Transportation Research Part A 139 (2020) 350–375

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Determinants of intention-to-use first-/last-mile automated bus service

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A R T I C L E I N F O

Keywords:
Intention-to-use
First-/last-mile
Automated bus service
User acceptance
Service quality attributes

A B S T R A C T

The successful adoption of a product or service by its target market or users relies on delivering a product or service in line with their needs and expectations. Failure to do so will likely result in a low rate of uptake or use of the product or service. This study sought to identify the criteria by which potential users of a first-/last-mile automated bus (AB) service would evaluate the service, and accordingly decide whether to use or disregard the service. This research investigated various explanatory factors affecting users' perceptions of the service's quality and utility, and which enhanced or diminished their intentions to use it. The data analysed in this study was collected from a survey conducted in February and March of 2018 in Stockholm, Sweden, during a trial operation of a first-/last-mile AB service. Three-factor theory analysis, commonly used to analyse services, was applied to this data in order to identify users' core perceptions about the service, which in turn influence their intention-to-use the service. Structural equation modelling was used to identify the significant factors that influence the identified perceptions influencing the intention-to-use the service. This study found that different subgroups of users prioritised different attributes. Prospective users (with no prior experience with the service) were most concerned with the frequency of service. Their intention-to-use the service greatly increased when the service frequency is comparable to the service frequency of a regular public bus service. Experienced users' intentions to continue using the service greatly increased when the buses were made more comfortable. This study additionally found that users' perceptions of the service's quality were also influenced by numerous factors including the passenger's age, income level, preferred mode of travel for daily trips, preferred mode of travel for first-/last-mile trips, being tech-savvy or not, and their level of familiarity with automated driving technology.

1. Introduction

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 and Odoni, 2016). Small automated buses (AB) such as EZ10 and Autonom Shuttle may be effectively implemented to improve first-/last-mile connections, and in turn increases the overall effectiveness and attractiveness of public transport.

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https://doi.org/10.1016/j.tra.2020.06.001
Received 14 November 2018; Received in revised form 23 May 2020; Accepted 3 June 2020
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AB 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 retains some of the flexibility of driving a personal car. Prospective riders, instead of having to walk some distance to nearby bus stop and/or endure lengthy waiting times for a bus during non-peak periods, can instead request AB service through a smartphone application, providing them with a shared-ride service at their doorstep within a shorter waiting time, resulting possibly 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.

AB services can also contribute to reducing road congestion during peak periods. Ride-sharing has been proven to be beneficial towards reducing vehicular traffic flow: at least 50% of single-person trips (based on the trip data collected from smartphone application) across 1267 zones over 30 days in the Orlando metropolitan area can be rendered shared-trip service with only a maximum five minutes increase in travel time, without changing the passengers' travel patterns (Gurumurthy and Kockelman, 2018). Furthermore, replacing low-demand bus lines with 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).

However, tangible economic and societal benefits in integrating ABs into the public transport system will only be achieved if AB-based services are widely accepted and adopted by a critical mass of commuters. Because AB service is still not commonly available and analysing people's actual usage of AB services was not feasible, for the purposes of this study we analysed people's intention-to-use (ITU) an AB service, since behavioural intention is a precursor to actual behaviour (Ajzen, 1991).

Users' perceptions of the AB service's attributes are important when it comes to understanding their intentions regarding the service. This argument is supported by findings from prior research in the field. Attributes of automated vehicles which have been found to significantly influence users' acceptance of their service include: on-board safety (Piao et al., 2016; Salonen, 2018), comfort (Eden et al., 2017), travel time (Bansal et al., 2016; Scheltes and de Almeida Correia, 2017), travel fare (Piao et al., 2016; Bansal et al., 2016) and the presence of a steward (Piao et al., 2016).

Simulation studies investigating the future impact of the implementation of ABs are typically based on assumptions derived from the findings of studies analysing people's intentions to hypothetically adopt AB service. Even though this hypothetical scenario approach is versatile, in that it allows researchers to explore a diversity of plausible responses by potential users, the utility of these studies in predicting real-world outcomes of the implementation and adoption of AB services is questionable. The argument is that when users are (subsequently) exposed to experiences with ABs, they may develop entirely different evaluative criteria from those proffered in the hypothetical models. As previously mentioned, the success of any product or service depends on the fulfilment of the users' expectation(s). A mismatch between the delivered service quality, and the users' anticipated experience, can diminish or deter their adoption of the service, ultimately, lead to resistance to using the service at all.

By conducting a trial operation of a first-/last-mile AB service in Kista, Stockholm, it was possible to identify the expected qualities and attributes of a first-/last-mile AB service among potential users who actually work, live or stay in the area. This research endeavours to determine the set of evaluative criteria that potential travellers use to decide whether they would accept or reject an AB service if it were made available. This study also examined how users' intention-to-use behaviour is further influenced by:

- socio-demographic characteristics;
- acceptable first-/last-mile travel time;
- awareness of technology;
- experience of taking first-/last-mile AB ride; and,
- existing travel modes.

This paper is organised into five sections. Section 1 provides an introduction to the research aims of this study. Section 2 provides a review of the relevant literature to assess the relationship between service quality expectations and intentions to use AB services, as well as the quantitative tools which may be deployed to measure the impacts of expectation on intention regarding the AB services. Section 3 explains the methods of data collection and data analysis used in this study. Findings and discussions are presented in Section 4. Finally, Section 5 is comprised of concluding remarks, an overview of the study's limitations, and suggestions for further research to extend the work of this study.

2. Literature review

This section begins with an exploration of the relationship between expected service attributes and intention-to-use of AB services, followed by a review of the means by which perceptions of AB or automated driving technology have been measured. Subsequently, past methods to quantify the effects of the expected level of service quality attributes on intention-to-use AB service are reviewed.

2.1. Expected service quality and attributes

Intention-to-use 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 between different modes of transport. Results from a meta-analysis of the theoretical models used in the study of travel mode selection by Lanzini and 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.

Expectation, or perception, is an important predictor of intention-to-use 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 and 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 and Dwivedi, 2015)
9. Motivational Model (Davis et al., 1992)
10. Uses and Gratification Theory (U&G) (Grellhesl and Punyanunt-Carter, 2012)
11. Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh and Zhang, 2010)

These models all highlight the necessity of considering users' perceptions of service quality when investigating intention-to-use. As such, these models offer a useful framework for research evaluating intention-to-use 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). Besides, users' service attribute perceptions also affect the diffusion rate of an emerging technology (Jensen et al., 2017). These perceptions should be considered when 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 intention-to-use an AB service.

2.2. Perceptions of Automated Vehicles (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 intention-to-use of AVs, as identified from a review conducted by Gkartzonikas and 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 intention-to-use 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 and Dimitrakopoulos, 2018a,b; Payre, Cestac, and Delhomme, 2014; Schoettle and Sivak, 2014), statistical analysis (Bansal and Kockelman, 2017; Buckley et al., 2018; Hulse et al., 2018; Liljamo, Liimatainen, and Pöllänen, 2018), factor analysis (Acheampong and Cugurullo, 2019; Haboucha et al., 2017; Hudson et al., 2019; Kaur and Rampersad, 2018), and structural equation modelling (Liu et al., 2019; Nwachukwu, 2014; Xu et al., 2018; Zhang et al., 2019). The stated choice experiment was applied by (Howard, 2014; Krueger et al., 2016; Shin et al., 2015) to predict the likelihood to adopt AV/automated driving technologies (Nielsen and 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 was 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 Technology Acceptance Model (TAM) have been used to investigate psychological constructs affecting the acceptance of AV (Buckley et al., 2018; Choi and and Ji, 2015; Jiang et al., 2019; Panagiotopoulos and Dimitrakopoulos, 2018a,b; Xu et al., 2018). The Theory of Planned Behaviour (TPB) was also used by (Buckley et al., 2018) to identify drivers' intention-to-use 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 and Dimitrakopoulos, 2018a,b). Prior experience was also found to affect perceived usefulness, trust and perceived ease of use (Xu et al., 2018).

2.3. Evaluative tools of expected levels of service quality

People's perceptions in terms of the expected level of service 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 intention-to-use 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 and Morpace International Incorporated, 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 and Ratanavaraha, 2016; Nwachukwu, 2014; Popuri et al., 2011; Efthymiou et al., 2018), confirmatory factor analysis (Hu et al., 2015; Jomnonkwao and Ratanavaraha, 2016; Ratanavaraha et al., 2016), and structural equation modelling (De Oña et al., 2013; Machado-León et al., 2016; Lai and Chen, 2011; Eboli and Mazzulla, 2008; Jen and Hu, 2003). Also, the relative weight of the list of tested factors is analysed using regression analysis (Chang and 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, Ibeas, and Cecin, 2011; Eboli and 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*. Fig. 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 have 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 Fig. 1. (Abenoza, Cats, and Susilo, 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

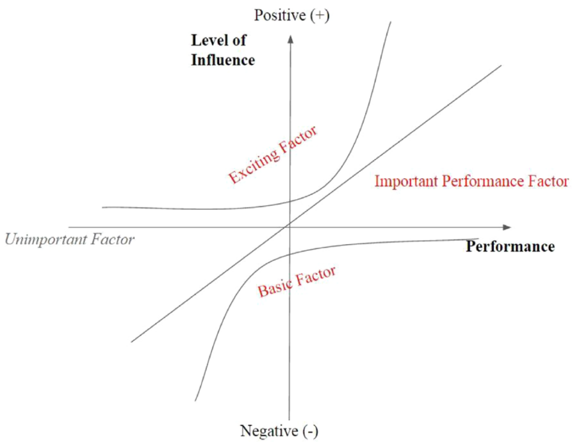

Fig. 1. Three-factor theory of satisfaction (Wu et al., 2018).

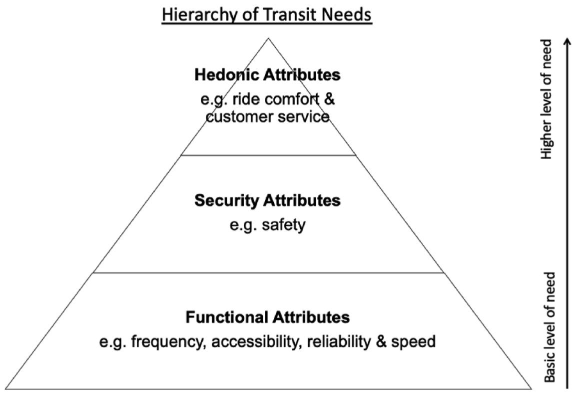

Fig. 2. Hierarchy of transit needs (adapted from Allen et al., 2019).

(transit) needs.

Users' transit needs are hierarchical, and can be arranged into a hierarchy of transit needs as shown in Fig. 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 address the non-linear relationship between attributes and overall satisfaction, it can also be used to identify the hierarchical needs of the users.

As an alternative to three-factor theory, Deb and Ali Ahmed (2018) proposed a method to assign a level of service (LOS) of the service quality attributes using confirmatory factor analysis (CFA) on perception and expectation, regression analysis for standardisation of the factor scores, and structural equation modelling to obtain the effect of perception and expectation on overall satisfaction. However, it has limitations because the level of service 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.

In this study, three-factor theory is first applied to categorise respondents' perceptions. It was selected because, unlike IPA, three-factor theory recognises that the relationships between service quality and overall satisfaction are not always linear. In our case, not all perceptions of the service quality and attributes have a linear relationship with commuters' intention-to-use the AB service. It was additionally deemed appropriate for this study because of its ability to classify service quality attributes according to travel satisfaction. This relates directly to the objective of this study, which is to identify the core perceptions that influence users' intention-to-use an AB service. After the three-factor theory, structural equation modelling (SEM) was used to analyse the relationships between perceptions and participants' intentions to use the first-/last-mile AB service. PPP

3. Methodology

This section explains the process of data collection and analytical approach used in the study.

3.1. Data collection

The data analysed in this study was collected from a survey conducted in conjunction with the *Autopiloten* project, which conducted a test operation of a first-/last mile automated bus service in the Science City in Stockholm, Kista. First-/last mile service typically serves a short travel distance, bringing passengers to/from 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 shuttles, which can accommodate up to 11 passengers (6 seated passengers and 5 standing passengers), were used in the project. These automated buses drove back and forth along the 750-metre route with a flexible timetable from 6am to 6 pm 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 20 km/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

Fig. 3. An EZ10, the small automated bus used in the trial operation in Kista, Stockholm (SARA 1 Research Team, 2018).

accounted for when the commuters pay for the single trip ticket (75 min access to all public transport services with a single trip ticket) or monthly pass. In essence, commuters do not need to pay extra to access first-/last-mile services after they have paid for the trip or monthly pass. The route of the trial operation and an image of the AB, the EZ10 bus, are shown in Figs. 3 and 4, respectively.

An online survey was administrated concurrently with the six-month trial operating period from January until June 2018 by a Swedish survey company recruited by the research team. Survey respondents were recruited by the survey company to take part in three rounds of online surveys throughout the period from February 2018 to June 2018. The data analysed in this study came from the data collected from the first round of the survey, collected from February 2018 through March 2018. The participants who completed all three rounds of surveys were entitled to participate in the contest to win one of ten cash prizes worth 1500 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). This area is a science and technology park, hosting many prominent technology companies as well as a technical university.

The significant explanatory variables found to affect acceptance of automated vehicles (AVs), including ABs, were included in the model: gender (Acheampong and Cugurullo, 2019; Hulse et al., 2018; Liljamo et al., 2018; Nazari et al., 2018; Nielsen and Haustein, 2018; Payre et al., 2014; Rödel et al., 2014; Salonen, 2018; Schoettle and Sivak, 2014), age (Bansal et al., 2016; Hudson et al., 2019; Nazari et al., 2018; Nielsen and Haustein, 2018; Rödel et al., 2014; Sanbonmatsu et al., 2018; Shin et al., 2015), annual income (Sanbonmatsu et al., 2018), and prior experience with automated vehicles (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

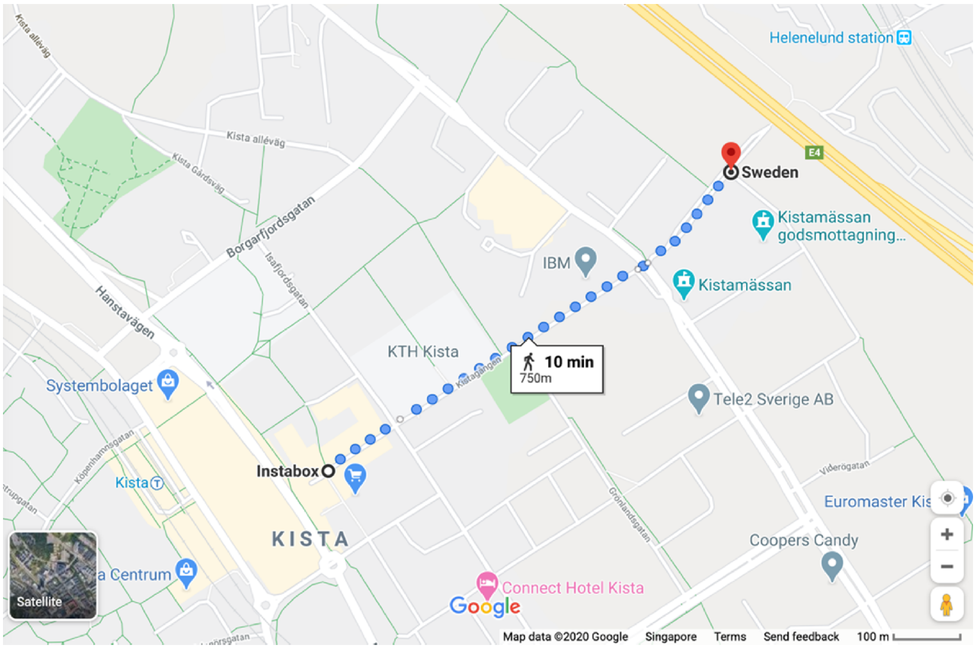

Fig. 4. The route of EZ10 operation during the trial period (Google Maps, 2020).

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 750 m 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 saving/loss 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 intention-to-use a first-/last-mile shared AB service if the service were made available to the respondent. ITU is rated on a five-point ordinal scale. The full survey questionnaire and Table B1 showing the socio-demographic distribution of the respondents are presented in Appendix B. The list of explanatory variables used in further analyses is shown in Table 1, and the descriptive statistics of the service attribute perception variables are shown in Table 2.

3.2. Data analysis

The approach to analysing the data of this study was undertaken in three distinct steps, as shown in Fig. 5.

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 (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 structural equation modelling in the third step. The following diagram explicates how the three-factor theory analysis (A) and regression analysis (B) were performed:

(A) Three-factor theory analysis

This analysis begins 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' intentions to use the first-/last-mile AB service is 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 intention-to-use 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 intention-to-use the AB service.

Performance factor

Table 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 750 m distance which is less than 10 min; 0 otherwise)	507	88.3

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 intention-to-use 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 intention-to-use the AB service.

(B) Regression Analysis

The main objective of regression analysis is 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 1. The significant variables will be included in the structural equation model in Step 3.

Step 3:

Structural equation models are constructed with the inputs from (A) three-factor theory analysis and (B) regression analysis. Structural equation modelling 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. Each perception is split into *low-performance indicator* (low appreciation of the service quality attribute with the responses "1" and "2" out of the 5-point Likert scale responses) and *high-performance indicator* (high appreciation of the service quality attribute with the responses "4" and "5" out of the 5-point Likert scale responses). Perception which is identified as a *basic factor* from three-factor theory analysis will have its *low-performance indicator* included in the structural equation model; perception which is identified as a *performance factor* from three-factor theory analysis will have both its *low-performance indicator* and *high-performance indicator* included in the structural equation model; perception which is identified as an *exciting factor* from three-factor theory analysis will have its *high-performance indicator* included in the structural equation model. The second layer is the regression of intention-to-use the AB service on the perceptions. Also, the structural equation

Table 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 *Stockholm* 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%

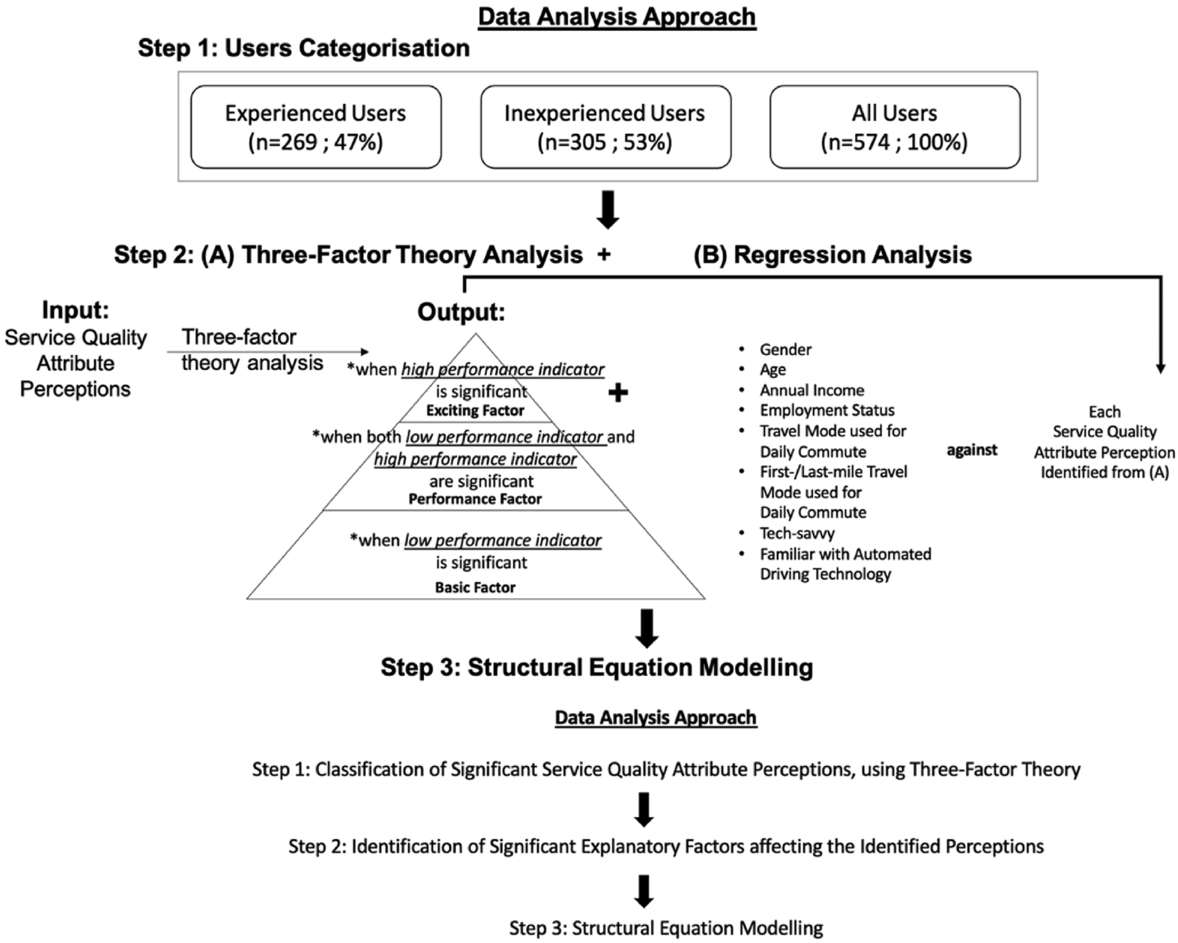

Fig. 5. Approach to data used in this study.

model serves 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 Section 4.

3.3. Statistical checks

The analyses involved both multiple regression analysis and structural equation modelling (an analysis which combines factor analysis and multiple regression analysis). A multiple regression assumptions check (Osborne and 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 and 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 *variance inflation factor (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 61 in Appendix A, 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 Fig. A1 in Appendix A), the normality assumption was fulfilled, as the points correspond reasonably well to the diagonal line, from bottom left to top right. Only

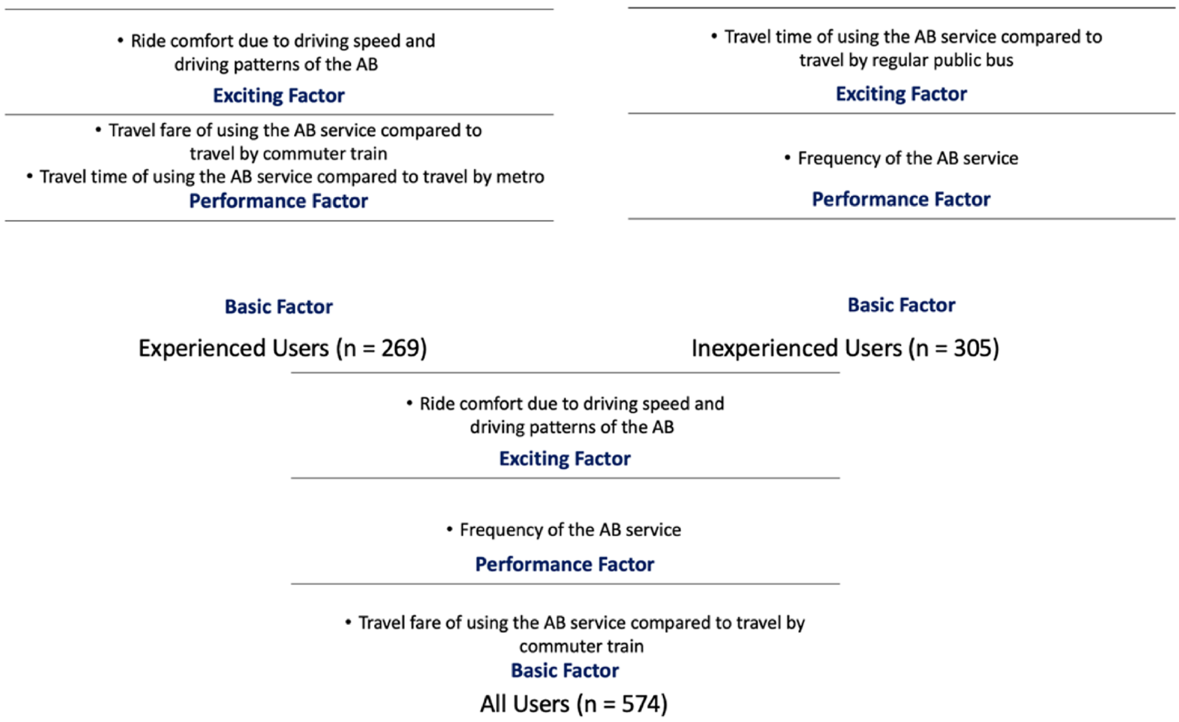

Fig. 6. Significant service quality attributes affecting intention-to-use of the first-/last-mile AB service, of experienced users, inexperienced users and all users.

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

Common method variance (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.

4. Results and discussion

This study applied three-factor theory analysis to categorise survey respondents' perceptions, and structural equation modelling 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 intention-to-use 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 (B) regression analysis. The following discussion explains the results from the (A) three-factor theory analysis and (B) regression analysis.

4.1. Results from (A) three-factor theory analysis

Tables A3–A5 in Appendix A show those service quality attribute perceptions found to be significant (with a p-value less than 0.10) from the regression analysis. Fig. 6 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.

There is no perception classified as a *basic factor* that affects the ITU of 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 inexperienced 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.

The results support the findings from Allen et al. (2019) about the existence of hierarchy of transit needs among the users of a transport service. The outcome obtained from all users shows a hierarchy which is similar to the hierarchy of transit needs. The basic factor, travel fare affects the users' accessibility to the service, and should be categorised as a *functional attribute* in the hierarchy of transit needs. Similarly, the performance factor, frequency also belongs to the functional attribute in the hierarchy of transit needs. These attributes are the basic level of needs. On the other hand, ride comfort which was identified as an exciting factor in the three-theory factor analysis belongs to the higher level of need in the hierarchy of transit needs as a *hedonic attribute*.

Besides, another finding from Allen et al. (2019) that showed users start to assign more weight to hedonic attributes after their essential transport needs are fulfilled is supported. The lower level needs: frequency and travel time which are related to reliability of a service appeared to be a performance factor and an exciting factor respectively for inexperienced users. On the other hand, the same factor of travel time appeared to be a performance factor instead of an exciting factor for experienced users. Furthermore, ride comfort which is a hedonic attribute appeared to be an exciting factor to experienced users.

4.2. Results from (B) regression analysis

Tables A6–A8 in Appendix A 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 Fig. 7. Fig. 7 shows only links which are significant ($p < 0.10$, or $p < 0.05$) from the regression analysis, as in Tables A6–A8 in Appendix A.

4.3. Results from Structural Equation Modelling

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 a p-value less than 0.10), as shown in Tables A6–A8 in Appendix A, were included in the SEM analysis.

4.3.1. 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 A2 in Appendix A shows the list of endogenous variables identified in the Hausman test. The endogenous variables were addressed in the SEM models, as shown in Fig. 7, by correlating the error terms of the endogenous variables with the error term of participants' ITUs.

4.3.2. Check for Model Fit

Model fit of the three SEM models was also analysed. 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. Table 3 shows the model fit measures of three SEM models.

4.3.3. CMIN/df (χ^2/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.

4.3.4. 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.

4.3.5. 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.

4.3.6. 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

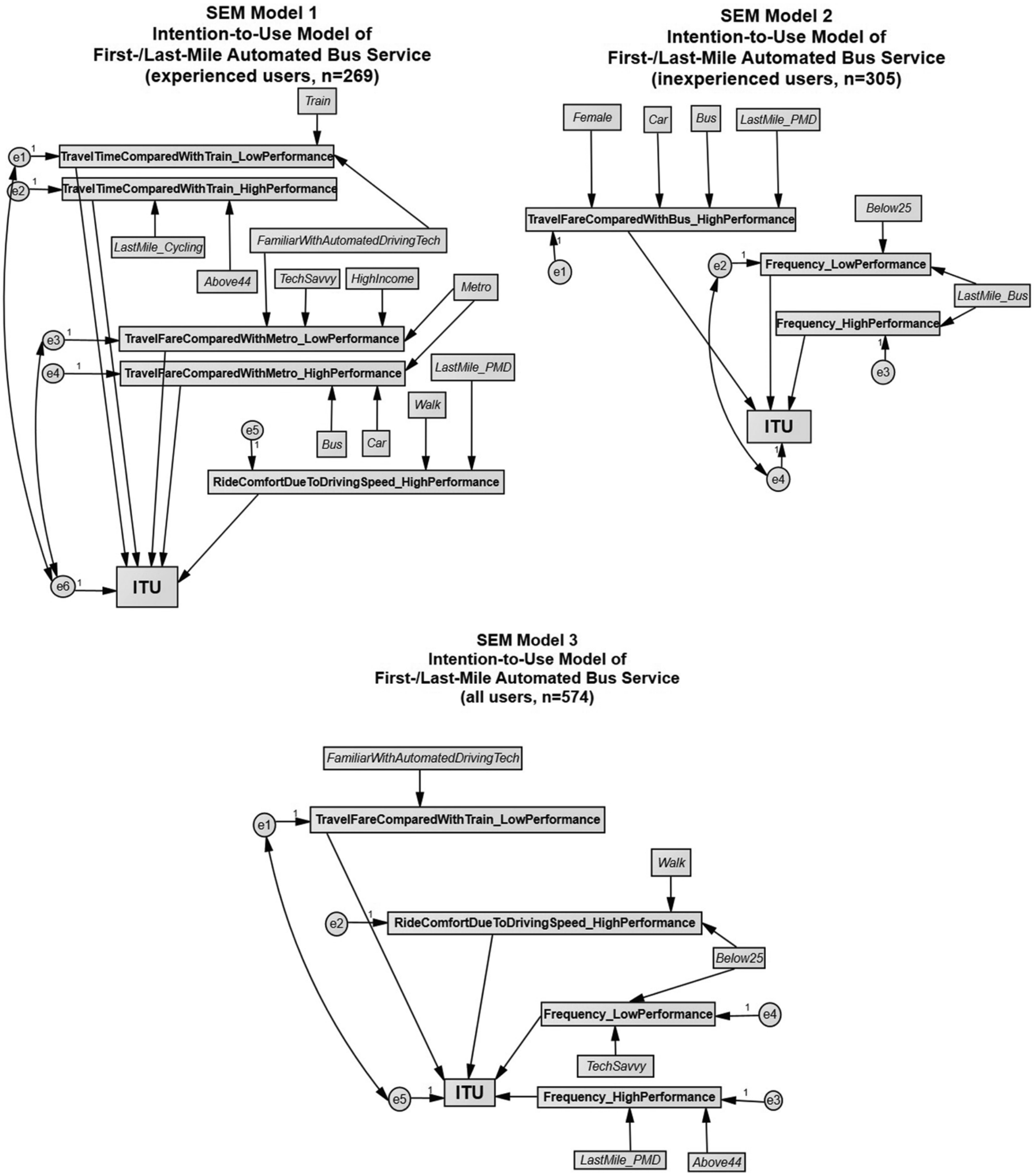

Fig. 7. SEM models used in the final analysis.

Table 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

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.

Fig. 8 shows the SEM models, with the estimates for significant variables (with a p-value less than 0.10) in bold. *Ride comfort due*

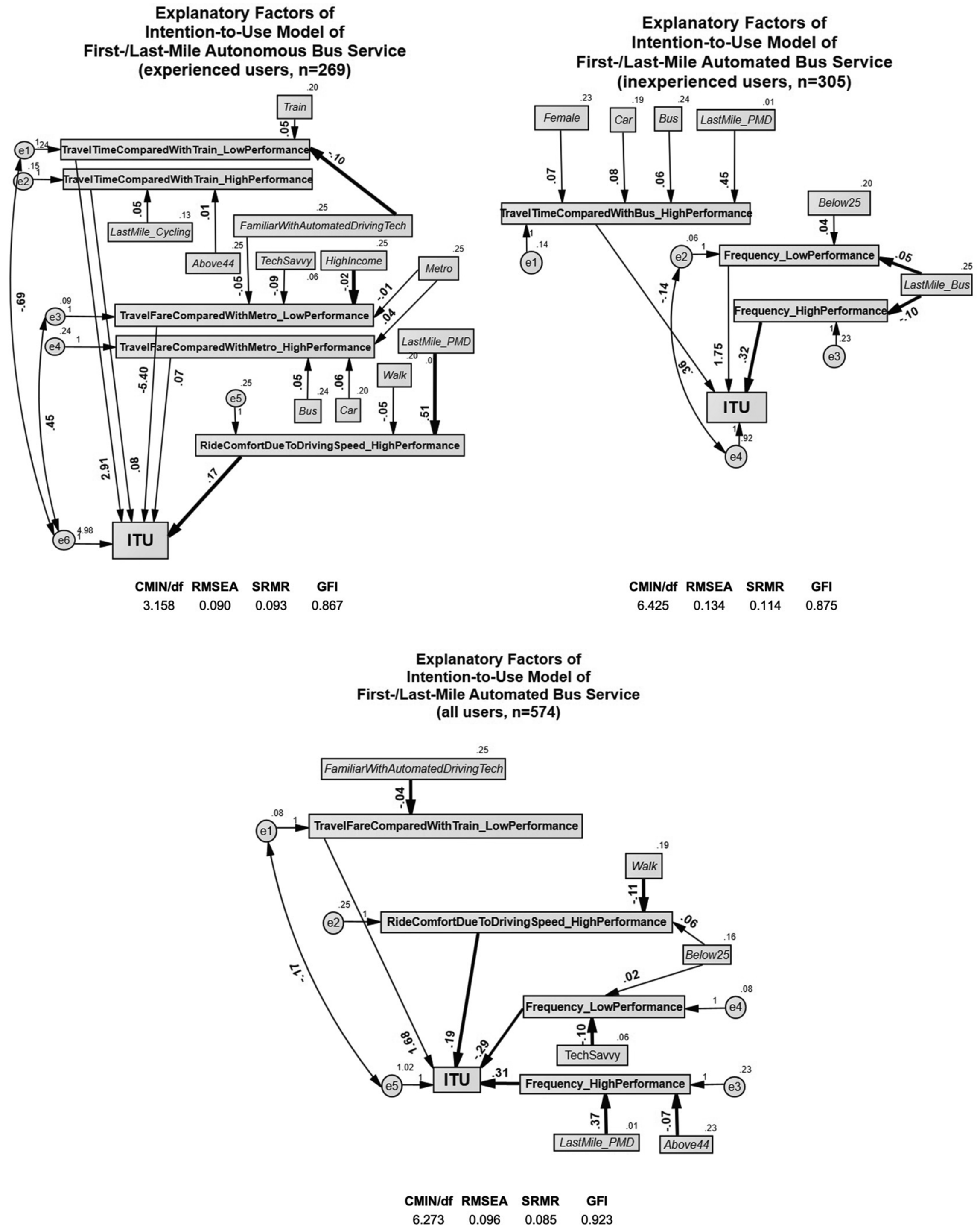

Fig. 8. SEM models with the coefficient estimates for which the significant variables with p-value smaller than 0.01 are bolded.

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.

4.4. *Effects of Explanatory Variables on ITU*

The explanatory variables in the SEM models not only affect service quality perceptions, but also participants' ITU of the first-/last-mile AB service. Table 4 shows their effects on ITU the AB service of (i) experienced users, (ii) inexperienced users, and (ii) all users.

(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 commuter train service, given same distance and route.

5. Conclusion

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' ITU the trialled first-/last-mile B 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 intentions to use 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 stand 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.

In conclusion, prospective passengers' intentions to use a first-/last-mile AB service is greatly influenced by the frequency of the AB service and ride comfort due to its driving pattern. As of now, the level of service is limited by the technical performance of the AB fleet as a whole. In the future, operators should be aware that commuters' intention-to-use an AB service is still subject to the ability of the selected AB fleet to deliver the expected level of service. Additionally, vehicle developers should continue to work on developing ABs which can deliver a service with both good frequency and a smoother riding experience. Due to competition with other emerging transport services, such as shared PMDs, and the current public bus service, it would be better to operate the AB service as a complementary service to existing first-/last-mile transport services under the same transport package with other first-/last-mile services. Policy makers and operators should be aware that any changes in the frequency of the AB service will affect the demand for shared PMD services and the existing first-/last-mile public bus service.

There are three limitations in this study. Firstly, 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. Secondly, the data was collected from a population who work, study or live in an area which hosts many technological organisations and tech-savvy people. As a result, the socio-demographics of the respondents are skewed towards being tech-savvy. Therefore, the suggested policies may only apply to areas with a significant tech-savvy population, defined as persons who are well informed about or know how to use computers, mobile phones and electronic devices. Whilst one may think that this may only apply to a few unique locations at the 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. Lastly, the proportion of the respondents who are business owners and use PMDs for first-/last-mile trips was very small. The findings associated with these socio-demographic groups should be treated carefully.

Past habits or prior experience has been found to be one of the factors influencing people's intention-to-use a new technology or service. Hence, moving forward, research should be conducted to investigate if there are changes in the levels of influence of service quality perceptions on intention-to-use a first-/last-mile AB service, and the factors that influence users' perceptions when they will have more opportunity to use an AB service over a longer period.

CRediT authorship contribution statement

Pei Nen Esther Chee: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft. **Yusak O. Susilo:** Conceptualization, Writing - review & editing, Supervision, Funding acquisition. **Yiik Diew Wong:** Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This study was conducted as part of first author's research programme while reading a joint NTU-KTH PhD degree, with a scholarship funded by Nanyang Technological University, Singapore. The project was funded by the Vinnova Strategic Innovation Programme Drive, Sweden (grant number 2016-05313), and ended in October 2018. It was coordinated by ITRL Integrated Transport Research Lab at KTH Royal Institute of Technology, and the research activities were conducted by KTH researchers in collaboration with Nobina AB. This work is also supported by Cost Action CA16222 (WISE-ACT), a European-wide network that explores the wider impacts of Autonomous and Connected Transport.

Appendix A

See Fig. A1 and Tables A1–A8.

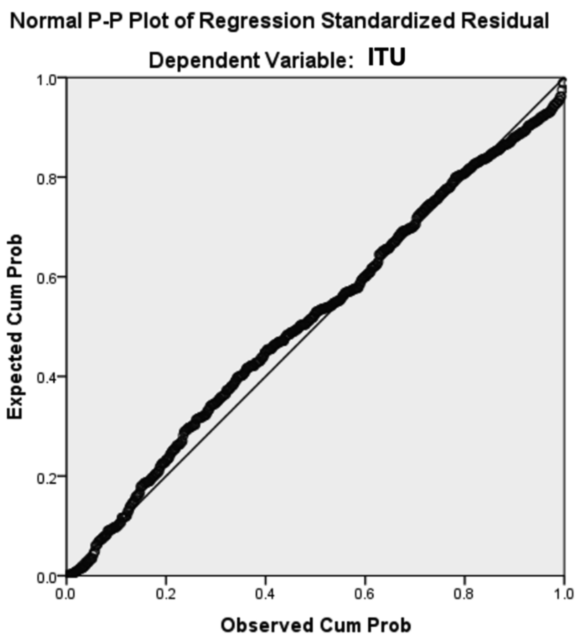

Fig. A1. Normal P-P plot of Regression Standardised Residual.

Table A1
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

Table A2
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 A3
Service attribute perceptions found to significantly influence intention-to-use first-/last-mile automated bus service of experienced users from three-factor theory analysis, 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	TravelFareComparedWithCommuter train_LowPerformance	−0.425	0.024
4	RideComfortDueToDrivingSpeed_HighPerformance	0.179	0.039
5	TravelFareComparedWithBus_MissingValue	−0.576	0.086

Table A4
Service attribute perceptions found to significantly influence intention-to-use first-/last-mile automated bus service of inexperienced users from three-factor theory analysis, 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 A5
Service attribute perceptions found to significantly influence intention-to-use first-/last-mile Automated Bus Service of all users from three-factor theory analysis, with the p-value less than 0.10.

No.	Variables	Estimate	p-value
1	TravelFareComparedWithCommuter train_LowPerformance	−0.905	0.001
2	TravelFareComparedWithCommuter train_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 A6
List of significant explanatory variables affecting each type of identified perception attributes from regression analysis (experienced users).

Dependent Variable	Significant Explanatory Variables	Estimate	p-value
TravelFareComparedWithCommuter train_LowPerformance	FamiliarWithAutomatedDriving Tech	−0.064	0.095
TravelFareComparedWithCommuter train_HighPerformance	Train	−0.157	0.033
	Above44	−0.145	0.048
	LM_Cycling	0.190	0.078
TravelTimeComparedWithMetro_LowPerformance	FamiliarWithAutomatedDriving Tech	−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 A7
List of significant explanatory variables affecting each type of identified perception attributes from regression analysis (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(PersonalMobilityDevice)	0.391	0.090

Table A8
List of significant explanatory variables affecting each type of identified perception attributes from regression analysis (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
TravelFareComparedWithCommuter train_LowPerformance	FamiliarWithAutomatedDrivingTech	−0.053	0.036
	AcceptableTravelTime	−0.064	0.087
RideComfortDueToDrivingSpeed_HighPerformance	Walk	0.056	0.064
	FamiliarWithAutomatedDrivingTech	−0.046	0.066
	TechSavvy	−0.094	0.074
	Cycle	−0.070	0.096

Appendix B. Survey questionnaire

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 m e.g. walking from Kista T-bana Station to Kista Convention Center, along Kistagången.**
   - 1–5 min
   - 6–10 min
   - 10–15 min
   - More than 15 min. 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	*Somewhat 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 NO operator/ steward on the automated bus.					
I feel _____when there is an operator/ steward 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 ____					

See Table B1.

Table B1
Socio-demographic distribution of respondents.

Characteristics/ sample group	Total (N = 574), %	
Gender		
Male	64.5	
Female	34.0	
Others	1.5	
Age		
Children (aged under 15)	0.0	
Young Adult (aged 15–24)	20.4	
Adult (aged 25–44)	42.9	
Middle-age Adult (aged 45–64)	31.2	
Elderly(aged above 65)	5.2	
Others	0.3	
Employment Status		
Working	59.1	
Business Owner	3.1	
At School	30.7	
On Sick Leave	0.5	
On Parental Leave	0.5	
Unemployed and Seeking for Work	4.2	
Permanently Retired from Work	1.2	
Others	0.7	
Education Background		
Compulsory school	1.4	
Upper secondary school	20.1	
Undergraduate level	11.0	
Graduate level	59.6	
Doctoral level	7.5	
Others	0.7	
Gross Monthly Income (before tax) in Swedish Kronor (SEK)		
Low-income (≤200,000 SEK)	16.5	
Middle-income (200,000–699,000 SEK)	36.5	
High-income (≥700,000 SEK)	21.2	
Others	25.8	
Technology Awareness		
Tech-savvy: well informed about or know how to use computers, mobile phones and electronic devices.	Yes	93.9
	No	5.6
	Others	0.5
Familiar with the technologies used to enable automated road vehicle to drive without human driver	Yes	56.8
	No	42.7
	Others	0.5
Existing Travel Modes		
Walk	Yes	26.7
	No	73.3
Cycling	Yes	13.9
	No	86.1
Regular Public Bus	Yes	39.2
	No	60.8
Metro	Yes	48.3
	No	51.7
Train	Yes	27.0
	No	73.0
Car	Yes	26.5
	No	73.5
Last Mile Travel Modes		
Walk	Yes	68.3
	No	31.7
Cycling	Yes	11.7
	No	88.3
Regular Public Bus	Yes	44.1
	No	55.7
	Others	0.2
Use electronic personal mobility devices – e-kick scooter, hover board and electric-powered wheel chair	Yes	1.0
	No	99.0
Automated Bus Ride Experience (Time Period** 1**)		
Never	52.6	

(*continued on next page*)

Table B1 (*continued*)

Characteristics/ sample group	Total (N = 574), %
1–5 times	44.9
6–10 times	1.6
11–15 times	0.2
More than 15 times	0.3
Others	0.4

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