be less comfortable. People who know well about automated driving technology are more sceptical with the safety of using an AV service.

Findings

The respondents are willing to pay more for PAV service if the service provides good ride comfort, is safe and is priced sensibly. Other than service quality attribute perceptions, age, income level, existing travel modes for daily trips, familiarity with automated driving technology and AB ride experience are important factors affecting WTP for the AV services. These align with the past findings by (Bansal, Kockelman, & Singh, 2016) in which age and income level were found to be significant factors affecting WTP for AV.

If PAV service is priced sensibly, existing car owners would switch from driving to using the service. The respondents who had taken AB ride trial operated in Kista, Stockholm perceived using an AV service to be safe and comfortable. There are two user groups which require special attentions. They are people who walk for daily trips and people who know well about automated driving technology. People who chose to walk for daily trips perceived the ride comfort in using an AV service to be bad. People who understand well about automated driving technology were sceptical about the safety of using an AV service.

Figure 4.5 Significant factors influencing WTP for three AV services: PAV, SAV and AB (with p-value less than 0.05)

Figure 4.6 Significant factors influencing service quality attribute perception (with p-value less than 0.05)

5 STUDY 2: CHANGES IN DECISION-MAKING PARAMETERS TO ADOPT FIRST-/LAST-MILE AB BUS WITH INCREASING RIDE EXPERIENCES

Study 2 addresses research question 3 through examining the changes in interactions of decision-making parameters to adopt first-/last mile AB service after the first usage and the subsequent usage of the service through a two waves panel study.

When it comes to attitudes towards an AB service, socio-demographic characteristics that are found to be significant in affecting acceptance of AV or AB include age (Bansal et al., 2016; Rödel et al., 2014), gender (Payre et al., 2014; Rödel et al., 2014; Salonen, 2018; Schoettle & Sivak, 2014), income (Sanbonmatsu et al., 2018), and technology awareness (Schoettle & Sivak, 2014). These variables were included in the analyses as controlled variables.

Similar to study 1, study 2 asked for users' perceptions about the following service attributes in the survey:

1. safety
2. cybersecurity
3. ride comfort
4. travel time
5. travel fare

However, to increase the level of confidence of the estimates of the model, only the service attributes found to be significant in study 1 are included in this study.

Herein, the following perceptions of service quality attributes are included in the model, namely:

1. safety
2. ride comfort
3. travel time.

Table 5.1 shows the list of indicator variables used for the perceptions of service quality attributes. Figure 5.1 shows the conceptual model explaining the transition of users' perceived service qualities and their effects on continuance intention of first-/last-mile AB service of the experienced users who had used the service at least once.

The model is applied to analyse the changes in users' valuation of a first-/last mile AB service of two user groups: 1. adopters (the experienced users who continued with the service) and 2. quitters (the experienced users who discontinued with the service). The model is developed in reference to the findings found from the literature review of the changes in the relationships of users' perceived values with ITU due to experience as explained in section 2.2. In a more specific way, this conceptual model addresses the influences of perceptions from the first usage on the perceptions from the subsequent usage and continuous intention in the subsequent usage, in reference to the past evidence obtained from the literature review in section 2.2.

Figure 5.1 Conceptual framework to examine the changes of perceived service qualities influencing continuance intention of first-/last-mile automated bus service of the experienced users who had used the service at least once

Table 5.1 List of indicator variables used to represent the service quality attributes

Indicator variable	Description	List of responses				
Safety						
Safety_Item1: SafetyOnRoad	safety perception about ability of an AB to interact safely with other vehicles on the road	1-Extremely Unsafe	2-Unsafe	3-Neutral	4-Safe	5-Extremely Safe
Safety_Item2: SafetyNoSteward	on-board safety without a steward on AB	1-Extremely Unsafe	2-Unsafe	3-Neutral	4-Safe	5-Extremely Safe
Service Quality						
RideComfort_Item1: RideComfortTech	ride comfort due to driving speeds and driving patterns of AB	1-Extremely Uncomfortable	2-Uncomfortable	3-Neutral	4-Comfortable	5-Extremely Comfortable
RideComfort_Item2: RideComfortFacility	ride comfort due to the facilities on AB	1-Extremely Uncomfortable	2-Uncomfortable	3-Neutral	4-Comfortable	5-Extremely Comfortable
Travel Time Reliability						
TravelTimeReliability_Item1: TravelTimeBus	time saving/loss travelling by AB in comparison to taking a regular bus service	1-Much Longer than the alternative option	2-Longer than the alternative option	3-Neutral	4-Shorter than the alternative option	5-Much Shorter than the alternative option
TravelTimeReliability_Item2: Frequency	frequency of AB service in comparison to the frequency of a regular public bus service	1-Not at all Better	2-Somewhat Better	3-Same Frequency	4-Better	5-Much better

5.1 Description of the responses

Two survey data sets: survey data set 1 collected from the first wave of panel survey and survey data set 2 collected from the second wave of panel survey were analysed in this study. Survey data set 1 was collected in period 1 and survey data set 2 was collected in period 2 in the following time frame:

Period 1 (P1): February to March 2018 (shortly after the service started its trial operation in January 2018), and

Period 2 (P2): April to May 2018 (after the service had been operating for about 4 months) in Stockholm.

604 responses were collected in period P1 and 532 responses in period P2. A total of 483 respondents completed both rounds of surveys. Out of the 483 respondents, 88 are the users who used the service for the first time (new users), 116 are experienced users who continued with the service in period P2 (the adopters) and 69 are the experienced users who discontinued with the service in period P2 (the quitters). Table 5. 2 shows the descriptions of the three experimental groups.

Table 5.2 Experimental groups in this study

Time period	Group 0-1 (New users)	Group 1-1 (Adopters)	Group 1-0 (Quitters)
Period P1 (Feb/Mar '18)	Have not taken any AB ride	Have taken at least one AB ride	Have taken at least one AB ride
Period P2 (Apr/May '18)	With increase in ride experience	With increase in ride experience	Without increase in ride experience
Sample count, n	88	116	69

Table 5.3 shows the percentage of socio-demographic characteristics of the respondents in each experimental group. Group 1-1 has fewer student population (about 20% less) than group 1-0 and group 0-1. Also, there are more respondents with high annual income in group 1-1. This skewness should be noted in the interpretation of the results.

Table 5.3 Percentage of socio-demographic characteristics of the respondents

Characteristics/ sample group	New users: Group (0-1) Without AB ride experience in period P1, and gain first experience in period P2 (n=88), %	Adopters: Group (1-1) With AB ride experience in period P1 and gain experience in period P2 (n=116), %	Quitters: Group (1-0) With AB ride experience in period P1 and gain no experience in period P2 (n=69), %	Total (n=273), %
<u>Gender</u>				
Male	73.9	75.0	72.0	69.6
Female	25.0	24.1	27.0	29.3
<u>Age</u>				
Young Adult (aged 15-24)	34.1	16.4	32.0	20.9
Adult (aged 25-44)	44.3	44.8	40.0	44.3
Middle-age Adult (aged 45-64)	20.5	34.5	24.0	30.8
Elderly (aged above 65)	1.1	4.3	4.0	4.0
<u>Employment Status</u>				
Employed	53.4	74.1	53.0	67.8
Unemployed	1.1	2.6	5.0	3.3
Student	45.5	23.3	42.0	28.9
<u>Education Background</u>				
Above bachelor's degree	67.0	81.9	31.0	77.7
Below bachelor's degree	33.0	18.1	68.0	22.3
<u>Gross Monthly Income (before tax) in Swedish Kronor (SEK)</u>				
Low-income (≤ 200,000 SEK)	22.7	12.9	22.0	16.5
Middle-income (200,000 - 699,000 SEK)	59.1	62.1	34.0	58.6
High-income (≥ 700,000 SEK)	18.2	25.0	18.0	24.9
<u>Technology Awareness</u>				
Tech-savvy: well informed about or know how to use computers, mobile phones and electronic devices.	96.6	97.4	95.0	96.0
Familiar with the technologies used to enable automated road vehicle to drive without human driver	53.4	50.0	57.0	52.7

5.2 Data analysis

The following social demographics variables were included in the analyses as controlled variables:

1. Age (years)
  - Young Adult (aged 15-24)
  - Adult (aged 25-44)
  - Middle-age Adult (aged 45-64)
  - Elderly (aged above 65)
2. Gender
  - Male
3. Gross Annual Income
  - Low-income (less than 200,000 SEK)
  - High-income (above 700,000 SEK)
4. Familiarity with automated driving technology
  - FamiliaritywithAutomatedTechnology

The proposed model as shown in Figure 5.1 was used to analyse the changes in users' valuation of the new users (group 0-1), the adopters (group 1-1) and the quitters (group 1-0). The analyses were performed by SEM with SPSS AMOS. SEM was selected because it allows testing of the model with complex patterns of relationship among the multitude of variables in the proposed model. The results for the two groups were compared and contrasted to find the effects of increasing ride experiences. Assumption checking of maximum likelihood estimation of SEM and model fit of the models were evaluated, and estimates of the significant factors are reported in section 5.3.

5.3 Results and discussion

Table 5.4 shows the means statistics of the indicator variables and ITU first-/last-mile AB service for the three experimental groups used in the SEM analysis, in period 1 (P1) and period 2 (P2). There was a significant decrease in ITU from the new users, (group 0-1). After initial usage, ITU was maintained for the experienced users who continued with the service (group 1-1) while ITU dropped for the experienced users who discontinued service (group 1-0). Members of group 1-0 were more dissatisfied by the travel time with the AB service.

5.3.1 Measurement Model

Maximum likelihood estimation of SEM was used based on two assumptions: 1. multivariate normal distribution of the indicator variables, and 2. large enough sample size. IBM's SPSS was used for statistical checks of the assumptions.

Assumptions Checking

Multicollinearity:

The correlation matrix of the variables was assessed to check on the multicollinearity assumption. All the variables did not have a bivariate correlation of 0.7 or more in the analysis. Secondly, two indicators: tolerance and variance inflation factor (VIF) of each variable were checked. Tolerance needs to be above 0.1 while VIF needs to be below 3 to rule out multicollinearity. By assessing the tolerance and VIF of the variables as shown in Tables C1 and C2 in Appendix C, the assumption of not having multicollinearity was fulfilled.

Outliers, normality, linearity, homoscedasticity, independence of residuals:

By assessing the normal probability plot (P-P plot) of the regression standardised residuals as shown in Figures C1 and C2 in Appendix C, normality assumption was fulfilled since the points lie along the diagonal line from bottom left to top right reasonably. The assumptions of multiple regressions are fulfilled.

Table 5.4 Means of indicator variables and intention-to-use first-/last-mile AB service for various groups

			Group 0-1		Group 1-1		Group 1-0	
			Without AB ride experience in period 1 and gain experience in period 2 (n=88), %		With AB ride experience in period 1 and gain experience in period 2 (n=116), %		With AB ride experience in period 1 and gain no experience in period 2 (n=69), %	
Independent Variable								
			Period 1 Mean	Period 2 Mean	Period 1 Mean	Period 2 Mean	Period 1 Mean	Period 2 Mean
Perception								
(1) safety perception about ability of an AB to interact safely with other vehicles on the road		(1-Extremely Unsafe; 2-Unsafe; 3-Neutral; 4-Safe; 5-Extremely Comfortable)	3.24	3.39	3.30	3.36	3.41	3.32
(2) onboard safety without a steward on AB		(1-Extremely Unsafe; 2-Unsafe; 3-Neutral; 4-Safe; 5-Extremely Comfortable)	3.38	3.25	3.42	3.37	3.38	3.20
(3) ride comfort due to driving speeds and driving patterns of AB		(1-Extremely Uncomfortable; 2-Uncomfortable; 3-Neutral;	3.52	3.42	3.44	3.41	3.42	3.51
(4) ride comfort due to the facilities on AB		(1-Extremely Uncomfortable; 2-Uncomfortable; 3-Neutral;	3.36	3.34	3.37	3.33	3.41	3.17
(5) time saving/loss travelling by AB in comparison to taking a regular bus service		(1-Much Longer than taking a non-autonomous bus ride; 2-Longer than taking	2.75	2.60	2.75	2.51	2.8*	2.38*
(6) frequency in comparison to the frequency of a regular public bus service		(1-Not at all Better; 2-Somewhat Better; 3-Same Frequency; 4-Better; 5-	3.84*	2.63*	3.79*	2.66*	3.65*	2.48*
Dependent Variable								
			Period 1 Mean	Period 2 Mean	Period 1 Mean	Period 2 Mean	Period 1 Mean	Period 2 Mean
Intention to use the first-/last-mile AB		(1-definitely not taking the autonomous bus ride, 2-probably not taking the autonomous bus ride, 3-neutral, 4-probably will	4.01*	3.51*	4.06	3.99	3.93	3.64
* Means are statistically different from independent samples T-test (with a p-value < 0.05)								

* Means are statistically different from independent samples T-test (with a p-value < 0.05)

Confirmatory Factor Analysis

CFA was performed to check the factor structure used in the models. The factor structure has a good model fit. Table 5.5 shows the model fit of the factor structure. The CMIN/df value which is less than 3, indicating a good model fit. Also, the factor structure model has p-value bigger than 0.05, CFI value more than 0.95 and RMSEA value less than 0.05. All these values indicate a good model fit. Table 5.6 shows the factor loadings of the indicator variables, and the composite reliability (CR) value and average variance extracted (AVE) value of the constructs. The factor loadings show the correlation coefficient of the variable with the latent construct. Ride comfort has good CR value which is larger than 0.7 and AVE value which is larger than 0.5. The other two constructs: safety and travel time reliability have CR values less than 0.7 and AVE values less than 0.5. Even though these two constructs do not have as good CR values and AVE values, they are deemed satisfactory because they are new measures which are still not well-established. The validity test is viewed as an exploratory test.

Table 5.5 Model fit indicators of the factor structure tested in confirmatory factor

Minimum discrepancy (CMIN/df)	p-value	Comparative fit index (CFI)	Root mean square error of approximation (RMSEA)
1.161	0.226	0.988	0.024

Table 5.6 Factor loadings of the indicator variables used in model 1 and model 2

Item descriptive, and loadings		
Construct	Item (Code)	Factor Loading
Safety_P1 AVE = 0.403 CR = 0.574	safety perception about ability of an AB to interact safely with other vehicles on the road (SafetyOnRoad)	0.633
	on-board safety without a steward on AB (SafetyNoSteward)	0.636
RideComfort_P1 AVE = 0.546 CR = 0.706	ride comfort due to driving speeds and driving patterns of AB (RideComfortTech)	0.753
	ride comfort due to the facilities on AB (RideComfortFacility)	0.724
TravelTimeReliability_P1 AVE = 0.350 CR = 0.518	time saving/loss travelling by AB in comparison to taking a regular bus service (TravelTimeBus)	0.576
	frequency of AB service in comparison to the frequency of a regular public bus service (Frequency)	0.607
Safety_P2 AVE = 0.326 CR = 0.491	safety perception about ability of an AB to interact safely with other vehicles on the road (SafetyOnRoad)	0.592
	on-board safety without a steward on AB (SafetyNoSteward)	0.549
RideComfort_P2 AVE = 0.540 CR = 0.701	ride comfort due to driving speeds and driving patterns of AB (RideComfortTech)	0.783
	ride comfort due to the facilities on AB (RideComfortFacility)	0.684
TravelTimeReliability_P2 AVE = 0.375 CR = 0.533	time saving/loss travelling by AB in comparison to taking a regular bus service (TravelTimeBus)	0.464
	frequency of AB service in comparison to the frequency of a regular public bus service (Frequency)	0.731

Model Fit

Model fit of the models (model 1 for group 0-1, model 2 for group 1-1 and model 3 for group 1-0) adopted in this study was examined. Table 5.7 shows the model fit measures of the tested models. CMIN/df, RMSEA, and SRMR were used to examine the model fit of the SEM models. CMIN/df should be less than 5 to indicate a good fit. All models have CMIN/df value less than 5. RMSEA value which is equal to or less than 0.08 indicates a reasonable error of approximation. Model 1 and model 2 have RMSEA value less than 0.08 and model 3 has RMSEA value slightly more than 0.08. SRMR is the square root of the difference between the hypothesised model and the residuals of the sample covariance matrix. A SRMR value which is less than 0.08 indicates a good fit. All models have SRMR value less than or equal to 0.08 The three indicators support that the models have a good model fit.

Table 5.7 Model fit measures of the tested models

Model Fit Indicators	Minimum discrepancy (CMIN/df)	Root mean square error of approximation (RMSEA)	Standardised root mean square residual (SRMR)
Model 1 (group 0-1)	1.482	0.074	0.080
Model 2 (group 1-1)	1.249	0.046	0.076
Model 3 (group 1-0)	1.486	0.085	0.080

5.3.2 Changes in users' valuations with increasing ride experiences

ITU of new users dropped after they used the first-/last-mile AB service. ITU was maintained for the experienced users who continued with the service (group 1-1) while ITU dropped for the experienced users who discontinued service (group 1-0). Figure 5.2 shows the significant variables identified from model 1 in which the changes in users' valuation from period 1 to period 2 of the new users (group 0-1) were investigated. Figure 5.3 shows the significant variables identified from model 1 in which the changes in users' valuation from period 1 to period 2 of the adopters (group 1-1) were investigated. Figure 5.4 shows the significant variables identified from model 2 in which the changes in users' valuation from period 1 to period 2 of the quitters (group 1-0) were investigated. Estimations with a p-value less than 0.1 are presented in Figure 5.2, Figure 5.3 and Figure 5.4, except for those with dotted line. The dotted lines show the relationships found to be insignificant in the analyses but are presented in the diagram to give a better overview of their relationship within the overall relationships.

ITU of new users (group 0-1) would be higher when they have higher pre-use ITU. The new users were more attracted to use the service when they perceived the ride comfort of AB ride to be good. The judging criteria of the adopters (group 1-1) changed with increasing ride experiences. Before the additional ride experiences, ITU of the adopters was affected by their level of satisfaction with the safety and travel time reliability of the service. However, the two perceptions did not contribute to the adopters' continuance intention with additional ride experiences. Continuance intention of the adopters was affected by their level of satisfaction with the ride comfort of the service instead of safety and travel time reliability of the service with increasing ride experiences. On another hand, without additional ride experiences, the

continuance intention expressed by the quitters (group 1-0) in period 2 was mainly related to their expressed ITU in period 1.

Users' perceptions of service quality attributes positively affect ITU, as demonstrated by the positive relationships of the service quality attribute perceptions with ITU. The result aligns with the findings from (Chiou, 2004) and (Chen, Hsiao, & Li, 2020) stating that users' satisfaction has a positive effect on users' continuance intention. Besides, the adopters' level of satisfaction with the safety and travel time reliability in period 1 affects the respective level of satisfaction after gaining additional ride experiences. Similarly, the quitters' level of satisfaction with the ride comfort and travel time reliability in period 1 affects the respective level of satisfaction in period 2.

Model 1: Changes in users' valuation of new users, group 0-1 (n=88)

** Significant estimate with p-value less than 0.05.

Figure 5.2 Changes in users' valuations of new users (group 0-1)

Figure 5.3 Changes in users' valuations of the adopters (group 1-1)

Figure 5.4 Changes in users' valuations of the quitters (group 1-0)

Findings

Results show that once users have gained more experience with first-/last-mile automated service, there is little change in terms of their willingness-to-use the service and their level of satisfaction with the quality of the service. However, the driving force which attracts the experienced users to continue with the service may change with an increase in ride experiences. For example, the experienced users were attracted to use the service because they perceived the safety and travel time reliability of the service to be good but chose to continue with the service after gaining additional ride experiences due to their appreciation with the ride comfort of the service. With an increase in ride experiences, the service quality needs of the experienced users evolved from the basic needs such as travel time reliability and safety to the higher level of need: ride comfort. This result is consistent with the findings in study 3.

6 STUDY 3: CHANGES IN DECISION-MAKING PARAMETERS TO ADOPT FIRST-/LAST-MILE AB BUS DUE TO USERS' RELATIVITY VALUE OF SERVICE QUALITY PROVISION

Study 3 addresses research question 4 through analysing the changes of the interactions of decision-making parameters to adopt a new transport service, driven by user's relativity value of service quality provision.

6.1 Description of the responses

Survey data set 1 was analysed in this study. Out of the 604 responses received in the first round of survey, 574 responses remained for use in this study, after eliminating the incomplete data and missing values. The list of explanatory variables used in the analyses in this study is shown in Table 6.1, and the descriptive statistics of the service attribute perception variables are shown in Table 6.2.

Table 6.1 List of explanatory variables used in the analyses
n (Out of 574) %

Gender				
	Female	1 if Female; 0 otherwise	195	34.0
Age (years)				
	Below 25	1 if below 25; 0 otherwise	118	20.6
	Above 44	2 if above 44; 0 otherwise	209	36.4
Annual Income				
	High Income	1 if annual income before tax is equal to and above 400,000 SEK; 0 otherwise	237	41.3
Employment Status				
	Work	1 if employed; 0 otherwise	339	59.1
	Business Owner	1 if business owner; 0 otherwise	18	3.1
	Student	1 if student; 0 otherwise	177	30.8
	Pensioner	1 if on pension; 0 otherwise	24	4.2
Travel Mode used for Daily Commute				
	Walking	(1 if by walking; 0 otherwise)	152	26.5
	Cycling	(1 if by cycling; 0 otherwise)	79	13.8
	Bus	(1 if by public bus; 0 otherwise)	226	39.4
	Metro	(1 if by metro; 0 otherwise)	278	48.4
	Commuter train	(1 if by commuter train; 0 otherwise)	154	26.8
	Car	(1 if by car; 0 otherwise)	151	26.3
First-/Last-mile Travel Mode used for Daily Commute				
	Walking	(1 if by walking for first-/last-mile; 0 otherwise)	391	68.1
	Cycling	(1 if by cycling for first-/last-mile; 0 otherwise)	67	11.7
	Bus	(1 if by public bus for first-/last-mile; 0 otherwise)	254	44.3
	Personal Mobility Device	(1 if by personal mobility device for first-/last-mile; 0 otherwise)	6	1.0
	Tech-savvy	(1 if tech-savvy; 0 otherwise)	540	94.1
	Familiar with Automated Driving Technology	(1 if familiar with automated driving technology; 0 otherwise)	327	57.0
	Have experience of taking AB ride trial operated in Kista *This variable is not included in the analyses of experienced users and inexperienced users	(1 if have taken at least one AB ride operated in Kista; 0 otherwise)	269	46.9
	Acceptable Travel Time-Less than 10 mins	(1 if acceptable travel time for first-/last-mile trip with 750m distance which is < 10 minutes; 0 otherwise)	507	88.3

Table 6.2 Descriptive statistics of the service attribute perception variables

	Percentage of the number of responses				
	1-Not at all Better	2-Somewhat Better	3-Same Frequency	4-Better	5-Much better
(1) frequency of AB service in comparison to the frequency of a regular public bus service	1%	8%	26%	49%	16%
	1-Extremely Unsafe	2-Unsafe	3-Neutral	4-Safe	5-Extremely Safe
(2) onboard safety with a steward on AB	1%	1%	34%	45%	18%
(3) onboard safety without a steward on AB	3%	20%	32%	38%	8%
(4) safety perception about ability of an AB to interact safely with other vehicles on the road	3%	27%	22%	40%	8%
	1-Extremely Uncomfortable	2-Uncomfortable	3-Neutral	4-Comfortable	5-Extremely Comfortable
(5) ride comfort due to driving speeds and driving patterns of AB	1%	8%	43%	42%	6%
(6) ride comfort due to the facilities on AB	1%	6%	57%	32%	4%
	1-Very Bad	2-Bad	3-Neutral	4-Good	5-Extremely Good
(7) onboard customer service on AB	2%	11%	55%	28%	4%
	1-Much Longer than the alternative option	2-Longer than the alternative option	3-Neutral	4-Shorter than the alternative option	5-Much Shorter than the alternative option
(8) time saving/loss travelling by AB in comparison to taking a regular bus service	8%	30%	42%	18%	2%
(9) time saving/loss travelling by AB in comparison to taking a metro	23%	38%	27%	10%	2%
(10) time saving/loss travelling by AB in comparison to taking a <i>Stockholm</i> commuter train	25%	37%	24%	11%	3%
(11) time saving/loss travelling by AB in comparison to taking a car serving the same distance and route	24%	40%	27%	8%	1%
	1-Much More Expensive than the alternative option	2-More Expensive than the alternative option	3-Neutral	4-Cheaper than the alternative option	5-Much Cheaper than the alternative option
(12) travel fare saving/loss of travelling by AB in comparison to taking a regular bus service serving the same distance and route	3%	6%	43%	41%	7%
(13) travel fare saving/loss of travelling by AB in comparison to taking a metro serving the same distance and route	3%	8%	44%	38%	7%
(14) travel fare saving/loss of travelling by AB in comparison to taking a commuter train serving the same distance and route	3%	7%	37%	41%	12%

6.2 Data analysis

The approach to analysing the data of this study was undertaken in three distinct steps, as shown in Figure 6.1.

Step 1:

The responses were categorised into three groups: (i) experienced users, (ii) inexperienced users, and (iii) all users. They were grouped according to their experience of taking a first-/last-mile AB ride in the trial operated in Kista. A total of 269 (47%) respondents had taken the first-/last-mile AB ride, and were grouped as 'Experienced Users'. The remaining 305 (53%) respondents who had not taken a ride were grouped as 'Inexperienced Users'. The total sample of all respondents (n=574) was grouped as 'All Users'.

Step 2:

This step consisted of, first, a three-factor theory analysis (X. Wu et al., 2018), followed by a regression analysis. Three-factor theory analysis was performed to identify the factors that impacted survey participants' intentions to use the AB service. Regression analysis was performed to identify the significant explanatory variables that contributed to the identification of factors from three-factor theory analysis, and these were subsequently included in the SEM in the third step. The following diagram explicates how the three-factor theory analysis (A) and regression analysis (B) were performed.

Figure 6.1 Approach to data used in this study

Three-factor theory analysis

This analysis began with recoding the original 5-point Likert Scale responses of the perceptions, either low-performance indicator (when the original responses are 1 or 2), high-performance indicator (when the original responses are 4 or 5), or missing values. Then, participants' ITU the first-/last-mile AB service was regressed on the indicators in the regression analysis.

According to three-factor theory, the perceptions can be grouped into three types of factors: 1. basic factor, 2. performance factor, and 3. exciting factor:

Basic factor

Perception is classified as a basic factor when its low-performance indicator is significant in the regression analysis. Basic factor means when the level of expectation/satisfaction about the service quality attribute falls below neutral point, the level of ITU the first-/last-mile AB service will decrease. However, when the level of

expectation/satisfaction about the service quality attribute is above neutral point, there is not much change in the level of ITU the AB service.

Performance factor

Perception is classified as a performance factor when both its low-performance indicator and high-performance indicator are significant in the regression analysis. Performance factor means any change (increase or decrease) in the level of expectation/satisfaction about the service quality will affect participants' intentions to use the AB service.

Exciting factor

Perception is classified as an exciting factor when its high-performance indicator is significant in the regression analysis. An exciting factor indicates that when the level of expectation/satisfaction about the service's quality is above the neutral point, the level of ITU first-/last-mile AB service will increase. However, when the level of expectation/satisfaction about the service's quality is below the neutral point, there will not be much change in the participant's level of ITU the AB service.

Regression Analysis

The main objective of regression analysis was to identify the significant explanatory variables affecting the core perceptions identified in the three-factor theory analysis. The list of variables used in the regression analysis is shown in Table 6.3. The significant variables were then included in the structural equation model in Step 3.

Step 3:

Structural equation models were constructed with the inputs from (A) three-factor theory analysis and (B) regression analysis. SEM was selected because of its ability to combine two layers of multiple regressions in one model. The first layer is the regression of the perceptions on the explanatory variables. The second layer is the regression of ITU the AB service on the perceptions. Also, the structural equation model served to explain the direct effects and indirect effects of the explanatory variables on both perceptions and intentions to use the AB service. Also, at this step, a Hausman test was performed to check the homogeneity of the variables in the structural equation models. Endogenous variables were addressed in the models. Model fit of the models was evaluated, and results are reported in the section 6.3.

6.2.1 Statistical checks

The analyses involved both multiple regression analysis and SEM (an analysis which combines factor analysis and multiple regression analysis). A multiple regression assumptions check (Osborne & Waters, 2002) was performed with the use of IBM's SPSS software, before the analyses of the study data. Additionally, the common method variance (CMV) (Podsakoff, MacKenzie & Podsakoff, 2012), or the variance attributed to the measurement method that results in false internal consistency, was also checked, to avoid CMV biases. It was performed using partial correlation in SPSS.

(1) Multiple Regression Assumptions Check:

Multicollinearity

Firstly, the correlation matrix of the variables was assessed to check the multicollinearity assumption. The variables do not have a bivariate correlation of 0.7 or more in the analysis. Secondly, two indicators – the tolerance and VIF of each variable – were checked. Tolerance needed to be above 0.1, while VIF needed to be

below 10. By assessing the two indicators of the variables as shown in Table D1 in Appendix D, the assumption of not having unacceptable multicollinearity is fulfilled.

Outliers, normality, linearity, homoscedasticity, independence of residuals

By assessing the normal probability plot (P-P plot) of the regression standardised residuals (shown in Figure D1 in Appendix D), the normality assumption was fulfilled, as the points correspond reasonably well to the diagonal line, from bottom left to top right. Only two outliers were identified. However, the outliers do not have much influence on the overall result of the model, because the maximum value for Cook's Distance is 0.127, which is less than 1. In conclusion, all the assumptions of multiple regression were fulfilled.

(2) Common Method Variance (CMV) Biases Check:

Partial correlation procedure in SPSS

CMV biases were checked by partialling out the first un-rotated factor in the exploratory factor analysis to determine if the theoretical relationships among the remaining variables of interest still held. The resulting sum of square variance should be below 50% to avoid CMV biases. The sum of square variance of the variables of interest (service quality perceptions) was 9.573%. It is low in comparison to the threshold of 50%. Hence, the result suggests that CMV bias in this study is low.

6.3 Results and discussion

This study applied three-factor theory analysis to categorise survey respondents' perceptions, and SEM to analyse the relationships between their perceptions and their intentions to use the trialled first-/last-mile AB service. Three-factor theory analysis was selected on the basis that the relationships between the service quality attributes and ITU are not always linear. Three structural equation models (SEM Model 1, SEM Model 2 and SEM Model 3) were constructed with the inputs from the analysis undertaken in Step 2: (A) three-factor theory analysis and a (B) regression analysis. The following discussion explains the results from the (A) three-factor theory analysis and (B) regression analysis.

Results from (A) three-factor theory analysis:

Tables D3, D4 and D5 in Appendix D show those service quality attribute perceptions found to be significant (with a p-value less than 0.10) from the regression analysis. Figure 6.2 shows the significant service quality perceptions affecting participants' intentions to use the first-/last-mile AB service, among experienced users, inexperienced users, and all users.

Figure 6.2 Significant service quality attributes affecting intention-to-use the first-/last-mile AB service, of experienced users, non-experienced users and all users

There is no perception classified as a basic factor that affects the ITU of experienced users and inexperienced users. However, when it comes to all users, low-performance indicators of the perception about the travel fare for using the AB service in comparison to travel by commuter train is found to be significant in influencing participants' ITU for a first-/last-mile AB service. Therefore, this perception is classified as a basic factor that influences the ITU of all users.

Perceptions about the frequency of the AB service is classified as a performance factor affecting the ITU of both inexperienced users, and all users. For experienced users, two perceptions are classified as performance factors: perception about travel time using the AB service in comparison to travel by metro, and perception about travel fare for using the AB service in comparison to travel by commuter train.

Perception about travel time using the AB service in comparison to travel by regular public bus is the exciting factor affecting the ITU of inexperienced users. Perception about ride comfort due to driving speed and driving pattern of the AB is the exciting factor affecting the ITU first-/last-mile AB service of experienced users and all users.

Results from (B) regression analysis:

Tables D6, D7 and D8 in Appendix D are the significant explanatory variables from the regression analyses. Together with the outputs from (A) three-factor theory analysis, the identified significant explanatory variables are included in the structural equation models for experienced users (SEM Model 1), inexperienced users (SEM Model 2), and all users (SEM Model 3), as shown in Figure 6.3. Figure 6.3 shows only links which are significant ($p < 0.10$, or $p < 0.05$) from the regression analysis, as in Tables D6-D8 in Appendix D.

Results from Structural Equation Modelling:

SEM was used to identify the significant factors that influence the identified perceptions influencing the ITU of experienced users, inexperienced users, and all users. Not all factors were included in the SEM analysis since the inclusion of non-significant factors would deteriorate model fit of the constructed models. Only the variables found to be significant (with p-value less than 0.10), as shown in Tables D6, D7 and D8 in Appendix D, were included in the SEM analysis.

Endogeneity Check

A check of endogenous variables was performed to avoid any adversarial impacts of endogeneity on the results. A Hausman test was used for this check. First, each explanatory variable was regressed on other explanatory variables, and the fitted values were saved. Then, the dependent variables were regressed on the explanatory variables used in the previous analysis and on the saved fitted values. The tested variable was deemed to be endogenous if the fitted value was significant (with a p-value less than 0.05). Table D2 in Appendix D shows the list of endogenous variables identified in the Hausman test. The endogenous variables were addressed in the SEM models, as shown in Figure 6.3, by correlating the error terms of the endogenous variables with the error term of participants' ITUs.

Figure 6.3 SEM models used in the final analysis

Check for Model Fit

Model fit of the three SEM models was also analysed. CMIN/df, RMSEA, SRMR and GFI were used to examine the model fit. Table 6.3 shows the model fit measures of three SEM models.

Table 6.3 Model fit measures of three SEM models

	CMIN/df	RMSEA	SRMR	GFI
SEM Model 1 (experienced users)	3.158	0.090	0.093	0.867
SEM Model 2 (inexperienced users)	6.425	0.134	0.114	0.875
SEM Model 3 (all users)	6.273	0.096	0.085	0.923

CMIN/df

CMIN/df should be less than 5 to indicate a good fit. SEM Model 1 has CMIN/df value less than 4. SEM Models 2 and 3 have CMIN/df value slightly more than 5, which indicates that the models are still close enough to good fit to be applicable in this study.

Root Mean Square Error of Approximation (RMSEA)

A RMSEA value equal to or less than 0.08 indicates a reasonable error of approximation. Again, all of these models were slightly greater than but still close to the threshold of 0.08. SRMR is the square root of the difference between the hypothesised model and the residuals of the sample covariance matrix.

Standardised Root Mean Square Residual (SRMR)

A SRMR value of less than 0.08 indicates a good fit. Model 1 exceeds the threshold by 0.013, Model 2 exceeds the threshold by 0.034, and Model 3 exceeds the threshold by 0.005. Since the discrepancies are very small, and not significantly far from 0.08, the models were deemed to be satisfactory.

Goodness of Fit (GFI)

A GFI value close to 1 indicates a perfect fit and GFI value more than 0.90 indicates a good model fit. SEM Model 3 has GFI value of more than 0.9 while SEM Models 1 and 2 are slightly less than 0.9. All the three SEM models fit well according to the descriptive measures of fit. Figures 6.5 shows the SEM models, with the estimates for significant variables in bold. Ride comfort due to driving speed and driving pattern of the AB was an exciting factor to the experienced users. On the other hand, instead of being a performance factor, frequency was found to be an exciting factor to the inexperienced users. Travel time and travel fare were insignificant to ITU of both the experienced users and inexperienced users.

**Explanatory Factors of
Intention-to-Use Model of
First-/Last-Mile Autonomous Bus Service
(experienced users, n=269)**

CMIN/df	RMSEA	SRMR	GFI
3.158	0.090	0.093	0.867

**Explanatory Factors of
Intention-to-Use Model of
First-/Last-Mile Automated Bus Service
(inexperienced users, n=305)**

CMIN/df	RMSEA	SRMR	GFI
6.425	0.134	0.114	0.875

**Explanatory Factors of
Intention-to-Use Model of
First-/Last-Mile Automated Bus Service
(all users, n=574)**

CMIN/df	RMSEA	SRMR	GFI
6.273	0.096	0.085	0.923

Figure 6.4 SEM models with the estimates for which the significant variables are bolded

Effects of Explanatory Variables on ITU

The explanatory variables in the SEM models not only affect service quality perceptions, but also participants' ITU the first-/last-mile AB service. Table 6.4 shows their effects on ITU the AB service of (i) experienced users, (ii) inexperienced users, and (iii) all users.

Table 6.4 Positive and negative indirect effect weightages of the significant explanatory factors on of experienced users, inexperienced users, and all users, with the strongest effect on top

Positive indirect effect weightages of the significant explanatory factors on ITU first-/last-mile AB service					
Experienced Users		Inexperienced Users		All Users	
LastMile_PMD (PersonalMobility Device)	0.087	LastMile_Bus	0.046	LastMile_PMD (PersonalMobilityDevice)	0.112
				TechSavvy	0.029
Negative indirect effect weightage of the significant explanatory factors on ITU first-/last-mile AB service					
Experienced Users		Inexperienced Users		All Users	
FamiliarWith Automated DrivingTech	-0.047			FamiliarWith Automated DrivingTech	-0.066
HighIncome	-0.007			Walk	-0.021
				Above44	-0.022

(i) Effects on ITU of experienced users:

Respondents who use personal mobility devices (PMD) for first-/last-mile have a higher ITU the first-/last-mile AB service. They perceive ride comfort due to driving speed and driving patterns of AB to be good. The respondents with high income have lower ITU the first-/last-mile AB service even though they perceive travel fare by AB service to be lower than metro service. Despite having a lower ITU the AB service, those who are familiar with automated driving technology perceive the travel time by AB service to be shorter than travelling by train, given the same route and distance.

(ii) Effects on ITU of inexperienced users:

The respondents who use the public bus system for first-/last-mile have higher ITU regarding the first-/last-mile AB service. Still, they perceive the frequency of the AB service to be worse than the frequency of a regular public bus service.

(iii) Effects on ITU of all users:

The respondents who use PMDs for first-/last-mile, or report being tech-savvy, have higher ITU scores in comparison to others. They perceive the frequency of the AB service to be better than a regular public bus service. Those who walk for daily trips, or are above 44 years old, have lower ITU scores in comparison to others. Those who walk for daily trips perceive ride comfort due to driving speed and driving pattern of AB to be poor. Those who are above 44 years old perceive the frequency of first-/last-mile AB service to also be poor. Again, despite having a lower ITU score, those who are familiar with automated driving technology perceive the travel fare of the service to be more affordable than the train service, given same distance and route.

Findings

The results indicate that perceptions of service quality vary according to age, income, existing travel modes for daily and first-/last-mile trips, tech-savviness, and familiarity with automated driving technology. The factors of age and income align with past findings. When the subject of the study, a first-/last-mile automated bus (AB) service, is featured as a transport service, travel characteristic variables such as travel modes used for daily trips and travel modes used for first-/last-mile trip also become important.

Two service quality attributes are prominent in influencing the respondents' WTU the trialled first-/last-mile AB service. They are service frequency and ride comfort due to both driving speed and driving pattern. Frequency of service has the greatest impact on ITU, followed by ride comfort due to driving speed and driving pattern. To the inexperienced users, who may also be called potential users, frequency of service is the key factor that influences their ITU of the AB service. Experienced users, who may also be called potential returning users, are concerned about the ride comfort due to driving speed and driving pattern. Enhancements to ride comfort due to driving speed and driving pattern acts as an exciting factor which encourages them to continue using the service.

Operators of an AB service should focus on improving the frequency of the service and the ride comfort due to technical performance of the AB. Operators should be aware that selected technical performance aspects of the AB, e.g. its driving speed and its driving/stopping pattern, have a significant impact on the level of service

delivered to passengers. Also, the findings indicate that first-/last-mile AB service is competing with existing first-/last-mile travel services, specifically emerging transport services such as shared personal mobility devices (PMDs) and current public bus services. If an AB service runs with satisfactorily high frequency, users of these other transport services would be attracted to consider the AB.

Among the findings of this study, one in particular stands out. Those who are familiar with automated driving technology perceive AB service to be a better transport option than commuter train service in terms of both travel time and fare price. Still, their ITU scores were low. Such contradictory views should be further investigated by future research.

7 STUDY 4: ASSESSING PEDESTRIAN MIDBLOCK ROAD-CROSSING RISK WHEN INTERACTING WITH AUTOMATED BUS

As a small focus in this thesis, study 4 addresses research gap 5 through analysing real-world interactions between pedestrians and AB when the pedestrians cross the road at the unsignalised midblock using LiDAR data. The objective is to derive important operational parameters to aid the design of road infrastructure and safety rules for safety purpose.

7.1 Description of the responses

Three timestamps were extracted from the LiDAR point clouds data for each identified pedestrian-AB interaction. At each time stamp, the relative distance between pedestrian and AB (r) and angle (θ) were recorded. First time stamp (t_1) was recorded when pedestrian starts to cross the road, as illustrated in Figure 7.1. Second time stamp (t_2) was recorded when pedestrian is at the point of intersection of the pedestrian's trajectory and AB's trajectory, as illustrated in Figure 7.2. Last time stamp (t_3) was recorded when pedestrian ends the crossing, as illustrated in Figure 7.3.

Figure 7.1 Illustration of the extracted data (relative distance and angle) at time stamp 1

Figure 7.2 Illustration of the extracted data (relative distance and angle) at time stamp 2

Figure 7.3 Illustration of the extracted data (relative distance and angle) at time stamp 3

Then, the following variables were calculated with the extracted from LiDAR data (relative distance between pedestrian and AB and the respective angle) at each time stamp:

1. Pedestrian road-crossing time:

$$\Delta t_1 = t_2 - t_1 ; \Delta t_2 = t_3 - t_2 ; \Delta t_{\text{total}} = t_3 - t_1$$

2. Longitudinal distance between pedestrian and AB when the pedestrian starts to cross the road,

$$\text{Equation 4.1: } y_{1(\text{Ped-AB})} = r_1 \times \sin \theta_1$$

3. AB average approaching speed,

$$\text{Equation 4.2: } v_{AB} = (y_{3(\text{Ped-AB})} - y_{1(\text{Ped-AB})}) / \Delta t_{\text{total}}$$

4. Pedestrian road crossing speed from the starting point to the point of intersection (the intersection point of pedestrian trajectory and AB trajectory),

$$\text{Equation 4.3: } v_{1(\text{Ped})} = (|r_1 \times \cos \theta_1|) / \Delta t_1$$

5. Pedestrian road crossing speed from point of intersection to ending point,

$$\text{Equation 4.4: } v_{2(\text{Ped})} = (| r_3 \times \cos \theta_3 |) / \Delta t_2$$

6. Time Difference to Point of Intersection,

$$\text{Equation 4.5: TDPI} = (y_{1(\text{Ped-AB})} / v_{AB}) - \Delta t_1$$

7.2 Data analysis

Time Difference to Point of Intersection (TDPI) was used as risk assessment indicator in this study. TDPI value obtained from the real-world interaction data is the risk a pedestrian is willing to take when the pedestrian crosses the road when encountering an oncoming AB.

Next, in order to investigate the relationship between pedestrian speed changing strategy and TDPI, pedestrian speed changing strategy was recorded. Two speed changing strategies were considered in this study: 1. decrease speed during the interaction or 2. increase speed during the interaction as obtained through comparing $v_{1(\text{Ped})}$ and $v_{2(\text{Ped})}$. Having a $(v_{2(\text{Ped})} - v_{1(\text{Ped})})$ value more than 0 m/s means the pedestrian increased speed during the interaction. Having a $(v_{2(\text{Ped})} - v_{1(\text{Ped})})$ value less than 0 m/s means the pedestrian decreased speed during the interaction.

Descriptive analysis was performed to find out minimum value, maximum value, mean, 25th percentile and 75th percentile of four variables: 1. TDPI indicator, 2. AB approaching speed, 3. longitudinal distance between pedestrian and AB when the pedestrian starts to cross the road, and 4. pedestrian road-crossing time. These four variables are useful to study their effects on pedestrians' speed changing strategy. Then, in order to find out the relationship of pedestrian road-crossing speed with risk (TDPI), a scatter plot of pedestrian road-crossing speed versus TDPI was plotted.

7.3 Results & Discussion

Comparing TDPI values of the pedestrian-AB interactions with some significant risk figures applied to the interaction between pedestrian and a non-automated vehicle

Smaller value of TDPI indicates higher safety risk and larger value of TDPI indicates lower safety risk. Figure 7.4 shows the scatter plot of pedestrian road-crossing speed

versus TDPI value. Results show pedestrians increase speed when there is smaller value of TDPI. Table 7.1 shows the statistics of minimum value, maximum value, median, mean, 25th percentile and 75th percentile of four variables. The 75th-percentile of the TDPI value for the group of pedestrians who increased speed (21.1s) is lower than the same indicator for the group of pedestrians who decreased speed (37.4s). This supports the earlier finding: pedestrians who increased speed were subjected to higher risk.

The 50th-percentile of TDPI value (median road-crossing risk threshold), 15.2s is higher than the average observed crossing gap of pedestrians when interacting with a conventional vehicle, 10.6s stated in (Rastogi et al., 2012). Also, crossing pedestrians decrease speed substantially when the TDPI value was above 75th-percentile of TDPI value, 26.4s.

Lastly, results from table 7.1 shows the group of pedestrians who increased speed were subjected to higher AB approaching speed, so their crossing distance (the longitudinal distance between pedestrian and AB) is higher than the group of pedestrians who decreased speed.

Figure 7.4 Plot of pedestrian road-crossing speed versus TDPI

Implication for the design of AB control algorithm

Figure 7.5 shows the boxplots of TDPI values of the pedestrians who decreased speed ($V_{2(Ped)} - V_{1(Ped)} < 0$) when interacting with AB, and TDPI of the pedestrians who increased speed ($V_{2(Ped)} - V_{1(Ped)} > 0$) when interacting with AB. Results show the pedestrians who increased speed were subjected to higher risk (with lower TDPI value). Instead of assuming slowing down as an unnecessary reaction, an AB shall take note that pedestrians with high road-crossing speed may feel unsafe so they increase their road-crossing speed. Therefore, instead of relying on pedestrians' road-crossing speed to decide its reaction plan, an AB should refer to the risk indicator e.g. TDPI to decide its behavioural reaction to the pedestrians.

The average pedestrian road-crossing time gap when the pedestrians interacted with the AB was found to be higher than the same indicator in the similar interaction with a non-AV. This implies that pedestrians may need extra time gap buffer when interacting with an AB than a non-AV. This could be due to the unfamiliarity of the pedestrians with the AB yet, while noting that ABs are being operated at a relatively much lower speed.

Figure 7.5 Boxplots of TDPI of crossing pedestrians who decreased or increased speed when interacting with an AB

Application of the results and the limitations

The results are applicable to the midblock road-crossing behaviour of a pedestrian, or several pedestrians (2 to 5 pedestrians) crossing together as a group, without using any road-crossing facilities. The results would not be applicable to road with median pedestrian refuge. There are several limitations in this study. First, there is small discrepancy in terms of the location of AB because the location of AB is taken from the point where LiDAR sensor was installed, i.e. on the left side of the vehicle, but not in the middle or front of the AB. Secondly, the sample size is small with $n = 42$, thus the results should be interpreted carefully. The individual characteristics such as age and gender were not explored in this study due to usage of LiDAR measurement device which does not capture any personal information of the road users. LiDAR was used in our study in order to comply with European Union's General Data Protection Regulation 2016/679 (European Commission, 2018). Lastly, the group of pedestrians who chose not to cross the road was not explored in this study due to the absence of the LiDAR data that recorded interactions occurring at the rear of the AB.

Table 7.1 Statistics of the four variables on speed change in pedestrian crossing

Speed Changing Strategy	Decrease Speed (n=28) versus Increase Speed (n=10)								Aggregated data (n=42)			
	Decrease Speed	Increase Speed	Decrease Speed	Increase Speed	Decrease Speed	Increase Speed	Decrease Speed	Increase Speed				
	Time difference to point of intersection, TDPI (s)	Time difference to point of intersection, TDPI (s)	AB approaching speed (m/s)	AB approaching speed (m/s)	Longitudinal distance between pedestrian and AB when pedestrian starts crossing the road (m)	Longitudinal distance between pedestrian and AB when pedestrian starts crossing the road (m)	pedestrian road-crossing time (s)	pedestrian road-crossing time (s)	Time difference to point of intersection, TDPI (s)	AB approaching speed (m/s)	Longitudinal distance between pedestrian and AB when pedestrian starts crossing the road (m)	pedestrian road-crossing time (s)
n	28	10	28	10	28	10	28	10	42	42	42	42
Mean	27.2	21.1	1.3	1.7	27.1	29.1	6.3	5.6	23.1	1.4	28.0	6.0
Minimum	6.4	6.5	0.2	0.5	3.0	11.6	3.2	3.0	4.8	0.2	3.0	2.8
25th Percentile	12.1	10.7	0.7	0.9	17.4	19.1	4.7	3.9	10.8	0.8	18.8	4.6
Median	17.9	15.9	1.2	1.8	28.2	31.4	5.7	5.9	15.3	1.3	29.2	5.7
75th Percentile	37.4	21.6	1.8	2.5	36.3	40.1	7.8	7.0	26.4	1.9	36.9	7.1
Maximum	96.2	76.7	3.1	2.6	47.6	40.6	11.6	8.8	97.3	3.1	53.9	11.6

8 CONCLUSION

The concluding chapter consist of three main parts: the concluding findings, the research contributions, the limitations, and the recommendations.

8.1 Conclusion

This research investigated the changes in users' decision-making parameters to adopt a first-/last-mile AB service in response to: 1. actual exposure to the service, 2. actual experiences with the service, and 3. the relativity of an individual's decision-making parameters with intention to use of the service. This research contributes to the research field of autonomous transport systems through studying the actual behaviour and attitudes in relation to a real, actually operating AB service.

Concluding points

- Users' service quality requirements towards different transport services are very different. The level of influence of each service quality requirement on the behavioural responses towards the service is different. Some service quality requirements have a higher influence while some service quality requirements have a lower influence on the behavioural responses towards the services. The difference is caused by the heterogenous nature of users' attitudes towards the service, the differences in users' interpretations of the service aspect, and the users' socioeconomic characteristics (Eboli & Mazzulla, 2011).
- Objective factors have both direct and indirect influences on the behavioural responses towards a new technology. In simpler terms, there are dominant perceptions towards the technology among the same group of people with the same socio-demographic characteristics/travel characteristics/familiarity with the technology. Such relationships act as the fundamental supports towards the use of objective factors in the conventional discrete choice models in which objective variables are dominant.
- Relationships between the objective factors with the associated perceptions are not stable when users have incomplete information about the technology. When users have no prior experience or information, their expectations are uncertain and

tentative due to the absence of pre-use information, and these expectations should not be used as firm criteria for evaluative judgements (Crompton & Love, 1995). A decision made without complete information about the technology is subject to logical fallacy. Consequently, the decision made is irrational and subject to changes after an individual gains full information about the new technology/service through actual experience with it.

- Actual ride experiences provide users greater information about the technology. The differences between users' expectations from using the new technology/service and the actual technology/service delivered result in positive (e.g. positive ITU) or negative (e.g. negative ITU) behavioural responses towards the new technology/service. This phenomenon is explained by the significant drop in ITU of the first-/last-mile AB service of the new users (i.e., those who trialled the new service for the very first time).
- As compared to the behavioural responses of the first time users, the behavioural responses of the adopters (users who continued with the service beyond the first trial) are more stable and consistent. Unlike the significant drop in ITU of the new users, ITU of the adopters is maintained at the same level.
- A reinforcement learning process was found to exist in the adopters of the first-/last mile AB service. This gives a strong evidence that users' level of information about a new technology/service has a significant impact on the stability of the representation of both the objective and subjective factors. In this research, level of information is measured as actual experience with a new technology/service. Users were assumed to have much greater information about a new technology/service after gaining actual experience with the technology/service.
- After users gain complete information about a new technology/service through actual experience with the technology/service, their requirements towards the technology/service change. They change from having lower LOS quality needs to higher LOS quality needs.

In conclusion, the utility functions of a new transport service such as AB service vary according to the adoption stages of the users. When it comes to transport modelling, having a selected set of objective factors or subjective factors to explain users' behavioural responses towards a new transport alternative like an AB service sounds like an ideal case. However, in reality users' acceptance of new transport alternative varies according to the adoption stage of users which corresponds to their level of information about the service.

Hence, it is important to include users' level of experiences with/level of information about a new transport alternative as a key variable when modelling the utility of a new transport alternative like an AB service. Specifically, when it comes to actual modelling, transport modellers need to be aware of the dynamic nature of the utility function of a new transport alternative such as AB service and set the states of the functions according to the users' adoption stages of the service, which can be defined in reference to the users' ride experiences.

Moving on, transport modellers of new transport such as AV/AB service should take note of the instability and possible fallacy of the representation of the objective and subjective factors as drawn from hypothetical studies. Other than obtaining the determinants through giving the users actual experience with a new technology/service by pilot test, methods such as providing respondents with information or a simulated scenario as close to the real service as possible can be used to close the users' information gap and results in more reliable representation of the objective and subjective factors used in the behavioural studies. Also, transport planners and operators should be aware that users need time to learn and adapt to AV/AB technology. Co-design approach which involves users in the development of a new technology/transport service can be adopted for better implementations of AV/AB services

Not only are individuals' behavioural responses an important factor to the successful implementation of first-/last-mile AB service, but so too is having good road infrastructure to support this implementation. Study 4 in this research demonstrated the use of LiDAR data to analyse pedestrians' midblock road-crossing behaviour when

interacting with an oncoming AB bus, and to derive important parameters to be checked against the existing road design principles.

Recommendations

There were a lot of debates on the safety of AV including AB in the past. Findings from this research have found that safety was not of a great concern to people who have taken AB ride trial operated in Kista, Stockholm. In order to attract people to use an AB service, an AB service should aim to deliver a service which can fulfil the basic travel needs of the passengers during the introductory phase. The basic travel needs include travel time reliability and reliable frequency. Then, it can gradually address the higher level of transit needs such as ride comfort.

Having car owners switching to shared AB service or first-/last-AB service would be strategic towards mitigating the traffic problems that arise from the private car usage. Findings from this research revealed that car owners were more in favour of an on-demand non-shared AV service than shared AB or first-/last-mile AB service. The existing car owners would switch from driving to using an on-demand non-shared AV service if the travelling cost is attractive. One possible way to encourage car owners to switch over to a shared AB service or first-/last-mile AB service would be to invite the group to use the service for a certain period of time and let them learn about the service so as to tune their perceptions towards public transport service and shared AB service or first-/last-mile AB service.

One distinctive characteristic of the commuter train station in the area is it is located within and very close to the residential area. On another hand, the operating route of the trial-operated first-/last-mile AB service is within the office area. Therefore, one of the possible reasons in which the commuter train users did not intend to ride the AB service is that the operating route did not serve their need. This means that the commuter train users are most likely work, or study in other areas so they did not intend to use the trial operated AB service which mainly served the people who work or study in the area. One insight from this finding is when designing a first-/last-mile AB service, it is important that the service operator takes the travel demand along the proposed operating route into consideration.

Findings from study 4 found that the safety risk of the pedestrian group who decreased speed was lower while the safety risk of the pedestrian group who decreased speed was lower while the safety risk of the pedestrian group who increased speed was higher. Even though the group who increased speed kept longer distance from the approaching AB when they started to cross the road, they increased speed due to higher AB approaching speed. Hence, when designing how an AB should respond to a pedestrian who crosses the road without using any crossing-facility, it is important that the AB should react in reference to the assessed safety risk, not solely based on the distance between the detected pedestrian and the AB.

Finally, transport planners should take note that once users have gained experience with first-/last-mile AB service, there is little change in terms of their ITU the service and their level of satisfaction with the quality of the service. However, the driving force which attracts the experienced users to continue with the service may change with an increase in ride experiences. For instance, the elderly were attracted to use the service because they perceived the service quality to be good, but they chose to continue with the service after gaining additional ride experiences due to the increase in their trust of the safety of the service and the travel time reliability.

Contradictory views to take note of

There were two contradictory views which warrant further investigation. People who understand well about automated driving technology were sceptical about the safety of using an AV service. Besides, people who were familiar with automated driving technology perceived AB service to be a better transport option than commuter train service in terms of both travel time and fare price. Still, their intention-to-use scores were low.

8.2 Contributions

Previous studies within the research field of automated transport systems have not researched much on the individual's learning process of a new innovation through experiencing, intending, attuning and acting. This research contributes to the research field through studying the actual behaviour and attitudes in relation to a real, actually operating AB service. This research is also a pioneer in deploying panel analysis to assess changes in users' decision-making parameters to adopt a new transport

innovation and identifying the hierarchy among service quality attributes for automated bus service using three-factor theory.

This research provides the theoretical background with early evidence (of implementing first/last-mile AB service) which transport modellers can build upon. Having a model based on a sound theoretical background would be helpful in transport modelling to generate stable results, model consistency and to give confidence in forecasting (Ortúzar & Willumsen, 2011). The theoretical frameworks used in study 1, study 2 and study 3 can be built upon to form utility functions of AB services. Practitioners can extend the frameworks with a choice model to form a hybrid choice model (e.g. integrated choice and latent variable model). Hybrid choice models provide a greater explanatory power and deeper understanding of the choice processes taking place in the users' "black box" with the combination of users' decision-making parameters (Bolduc & Alvarez-Daziano, 2010; Temme et al., 2008).

Besides, service operator can adopt the theoretical framework outlined in the study 3 to obtain information to aid design, maintenance and improvement of AB services. Also, the relevant attributes of first-/last-mile AB service have been outlined. Additionally, study 4 demonstrated the use of LiDAR data to analyse pedestrians' midblock road-crossing behaviour when interacting with an oncoming AB bus, and to derive important parameters to be checked against the existing road design principles."

8.3 Limitations

To begin, the findings obtained are based on the responses collected from people who lived in or around Kista Science City and the Helenelund train station, which is a science and technology park that encompasses many prominent technology companies as well as a technological university. The socio-demographics of the respondents were skewed more towards the tech-savvy (defined as the ones who are well-informed about or know how to use computers, mobile phones, and electronic devices) and the highly educated. This constitutes a limitation of the findings in this study in that there are not generic perceptions from more evenly distributed groups of people. Therefore, the suggested policies may only be applied to areas with a significant highly educated and tech-savvy population. Whilst one may think that this may only be applied to a few unique locations at present, it is worth considering that

younger generations with greater familiarity and facility with advanced technologies as part of their daily lives will represent an ever-larger segment of the population; as such, these policy suggestions may become more relevant in the future.

The trial operation of AB service in Kista was subject to 20km/h operating speed limit. Therefore, the travel time by using the service might not be comparable to the travel time by using a conventional bus service. Secondly, due to the fact that it was a trial operation, the frequency of the AB service was not guaranteed. Therefore, the service quality delivered during the trial operation could be different from the service quality delivered by an actual AB service. Still, the trial operation was able to provide the respondents experiences with an AB which would later be deployed in the actual operation of a first-/last-mile AB service in Stockholm.

Additionally, the results associated with WTP for SAV and AB in *study 1* should be treated carefully given that the normality assumptions of the WTP models are not fully satisfactory.

Furthermore, in *study 2*, the treatment group in model 1, group 1-1, has a smaller student population (about 20% less) and more respondents with a high annual income than the comparison group in model 2, group 1-0. This poses a limitation to the interpretation of the results. Also, practitioners should be aware that the coefficients of the standardised total effects of the socio-demographic characteristics are meant for comparison of the effect strengths and not for actual demand prediction.

Moreover, in *study 3*, the estimates should be treated carefully due to the potential influences from the small sample size (574 responses) of many variables identified in the analysis. Also, the proportion of the respondents who are business owners and use PMDs for first-/last-mile trips was very small in *study 3*. The findings associated with these socio-demographic groups should be treated carefully.

The results obtained from *study 4* are applicable to the midblock road-crossing behaviour of a pedestrian, or several pedestrians (two to five pedestrians) crossing together as a group, without using any road-crossing facilities. The results would not be applicable to roads with median pedestrian refuge. Also, in *study 4*, there is a small

discrepancy in terms of the location of the AB because the location of the AB is taken from the point where the LiDAR sensor was installed, that is, on the left side of the vehicle, but not in the middle or front of the AB. Additionally, the sample size in *study 4* is small with $n = 42$, thus the results should be interpreted carefully.

Additionally, in *study 4*, the individual characteristics such as age and gender were not explored due to usage of the LiDAR measurement device, which does not capture any personal information of the road users. LiDAR was used to comply with the European Union's General Data Protection Regulation 2016/679 (European Commission, 2018).

Finally, in *study 4*, the group of pedestrians who chose not to cross the road was not explored due to the absence of the LiDAR data that recorded interactions occurring at the rear of the AB.

8.4 Future works

Dynamical systems theory provides a large variety of tools for analysis of the temporal behaviour of the systems. These tools can be used to identify equilibrium points and limit cycles, to characterise local and global structure based on stability, and to check independence of such behaviour on parameters (Abraham, 1992; Strogatz, 1994). Subsequently, a set of state variables, which can uniquely characterise the behaviour, can be identified to find out laws that describe how states evolve over time.

A dynamical system provides a functional mathematical model which can be used to describe evolution of the state of the system over time. A system is dynamical if the mathematical tools and concepts of a dynamical system can be applied into analysis of the behaviour (Ashby, 2011; Skarda & Freeman, 1987; Kelso, 1995; Tutzauer, 1986; R. D. Beer, 1995; Port, 1995; R. Beer et al., 1999; Thelen et al., 2001).

A dynamical system is specified as $\langle T, S, X_t \rangle$ comprising of an ordered time set T , a state space S , and an evolution operator $X_t: S \rightarrow S$, which transforms an initial state $s_0 \in S$ at time $t_0 \in T$ to another state $s_t \in S$ at time $t_t \in T$. Time set T can be either continuous or discrete; state space S can be numerical or symbolic, continuous or discrete, or a hybrid of continuous and discrete and infinite or finite in dimension, decided by the number of variables to describe the state of the system fully. Evolution

X can be defined implicitly or given explicitly, stochastic or deterministic, and with autonomous or non-autonomous inputs.

Since individuals' behavioural responses are dynamic due to the dynamic nature of individuals' perceptions towards a new transport service/innovation, future research should focus on how the dynamical systems theory can be applied to translate the dynamic process in the adoption of a new transport service into a mathematical model, which can aid demand forecasting of the new transport service. Other factors, including built environment and habits, should also be considered in the models.

Von Behren et al. (2018) found that an individual's positive perceptions of a transport mode may not always contribute to actual usage of the transport mode. Hence, future research should investigate the connection between the individual's perceptions and preferences with their actual usage behaviour.

Additionally, future research shall investigate how the user's information gap about a new technology can be minimised in other ways such as simulation or better survey design. Also, to investigate the effects of these approaches on the reliability of the representations of the identified predictors.

Furthermore, future research should use automatic data extraction with machine learning for data extraction and analysis so that the sample size can be expanded for a more comprehensive analysis and for more accurate data extraction. Moreover, future works should incorporate automated object detection of pedestrians and automated data extraction so that a more comprehensive analysis on big pedestrian-AV interaction data can be performed. Machine learning can help to classify the extracted operational parameters according to individual characteristics and road specifications to enhance the perceptions of the AV under more complex scenarios and road situations. Most importantly, manufacturers of AVs should also consider the perceptions of other road users when designing the safety framework of an AV.

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APPENDIX A

Survey questionnaire in the first round of longitudinal survey

Part 1

Do you live or work in /around Helenelund or Kista Science City?

- Yes, I live in / around Helenelund or Kista Science City.
- Yes, I work in / around Helenelund or Kista Science City
- No

Gender:

- Male
- Female
- Others. Please specify: _____

Age (years):

- 0 - 14
- 15 – 24
- 25 – 34
- 35 – 44
- 45 – 54
- 55 – 64
- Above 65

Employment Status:

- Arbetar (working)
- Egen företagare (own company)
- Studerar/går i skola (study/school)
- Sjukskriven (sick leave)
- Föräldraledig (parental leave)
- Arbetssökande (searching for jobs/unemployed)
- Ålderspensionär/sjukpensionär (retired/pre-pensioner due to illness)
- Annan, nämligen: _____ (otherwise, namely)

Annual Income:

- Below 100.000 kronor
- 100.000 – 199.000 kronor
- 200.000 – 299.000 kronor
- 300.000 – 399.000 kronor
- 400.000 – 499.000 kronor

- 500.000 – 599.000 kronor
- 600.000 – 699.000 kronor
- 700.000 – 799.000 kronor
- More than 800.000 kronor
- Do not want to specify

How do you usually commute?

- ❖ Walk
- ❖ Cycling
- ❖ By Public Bus / Buses
- ❖ By Metro
- ❖ By Train
- ❖ By Car
- ❖ Others. Please specify: _____

Do you consider yourself a tech-savvy[#] person?

tech-savvy - well informed about or know how to use computers, mobile phones and electronic devices.

- Yes, I am a tech-savvy person.
- No, I am not a tech-savvy person.

Do you know what the underlying technologies are used to enable automated road vehicle[#] to drive without human driver?

automated road vehicle - also called as driverless road vehicle or self-driving road vehicle. This type of road vehicle can run without need of human assistance on driving activities. e.g. driverless car, driverless truck and driverless bus.

- Yes, I know well about the technologies. The technologies are: _____
- No, I do not know enough about the technologies.

Have you taken automated bus ride trial operated in Kista?

- Yes. I took the automated bus ride 1 – 5 times
- Yes. I took the automated bus ride 6 – 10 times
- Yes. I took the automated bus ride 10 – 15 times
- Yes. I took the automated bus ride more than 15 times
- No, I never took the automated bus ride.

In the following session, we would like to gather your feedback about this form of travel, which is travelling from/ to a transport hub (a metro station/ a train station/ a bus terminal) to/from the place where you live, study or work.

1. What kinds of transports do you use for such travel (from/ to transport hub to/ from where you live, study and work)?
  - Walk
  - Cycling
  - Taking public bus
  - Use electronic personal mobility devices – e-kick scooter, hover board and electric-powered wheelchair
  - Others. Please specify: _____

2. What is your acceptable travel time from/to a transport hub (a metro station/ a train station/ a bus terminal) to/from your home, school or workplace assuming that the travel distance is 750 metres e.g. walking from Kista T-bana Station to Kista Convention Center, along Kistagången.
  - 1 to 5 minutes
  - 6 to 10 minutes
  - 10 to 15 minutes
  - More than 15 minutes. Please specify: _____

Part 2 - Please answer the questions listed in Part 2 from the point of view of a passenger or potential passenger of the automated bus service operated by an automated bus in Kista.

- i. What would be your answer to the following questions?
*Choose only one answer per row

Frequency of the service					
	Not at all Better	Somewh at Better	Same Frequency	Better	Much better
I feel that the frequency of the automated bus service should be _____ than the frequency of a regular public bus service.					
Safety					
	Extremely Unsafe	Unsafe	Neutral	Safe	Extremely Safe
I _____ feel _____ if there is <u>NO operator/ steward</u> on the automated bus.					
I _____ feel _____ when <u>there is _____ an operator/ steward</u> on the automated bus.					

From the point of view of a non-automated car driver, I feel _____ when I encounter an automated bus on public road.					
Ride comfort					
	Extremely Uncomfortable	Uncomfortable	Neutral	Comfortable	Extremely Comfortable
I feel that the level of on-board comfortability due to driving speed and driving patterns of the automated bus would be:					
I feel that the level of on-board comfortability due to the facilities inside the automated bus would be:					
Staff and assistance					
	Very Bad	Bad	Neutral	Good	Extremely Good
I feel that the on-board customer service would be:					

Length of trip time					
	Much Longer than taking a non-automated bus ride	Longer than taking a non-automated bus ride	Same	Shorter than taking a non-automated bus ride	Much Shorter than taking a non-automated bus ride
Given same travel distance and route, I feel that travel time of taking an automated bus ride would be: (i)					
	Much Longer than taking metro	Longer than taking metro	Same	Shorter than taking metro	Much Shorter than taking metro
Given same travel distance and route, I feel that travel time of taking an automated bus ride would be: (ii)					
	Much Longer than taking commuter train	Longer than taking commuter train	Same	Shorter than taking commuter train	Much Shorter than taking commuter train
Given same travel distance and route, I feel that travel time of taking an automated					

bus ride would be: (iii)					
	Much Longer than driving a car	Longer than driving a car	Same	Shorter than driving a car	Much Shorter than driving a car
Given same travel distance and route, I feel that travel time of taking an automated bus ride would be: (iv)					
Travel Fare					
	Much More Expensive than taking a non-automated bus ride	More Expensive than taking a non-automated bus ride	Same	Cheaper than taking a non-automated bus ride	Much Cheaper than taking a non-automated bus ride
Given same travel distance and route, I feel that travel fare of taking an automated bus ride (single ride) would be: (i)					
	Much More Expensive than taking metro	More Expensive than taking metro	Same	Cheaper than taking metro	Much Cheaper than taking metro

Given same travel distance and route, I feel that travel fare of taking an automated bus ride (single ride) would be: (ii)					
	Much More Expensive than taking commuter train	More Expensive than taking commuter train	Same	Cheaper than taking commuter train	Much Cheaper than taking commuter train
Given same travel distance and route, I feel that travel fare of taking an automated bus ride (single ride) would be: (iii)					
Intention-to-use public bus service operated by automated bus					
	Definitely Not Using this service	Probably Not Using this service	Neutral	Probably Uses this service	Definitely Use this service
If this service is available in the area where I live, work or study, I would					

On top of the public transport monthly pass fare you are paying now, how much would you be willing to pay to access the following autonomous bus services

*Choose only one answer per column

	Personalised Automated Bus Service (You can choose your boarding point and alighting point; Not sharing the bus with others; With less than 3 minutes waiting time)	Shared Automated Bus Service (Fixed boarding point and alighting point; Sharing the bus with others; With less than 3 minutes waiting time)	Shared Automated Bus Service (Fixed boarding point and alighting point; Sharing the bus with others; With more than 3 minutes waiting time)
0 SEK			
Up to 50 SEK			
Up to 100 SEK			
Up to 150 SEK			
Up to 200 SEK			
Up to 250 SEK			
Up to 300 SEK			
Up to 400 SEK			
More than 400 SEK			

Survey questionnaire in the second round of longitudinal survey

Name:

How do you usually commute? (You can choose more than one answer.)

- ❖ Walk
- ❖ Cycling
- ❖ By public bus
- ❖ / buses
- ❖ By autonomous bus ride
- ❖ By metro
- ❖ By train
- ❖ By car
- ❖ By car with Park and Ride (park car and take metro/train/long distance bus to your destination)
- ❖ By private shuttle service
- ❖ Others. Please specify: _____

Do you know what are the underlying technologies used to enable autonomous road vehicle[#] to drive without human driver?

Autonomous road vehicle - also called as driverless road vehicle or self-driving road vehicle. This type of road vehicle can run without need of human assistance on driving activities. e.g. driverless car, driverless truck and driverless bus.

- Yes, I know well about the technologies.
- No, I do not know enough about the technologies.

How many times have you taken the autonomous bus ride operating along Kistagången?

- 1 – 5 times
- 6 – 10 times
- 10 – 15 times
- more than 15 times
- Never

Paragraph:

Last mile is a term used in transport. It refers to a travel trip between a metro station / a train station to where you work, study or live. In the upcoming session, we would like to gather your feedback about such trip.

About frequency

I think its frequency is _____ the frequency of the normal bus service.

- not at all better than
- somewhat better than
- same as
- better than
- much better

About safety

I would feel _____ because the steward was on the AB bus.

- extremely unsafe
- unsafe
- the same
- safe
- extremely safe

I feel AB bus's interactions with other road users on the road to be _____.

- extremely unsafe
- unsafe
- the same
- safe
- extremely safe

About ride comfort

I think that the level of on-board comfortability due to driving speed and driving patterns of the automated bus is:

- extremely uncomfortable
- uncomfortable
- neutral
- comfortable
- extremely comfortable

I think that the level of on-board comfortability due to the facility inside the automated bus is:

- extremely uncomfortable
- uncomfortable
- neutral
- comfortable
- extremely comfortable

About travel time with the AB

Given the same travel distance and route, I think that the travel time (including waiting time) of taking the automated bus ride is:

- much longer than taking the normal bus ride
- longer than taking the normal bus ride
- same as taking the normal bus ride
- shorter than taking the normal bus ride
- much shorter than taking the normal bus ride

Intention-to-use the AB

Skip this question if you have not taken the autonomous bus ride:

Will you take the automated bus ride again?

- definitely not taking the automated bus ride again
- probably not taking the automated bus ride again
- neutral
- probably will take the automated bus ride again
- definitely will take the automated bus ride again

APPENDIX B

Table B1 Pattern matrix of the service quality attribute perceptions included as the indicators for the latent variables in structural equation model

Pattern Matrix^a

	Factor				
	1	2	3	4	5
SafetyWithoutSteward			0.579		
Safety_Pedestrian			0.758		
Safety_OnRoad			0.836		
Cybersecurity_ Hacked				1.004	
Cybersecurity_GPS				0.663	
RideComfort_Tech					0.865
RideComfort_ Facilities					0.726
OverallRideComfort					0.411
Time_RegularPublicBus		0.522			
Time_Metro		0.903			
Time_Train		0.802			
Time_Car		0.601			
Fare_RegularPublicBus	0.803				
Fare_Metro	0.904				
Fare_Train	0.854				

Extraction Method: Maximum Likelihood.

Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Table B2 Factor correlation matrix of the extracted factors from the indicators of the latent variables in structural equation model

Factor Correlation Matrix

Factor	1	2	3	4	5
1	1.000	0.297	0.285	0.092	0.254
2	0.297	1.000	0.317	0.089	0.366
3	0.285	0.317	1.000	0.020	0.505
4	0.092	0.089	0.020	1.000	0.124
5	0.254	0.366	0.505	0.124	1.000

Extraction Method: Maximum Likelihood.

Rotation Method: Promax with Kaiser Normalization.

Assumptions checking for Multiple Linear Regression

Linear regression analyses were performed for Model A (explanatory variables against WTP for Service Type 1), Model B (explanatory variables against WTP for Service Type 2), and Model C (explanatory variables against WTP for Service Type 3). For valid multiple linear regression, three assumptions were checked. Firstly, the residuals of the regression have to be normally distributed. This assumption can be checked by looking at the histograms and normal p-p plot of the residuals of the regression. The histograms and normal p-p plots of the residuals of the regression as shown in Figure B1- B6 show that the distributions are not fully follow normal distribution. However, the discrepancies are not a lot from normal distribution and deemed to be acceptable.

Figure B1 Histogram of the residuals of regression of Model A (explanatory variables against WTP for Service Type 1)

Figure B2 Normal P-P Plot of the residuals of regression of Model A (explanatory variables against WTP for Service Type 1)

Figure B3 Histogram of the residuals of regression of Model B (explanatory variables against WTP for Service Type 2)

Figure B4 Normal P-P Plot of the residuals of regression of Model B (explanatory variables against WTP for Service Type 2)

Figure B5 Histogram of the residuals of regression of Model C (explanatory variables against WTP for Service Type 3)

Figure B6 Normal P-P Plot of the residuals of regression of Model C (explanatory variables against WTP for Service Type 3)

Secondly, there must be no or little multicollinearity in the data. The correlation coefficients among the independent variables are less than 0.8 except two pairs: EM_Pension-Age4 (correlation matrix=0.811) and EM_Study-EM_Work (correlation matrix=-0.802). This assumption is accepted since there is only small multicollinearity in the data.

Lastly, the data should be homoscedastic. This can be checked by assessing the scatter plots of residuals versus predicted values of the models as shown in Figures B7, B8 and B9. Since there is no clear pattern of specific shape in the distribution, the data can be considered sufficiently homoscedastic.

Figure B7 Scatterplot of residuals versus predicted values of Model A

Figure B8 Scatterplot of residuals versus predicted values of Model B

Figure B9 Scatterplot of residuals versus predicted values of Model C

APPENDIX C

Table C1 Report of multicollinearity check indicator's, variance inflation factor (VIF) for data set 1

	Collinearity Statistics	
	Tolerance	VIF
Frequency_P1	0.758	1.319
SafetyNoSteward_P1	0.697	1.435
SafetySteward_P1	0.829	1.206
SafetyOnRoad_P1	0.728	1.374
RideComfortTech_P1	0.637	1.570
RideComfortFacility_P1	0.637	1.570
CustomerService_P1	0.872	1.147
TravelTimeBus_P1	0.783	1.277
Frequency_P2	0.798	1.253
SafetySteward_P2	0.765	1.307
SafetyNoSteward_P2	0.667	1.498
SafetyOnRoad_P2	0.759	1.317
RideComfortTech_P2	0.625	1.601
RideComfortFacility_P2	0.676	1.480
CustomerService_P2	0.837	1.195
TravelTimeBus_P2	0.829	1.206
a. Dependent Variable: IntentionToUse_P1		

Table C2 Report of multicollinearity check indicator's, variance inflation factor (VIF) for data set 2

	Collinearity Statistics	
	Tolerance	VIF
Frequency_P1	0.758	1.319
SafetyNoSteward_P1	0.697	1.435
SafetySteward_P1	0.829	1.206
SafetyOnRoad_P1	0.728	1.374
RideComfortTech_P1	0.637	1.570
RideComfortFacility_P1	0.637	1.570
CustomerService_P1	0.872	1.147
TravelTimeBus_P1	0.783	1.277
Frequency_P2	0.798	1.253
SafetySteward_P2	0.765	1.307
SafetyNoSteward_P2	0.667	1.498
SafetyOnRoad_P2	0.759	1.317
RideComfortTech_P2	0.625	1.601
RideComfortFacility_P2	0.676	1.480
CustomerService_P2	0.837	1.195
TravelTimeBus_P2	0.829	1.206
a. Dependent Variable: IntentionToUse_P2		

Normal P-P Plot of Regression Standardised Residual

Dependent Variable: IntentionToUse_P1

Figure C1 Normal P-P plot of service attribute perceptions versus intention-to-use in period 1

Normal P-P Plot of Regression Standardised Residual

Dependent Variable: IntentionToUse_P2

Figure C2 Normal P-P plot of service attribute perceptions versus intention-to-use in period 2

APPENDIX D

Table D3 Tolerance and variance inflation factor (VIF) value of each independent variable

No.	Variable	Tolerance	VIF
1	Frequency_HighPerformance	0.698	1.432
2	Frequency_LowPerformance	0.753	1.328
3	Frequency_MissingValue	0.947	1.056
4	SafetyWithoutSteward_ HighPerformance	0.597	1.675
5	SafetyWithoutSteward_ LowPerformance	0.576	1.735
6	SafetyWithoutSteward_ MissingValue	0.624	1.603
7	SafetyWithSteward_ HighPerformance	0.799	1.252
8	SafetyWithSteward_ LowPerformance	0.886	1.128
9	SafetyWithSteward_ MissingValue	0.829	1.206
10	SafetyOnRoad_ HighPerformance	0.507	1.972
11	SafetyOnRoad_ LowPerformance	0.549	1.822
12	SafetyOnRoad_ MissingValue	0.775	1.289
13	RideComfortDueToDrivingSpeed_ HighPerformance	0.62	1.614
14	RideComfortDueToDrivingSpeed_ LowPerformance	0.737	1.357
15	RideComfortDueToDrivingSpeed_ MissingValue	0.594	1.683
16	RideComfortDueToFacilities_ HighPerformance	0.628	1.592
17	RideComfortDueToFacilities_ LowPerformance	0.79	1.265
18	RideComfortDueToFacilities_ MissingValue	0.642	1.558
19	OnBoardCustomerService_ HighPerformance	0.764	1.31
20	OnBoardCustomerService_ LowPerformance	0.831	1.203

21	OnBoardCustomerService_ MissingValue	0.964	1.038
22	TravelTimeComparedWithBus_ HighPerformance	0.653	1.53
23	TravelTimeComparedWithBus_ LowPerformance	0.567	1.763
24	TravelTimeComparedWithBus_ MissingValue	0.806	1.241
25	TravelTimeComparedWithMetro_ HighPerformance	0.469	2.131
26	TravelTimeComparedWithMetro_ LowPerformance	0.298	3.353
27	TravelTimeComparedWithMetro_ MissingValue	0.722	1.385
28	TravelTimeComparedWithCommuter train_ HighPerformance	0.421	2.373
29	TravelTimeComparedWithCommuter train_ LowPerformance	0.27	3.701
30	TravelTimeComparedWithCommuter train_ MissingValue	0.555	1.802
31	TravelTimeComparedWithCar_ HighPerformance	0.674	1.484
32	TravelTimeComparedWithCar_ LowPerformance	0.505	1.981
33	TravelTimeComparedWithCar_ MissingValue	0.594	1.684
34	TravelFareComparedWithBus_ HighPerformance	0.374	2.675
35	TravelFareComparedWithBus_ LowPerformance	0.502	1.993
36	TravelFareComparedWithBus_ MissingValue	0.6	1.666

37	TravelFareComparedWithMetro_ HighPerformance	0.258	3.883
38	TravelFareComparedWithMetro_ LowPerformance	0.378	2.646
39	TravelFareComparedWithMetro_ MissingValue	0.519	1.926
40	TravelFareComparedWithCommuter train_ HighPerformance	0.304	3.292
41	TravelFareComparedWithCommuter train_ LowPerformance	0.412	2.427
42	TravelFareComparedWithCommuter train_ MissingValue	0.563	1.776

Normal P-P Plot of Regression Standardized Residual

Figure D1 Normal P-P plot of Regression Standardised Residual

Table D4 List of endogenous variables out of the identified significant perceptions from the three-factor analysis

For experienced users:

Endogenous Variable	p-value of the responding fitted values
Frequency_LowPerformance	0.040
SafetyWithSteward_LowPerformance	0.047
TravelTimeComparedWithTrain_LowPerformance	0.029
TravelFareComparedWithMetro_LowPerformance	0.000
TravelFareComparedWithTrain_LowPerformance	0.037

For inexperienced users:

Endogenous Variable	p-value of the responding fitted values
Frequency_LowPerformance	0.000
Frequency_HighPerformance	0.000
TravelFareComparedWithTrain_LowPerformance	0.014

For all users:

Endogenous Variable	p-value of the responding fitted values
SafetyOnRoad_HighPerformance	0.034
SafetyOnRoad_LowPerformance	0.036
RideComfortDueToFacilities_HighPerformance	0.038
OnBoardCustomerService_HighPerformance	0.092
TravelFareComparedWithMetro_LowPerformance	0.002
TravelFareComparedWithTrain_LowPerformance	0.028

Table D5 Service quality attribute perceptions found to significantly influence intention-to-use First-/Last-mile Automated Bus Service of experienced users, with the p-value less than 0.10

No.	Variable	Estimate	p-value
1	Frequency_LowPerformance	-0.240	0.089
2	Frequency_HighPerformance	0.237	0.006
3	TravelFareComparedWithCommutertrain_LowPerformance	-0.425	0.024
4	RideComfortDueToDrivingSpeed_HighPerformance	0.179	0.039
5	TravelFareComparedWithBus_MissingValue	-0.576	0.086

Table D6 Service quality attribute perceptions found to significantly influence intention-to-use First-/Last-mile Automated Bus Service of inexperienced users, with the p-value less than 0.10

No.	Variable	Estimate	p-value
1	Frequency_LowPerformance	-0.405	0.052
2	Frequency_HighPerformance	0.217	0.061
3	TravelTimeComparedWithBus_HighPerformance	0.237	0.099

Table D7 Service quality attribute perceptions found to significantly influence intention-to-use first-/last-mile Automated Bus Service of all users, with the p-value less than 0.10

No.	Variables	Estimate	p-value
1	TravelFareComparedWithCommutertrain_LowPerformance	-0.905	0.001
2	TravelFareComparedWithCommutertrain_HighPerformance	-0.386	0.029
3	TravelTimeComparedWithMetro_LowPerformance	0.372	0.051
4	TravelTimeComparedWithMetro_HighPerformance	0.541	0.014
5	RideComfortDueToDrivingSpeed_HighPerformance	0.265	0.050
6	TravelFareComparedWithBus_MissingValue	-0.823	0.086
7	RideComfortDueToFacilities_MissingValue	-0.909	0.089

Table D8 List of significant explanatory variables affecting each type of identified perception attributes (experienced users)

Dependent Variable	Significant Explanatory Variables	Estimate	p-value
TravelFareComparedWithCommutertrain_LowPerformance	FamiliarWithAutomatedDrivingTech	-0.064	0.095
TravelFareComparedWithCommutertrain_HighPerformance	Train	-0.157	0.033
	Above44	-0.145	0.048
	LM_Cycling	0.190	0.078
TravelTimeComparedWithMetro_LowPerformance	FamiliarWithAutomatedDrivingTech	-0.153	0.018
	TechSavvy	-0.302	0.022
	Metro	0.130	0.054
TravelTimeComparedWithMetro_HighPerformance	Metro	-0.126	0.014
	Bus	0.123	0.044
	Car	-0.102	0.088
	HighIncome	-0.092	0.093
RideComfortDueToDrivingSpeed_HighPerformance	Walk	-0.174	0.025
	Bus	0.148	0.057
	LastMile_PMD (PersonalMobility Device)	0.549	0.061

Table D9 List of significant explanatory variables affecting each type of identified perception attributes (inexperienced users)

Dependent Variable	Significant Explanatory Variables	Estimate	p-value
Frequency_LowPerformance	Below25	0.101	0.014
	LastMile_Bus	0.076	0.047
Frequency_HighPerformance	LastMile_Bus	-0.156	0.033
TravelTimeComparedWithBus_HighPerformance	Female	0.110	0.031
	Bus	0.117	0.039
	Car	0.131	0.046
	LastMile_PMD (PersonalMobility Device)	0.391	0.090

Table D10 List of significant explanatory variables affecting each type of identified perception attributes (all users)

Dependent Variable	Significant Explanatory Variables	Estimate	p-value
Frequency_ LowPerformance	TechSavvy	-0.098	0.059
	Below25	0.067	0.070
Frequency_ HighPerformance	Above44	-0.096	0.067
	LastMile_PMD(PersonalMobilityDevice)	0.362	0.072
TravelFareComparedWith Commutertrain_ LowPerformance	FamiliarWithAutomated DrivingTech	-0.053	0.036
	AcceptableTravelTime	-0.064	0.087
RideComfortDueToDriving Speed_ HighPerformance	Walk	0.056	0.064
	FamiliarWithAutomated DrivingTech	-0.046	0.066
	TechSavvy	-0.094	0.074
	Cycle	-0.070	0.096