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The dynamic and long-term changes of automated bus service adoption

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ABSTRACT

Integrating automated buses (ABs) into the public transport system may have potentials of providing more environment-friendly and cost-efficient mobility solutions by improving travel safety, reducing cost and decreasing congestion. However, the realization of the potentials depends not only on innovative technologies but also on users' acceptance of the ABs service. Whilst there has been a number of studies exploring the acceptance and adoption of ABs services, hardly any longitudinal studies have analyzed the long-term changes of individuals' behavior in adopting AB services. This paper aims to add knowledge on user acceptance of ABs in public transport based on empirical evidence in a real-life deployment context. Three waves of surveys that investigated users' travel attitudes and behaviors towards the automated bus were conducted at three different time points (six months, 11 months, and 14 months after the launch). The relationship between socio-demographic variables, travel experience variables, and attitude variables is modeled using structural equation modelling (SEM). Factors that influence experienced users to continue using the service were found to dynamically change over time. Initially, people were attracted to use the service if they perceived the information of the service to be sufficient, but they were demotivated to continue using the service if the comfort was worse, frequency was lower, or travel time was longer than expected. The results show that previous experience of adopting the ABs has impacts on different attitude variables. In order to promote individuals' continued use of ABs, the public transport authorities and operators should work closely to increase the frequency of the services. It is also necessary to enhance the comfort of the ABs.

1. Introduction

Applying automated vehicles (AVs) in on-demand mobility and ridesharing could bring potential benefits, such as decreasing accident rates, increasing the capability of fulfilling travel demands, as well as reducing private car usage and greenhouse gas (GHG) emissions (Fagnant and Kockelman, 2015; Milakis et al., 2017). Furthermore, integrating AVs into the public transport system has drawn increasing attention as they may offer more environment-friendly and cost-efficient mobility solutions (Meyer et al., 2017). This potential integration has been investigated through implementation tests in different scenarios (Bernhard et al., 2020). Following the European roadmap for automated driving (Dokic et al., 2015), there have been many initiatives within Europe, such as CityMobil and

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CityMobil 2 (Alessandrini et al., 2014), CAST (Christie et al., 2016), EUREF (Nordhoff et al., 2018), and SARA1 (Pernestål et al., 2018).

A successful integration of AVs into public transport is not only dependent on innovative technologies but also on user acceptance. As Saffarian et al. (2012) stated, user acceptance could be a critical factor for whether an autonomous system will be successfully implemented or not. Users' perceptions towards AVs are closely connected to many challenges that need to be solved in order to enable transition from traditional vehicles to AVs (Wicki et al., 2020). It is unrealistic to assume that people would accept and adopt AVs only because this disruptive technology may bring certain advantages (Azad et al., 2019; Jing et al., 2020). Menon et al. (2016) found that 61.5% of drivers in the US indicated that they would not use AVs. People may just try AVs out of curiosity but not really accept and adopt them since they do not want to lose control of the vehicle or change their travel habits (Krueger et al., 2016; Anania et al., 2018; Chee et al. 2020a, 2020b; Guo et al. 2020a, 2020b).

There have been some studies focused on understanding user acceptance of AVs with the aim of providing knowledge and guidance in applying AVs as a solution for smart and sustainable mobility. Becker and Axhausen (2017) reviewed what survey methods had been used in the literature to understand the variables and predictors on acceptance of AVs. They also compared the influences of the variables and predictors in different groups of people with regard to AVs acceptance. Gkartzonikas and Gkritza (2019) took the behavioral intention perspective and studied users' behavioral characteristics and perceptions affecting their willingness to use AVs. They identified that attitudinal components (comfort, safety, etc.) were generally considered in discussing common potentials and challenges in adoption of AVs. Jing et al. (2020) reviewed studies on psychological factors and behavior theories in discussing the acceptance of AVs. They found that the utilization of behavior theories was useful in improving the understanding of acceptance of AVs.

However, there are some limitations in the previous literature on acceptance of AVs, as Pointed out by Zoellick et al. (2019). First, there are no standards on what perspectives should be taken into account when modeling user acceptance of AVs; second, the diversity of methods has made it difficult to set unified definitions of concepts and operations; and third, the analysis based on empirical evidence of AVs in real-life scenarios are rather limited or even lacking. The last limitation not only made it difficult to validate the results, but also made it impossible to generalize findings from studies on real-life and simulated scenarios.

Focusing on the third limitation identified by Zoellick et al. (2019), this paper aims to add knowledge on user acceptance of automated buses (ABs) when deployed as a fully operational, integrated, public transport service on public roads. The contribution of this study is three-fold. First, the ABs are operated as a part of actual public transportation within the current public traffic system. Second, three waves of data are collected from a consistent group of respondents during different periods after the launch of the ABs. This can capture the dynamic changes of user acceptance. The continuous longitudinal study can also eliminate potential bias due to non-continuous surveys and non-consistent respondents. Third, the longitudinal data collection enables investigation of whether key factors influencing users' acceptance change during the time that the ABs have been accessible to the users.

This study identifies the key factors of user attitudes and AV attributes based on the technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT), based on Venkatesh and Bala (2008), Venkatesh et al. (2003), and Venkatesh et al. (2012). Three waves of surveys that investigated users' travel attitudes and behaviors towards the automated bus were conducted during three periods (six months, 11 months and 14 months after the launch of the AB service). The dynamic and long-term changes of AB service adoption were investigated through a longitudinal analysis and key factor analysis.

The paper is structured into the following five sections. Section 2 is the literature review on factors of user acceptance based on TAM and UTAUT. Section 3 presents the main methods that are used. Sections 4 presents the real-life trial of the automated bus and the three waves of survey data. Section 5 shows the results and related discussion. Finally, section 6 concludes the paper with the main takeaways.

2. Overview of studies on user acceptance of AVs

Most studies that have investigated factors influencing user acceptance of AVs have followed the TAM or/and UTAUT (Zoellick et al., 2019). Davis et al. (1989) proposed TAM by applying perceived usefulness and perceived ease of use as two major factors determining user acceptance of new technologies. Although TAM was designed to be applied to information system and technology innovations, it has been adapted to model the user acceptance of AVs (Panagiotopoulos and Dimitrakopoulos, 2018).

Venkatesh et al. (2003) proposed the model of unified theory of acceptance and use of technology (UTAUT) by applying performance expectancy, effort expectancy, and social influence as key factors in investigating acceptance. Performance expectancy was defined as the extent of improvement on performance by using a system, and effort expectancy was defined as the degree of ease to use a system (Venkatesh et al., 2003). The performance expectancy and effort expectancy in UTAUT correspond to the perceived usefulness and perceived ease of use in TAM. In UTAUT, age, gender, and experience are used to moderate the relationships between effort expectancy, social influence, and intention-to use (Bernhard et al., 2020). In UTAUT, the factors from social influence were considered, and in a further model of UTAUT2, factors of hedonic motivation, price value, and habit were also included (Venkatesh et al., 2012). There have been many studies using TAM and UTAUT, and there are other acceptance models that have been used to understand AVs acceptance. A more detailed review for a comparison study of the models can be found in Rahman et al. (2017) and Jing et al. (2020).

In the review of recent studies, factors related to trust, risk and performance expectancy were found to be crucial to understanding user acceptance of AVs. Ghazizadeh et al. (2012) modified TAM by integrating trust and compatibility and found that trust had a direct effect on users' acceptance. Benleulmi and Blecker (2017) identified that perceived safety risk through trust had an indirect effect on user acceptance. In the studies that Choi and Ji (2015) and Xu et al. (2018) conducted, they also incorporated trust and perceived risk into TAM. However, perceived risk was found not to directly influence users' acceptance. Kaur and Rampersad (2018) took reliability, security risk, and privacy risk as trust factors, and regarded trust and performance expectancy to be the two main factors that affect users' acceptance directly. Madigan et al. (2016) found performance expectancy to have the strongest impact to influence users' acceptance of automated minibuses based on UTAUT. In a subsequent study by Madigan et al. (2017), hedonic motivation, performance expectancy, social influence and facilitating conditions were found influential, while effort expectancy did not show significant influence. Nordhoff et al. (2018) included characteristics of the minibus (design, space) into the UTAUT and found that these influenced users' acceptance of adopting the service.

In the review of the abovementioned studies, one common thing was noticed: most studies were based on limited demonstrations of certain AV concepts, which makes it difficult to generalize the results. There was a lack of continuous empirical evidence to validate the findings and examine how users react to new AV mobility services over time. However, it is important to capture the dynamic changes of users when adopting a new transport option over time, since it can help the transport providers design appropriate strategies for attaining current users and attracting potential new users (Termida et al., 2017). It is also important to acknowledge that the dynamic changes of user acceptance also vary among groups with different travel needs and behaviors (Susilo and Cats, 2014). Therefore, scholars have suggested using continuous observations on the same group of people at different time points to observe the dynamic changes of user acceptance (Axhaussen et al, 2007; Järv et al., 2014; Termida et al., 2017).

A longitudinal panel survey is one approach that can be used for continuous observations and to capture changes in the same individuals over time. It collects information of the same set of variables from the same sample group over at least two different time points (Lynn, 2009). In the transportation sector, longitudinal panel surveys have been acknowledged to be effective in understanding the changes of people's travel behavior and to assess the effects of new mobility service options (Chu, 2015; Circella, et al., 2019). For example, Thøgersen (2006) found that the use of public transport would positively influence people's attitudes and perceptions towards public transport based on a three-wave panel interview during 1998–2000. Jensen et al. (2013) used a two-wave panel survey three months before and after introduction of electric vehicles and found changes in individual preferences after using an electric vehicle. Termida et al. (2016) used a three-wave panel survey distributed over eight months and found individuals would change their choice of using a new tram extension from pervious choices.

However, many studies that applied longitudinal analysis have mainly focused on users' value pre-use of the AVs instead of post-use (Chee et al., 2020). Few studies have been found to consider scenarios of both pre-use and post-use. Distler et al. (2018) compared the differences between pre-use acceptability and post-use acceptance of on demand autonomous shuttles, based on results from three workshops with 14 participants. They found that participants were reassured about safety concerns but perceived the operation as ineffective. Xu et al. (2018) found differences before and after experiencing an automated car among 300 college students. Positive perceptions were received for the usefulness, trust and ease-of-use of the automated car. However, these two studies had either a limited or a biased sample. In particular, they did not examine the potential users' change in acceptance after the first experience, which is more useful for promoting the use of AVs. There are very few studies investigating how user acceptance could change if the automated vehicles were integrated in the public transport, based on longitudinal panel surveys. Chee et al. (2020a) examined what factors could affect the willingness to pay for using automated buses based on a three-wave panel survey over five months. Their study is significant since the surveys were based on an actual first/last mile automated bus service operated in Sweden. The separate structural equation models considered the dynamic changes of the acceptance. The results showed that service quality, ride experience, concern for cybersecurity, and willingness to pay differed among the individuals with different socio-demographic characteristics.

To summarize, based on the brief literature discussion above, there is a lack of studies addressing on factors that may affect the user adoption of Abs, especially with empirical evidence.TAM and UTAUT can provide insights into which factors to consider in checking user acceptance of ABs. It is important to consider both the pre-use and post-use of ABs through continuous observations on the same group. A longitudinal panel survey can enable this. Empirical evidence that can provide a comprehensive dataset is crucial in studying ser acceptance of ABs services.

3. Method

This paper is based on a longitudinal panel survey with three waves of questionnaires conducted within an eight-month interval. Structural equation modeling (SEM) is used for the analysis of the data. There are mainly three reasons for using SEM in this study. First, it can estimate multiple correlated variables simultaneously with the inclusion of latent variables (West et al., 2012). Second, SEM is able to estimate complex models and account for measurement error when an integrated latent variable is composed of multiple variables (Thøgersen, 2006). Third, SEM is able to handle a large number of endogenous and exogenous variables by including unobserved or latent variables and specifying them as linear combinations of the observed variables (Golob, 2003).

In this study, the UTAUT is mainly used as one aspect to set the questionnaire design to collect data for variables that are crucial in the longitudinal analysis. Socio-demographic characteristics, such as gender, age, income, education and technology awareness are regarded as individually controlled variables (Bansal et al., 2016; Salonen, 2018). Performance expectancy is regarded as the degree of benefits that using ABs will provide to users. Effort expectancy is regarded as the degree of ease associated with the use of ABs. Social influence is regarded as the degree to which others (e.g. family and friends) would have influence on the adoption of ABs. The attributes that may influence these factors are vehicle safety, on-board steward, travel comfort, travel time, driving operations, and travel experience of other transport modes.

There are some other variables which may affect the users' adoption of ABs but were not included in the study. For example, the suitability of the route characteristics in serving individual's daily needs, their willingness to share the ride with strangers on regular basis, their willingness to use the vehicle on higher cruising without steward, responsibility on accidents, potential benefits on reducing pollution, cybersecurity (Bansal et al., 2016; Bansal & Kockelman, 2018; Chee et al., 2020a). These safety and needs related issues are also important in influencing the adoption behaviors.

However, the survey design had to prioritize certain questions to make sure the measurement of those variables in the model can be done by minimizing the risk of non-response due to too many questions. The surveys were therefore designed so that they would not take a respondent longer than 30 min to answer to make sure to retain their participation over 3 different waves in 7 months apart.

Fig. 1 illustrates the SEM conceptual model of how different variables could influence the user's likelihood of adopting ABs. The structure in Fig. 1 shows the categorization of variables in the analysis, i.e. (1) the users' socio-demographic variables, (2) users' usage and experience of other travel modes, and (3) the latent variables. The socio-demographic characteristics of the individuals are controlled variables that include age, gender, education, employment status, car ownership, gross yearly income of household, whether they live or work in the neighborhood, and technology awareness. The ABs service performance attributes, including frequency, speed, steward, information, ride comfort, and travel time, are considered as non-parametric latent variables to check user perception. Experiences of other transport modes is also included in the model since this relates to the user expectation and social influence. The latent variables are the subjective variables towards the given automated bus service, whilst the experience in Fig. 1 is meant to describe the users' experience towards all other travel modes. In the estimation, the experience variables and individual characteristics are being treated at the same level. The individual characteristics are treated as fixed, as the socio-demographic variables are not likely to change overtime, whilst the chosen travel modes and user experiences change over time.

Normally, the adoption process may be assumed to be sequential, which means that the socio-demographic variables influence one's built environment selection of travel mode experience, and then shape the appreciation of service quality indicators that leads to a particular adoption behavior of a new travel mode alternative. This process normally could happen on an environment that is stable with no significant change in the built environment and accessibility conditions.

However, when a neighborhood is continuously expanding on daily basis, the built environment for travel modes selection is also dynamically changing, the adoption process of ABs cannot be assumed to be sequential. The dynamic changes may lead to the adoption of ABs beyond the learning evolution process that is induced by socio-demographic variables. Therefore, the model in this paper treats the "experienced travel modes" parallel with the "socio-demographic (controlled) variables". A relationship lines also is established from these two variable categories to the "adoption behavior of ABs" as is shown in Fig. 1.

The model representing the conceptual framework has the following form:

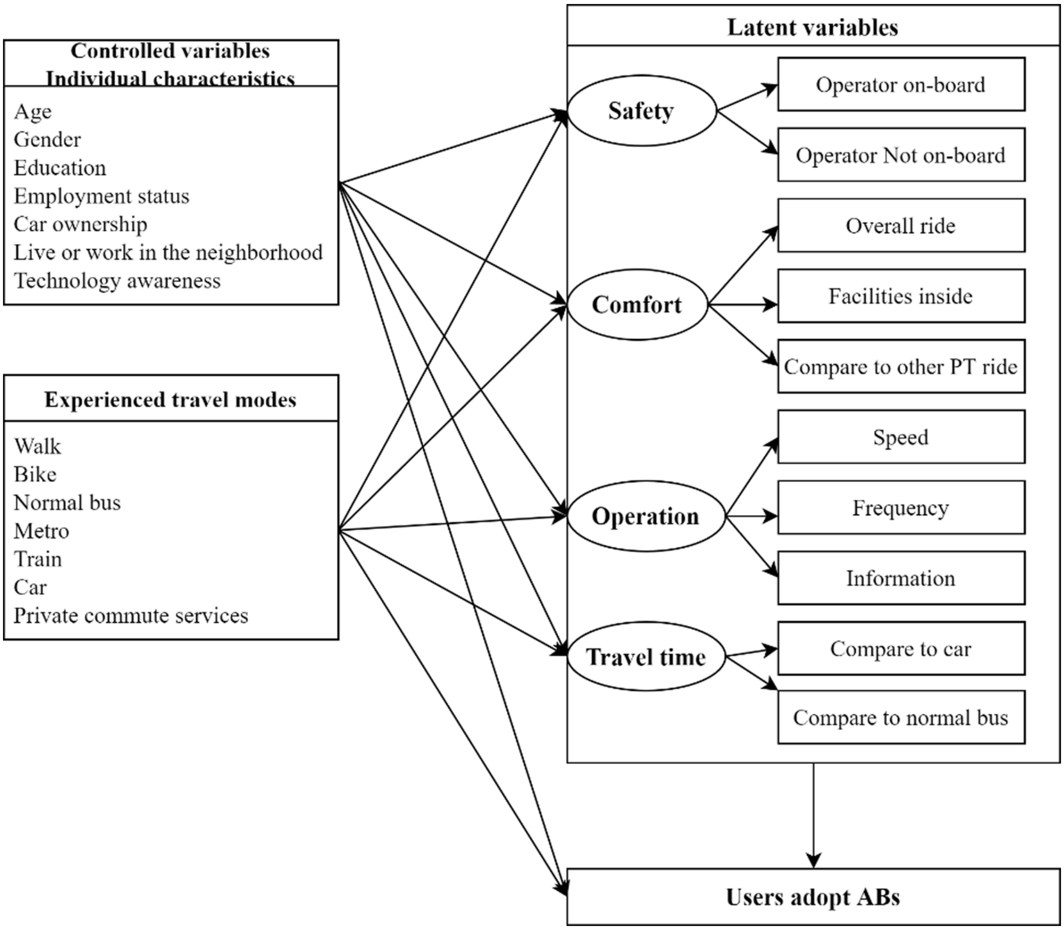


Fig. 1. Conceptual framework for factors influencing users adopting automated buses.

$$UA_{n,t} = \alpha_t + \beta_{CV,t} CV_{n,t} + \beta_{TM,t} TM_{n,t} + \beta_{LV,t} LV_{n,t} + \varepsilon_t \tag{1}$$

In Equation (1), the dependent variable $UA_{n,t}$ is defined as the user acceptance of an individual n that adopted the ABs at wave t. The acceptance is based on the vector of control variables (CV), the experience of other transport modes (TM), and the vector of the latent variables (LV); $\beta_{CV,t}$, $\beta_{TM,t}$ and $\beta_{LV,t}$ are respectively vectors of coefficients associated to each attribute. α_t is a constant estimate, and ε_t is a random error term. This enables both users and non-users with the distribution of actual users in each waves can be captured.

The model does not prior a certain independent variable over another. One main reason is that in the UTAUT, it usually regard different factors equally important so that the information collected to measure the variables will not be biased. Second, empirical study on user adoption of ABs is still rare and there is not enough evidence showing which variables are more important than the other. Therefore, let the coefficients denote how the exogenous variables influence the endogenous variable and make corresponding interpretation is one of the purpose of the SEM model in this paper.

Based on the conceptual framework in Fig. 1, the longitudinal analysis will check the behavioral change of users adopting ABs over time. Individuals may adjust their attitudes, perceptions and behaviors based on previous experience (Jensen et al., 2013). Previous experience would in turn influence the current use, mediated by attitudes and perceptions (Thøgersen, 2006).

Fig. 2 illustrates the conceptual framework of the longitudinal analysis. The framework shows the influence paths from the previous behavior of adopting AB to the behavior measured at a following time period. It can also capture how people's pervious behavior of adopting ABs could influence how they would perceive the performance attributes at a following time period. The detailed information on the controlled variables, travel modes experienced, and latent variables are the same as listed in Fig. 1. All exogenous and endogenous variables are treated as explanatory variables. A more comprehensive version of Fig. 2 can be checked further in Appendix 2.

The changing usage frequency has also been taken into account to capture the dynamic user behavior change over time. The usage frequency that users made in previous period is the input for the subsequent period in the model. This inclusion can be seen in equations (2), 3 and 4, which can capture the change of usage dynamically over different period of observation. This adds a unique aspect of this study.

$$UA_{n,t-1} = \alpha_{t-1} + \beta_{CV,t-1} CV_{n,t-1} + \beta_{TM,t-1} TM_{n,t-1} + \beta_{LV} LV_{n,t-1} + \varepsilon_{t-1} \tag{2}$$

$$\varepsilon_t = \gamma \varepsilon_{t-1} + \xi_t \tag{3}$$

$$UA_{n,t} = \alpha_t + \beta_{CV}, tCV_{n,t} + \beta_{TM,t} TM_{n,t} + \beta_{LV,t} LV_{n,t} + \gamma\left(UA_{n,t-1} - \alpha_{t-1} - \beta_{CV,t-1} CV_{n,t-1} - \beta_{TM,t-1} TM_{n,t-1} - \beta_{LV} LV_{n,t-1}\right) + \xi_t \tag{4}$$

According to Equation (1), the model for wave t-1 can be written as Equation (2). If we assume that the random error ε_t at wave t is related to the random error ε_{t-1} at wave t-1, and ξ_t being the error term to capture the heterogeneity of time of survey as described by Equation (3), the SEM model in the longitudinal analysis can be transformed into Equation (4), which means the adoption of ABs at a later time depends on the adoption experience of the previous time.

4. Empirical evidence

The empirical evidence of the ABs service was collected in the area of Barkarby, Stockholm. In that area, 18,000 new residential dwellings, 140 city blocks, 10,000 new workplaces, a 4 km new metro line with two stations and a new connected bus center will be in place by 2030 at the latest, according to a long-term city panning project, named Barkarbystaden. In the transportation-planning sector, autonomous door-to-door shuttles, electrified bus rapid transit, autonomous city buses and other transport modes are planned to run in the area to form a new integrated system of mobility as a service. To fulfill such a vision, the area is undergoing many initiatives with pilots and test beds (Järfälla municipality, 2016).

Among the ongoing initiatives, ABs have been running on a regular schedule for the service providers since October 2018 driven by a project known as MMiB (Modern Mobility in Barkarby, Guo et al., 2020a). This is among those first trials that integrated self-driving buses on real-life public streets and in regular public transport in Europe. The project develops new technology and provides the rapidly growing Barkarby town and its inhabitants with a first/last mile solution for transport. Three buses have operated as a regular service as bus line 549.

As shown in Fig. 3, an excerpt from the municipality plan, the bus line has four bus stops with the central square and the shopping center as two ends. The speed of the buses is around 15 km/h, and the length of the line is 2.5 km. The buses run Monday to Friday from 06:41 to 18:41 and Saturday from 11:46 to 18:26, with 15 min frequency.

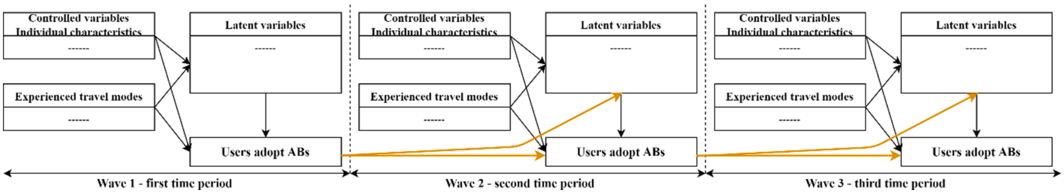


Fig. 2. Conceptual framework for the longitudinal analysis of user change in adopting ABs.

Fig. 3. The automated bus (left, *Source:* Drive Sweden) in line 549, and the bus stops (right, *Source:* OpenStreetMap).

In order to understand changes in users adopting the bus service, three waves of panel data were collected. The data collected over the three waves were all based on online surveys. The recruitment of the participants and the collection procedures were mainly conducted by a survey company. Fig. 4 shows the different time periods of the data collections.

The three waves were conducted respectively in March, September and December 2019. In the original recruitment design, the sample size is expected to mimic the population of the neighborhood. Statistically, based on socio-demographic distribution of the population in Barkarbystaden is about 10,000 individuals and with a confidence level of 95%, a panel with at least 500 individuals should be representative enough to describe the given resident population.

In order to have at least 500 people to participate continuously through all three waves to enable the longitudinal behavioral analysis, 750 participants were recruited for wave 1, of whom 600 participate in wave 2, and of whom almost 500 participated in wave 3. In wave 3, an extra 200 people were recruited to ensure the statistical confidence level, of whom 148 participated. Among the 750 participants invited to the survey, 519, 573 and 584 responded to the survey in each wave and 393 attended all three waves.

This way of survey design can enable a scientifically robust enough analysis to draw conclusion and recommendation for the given study area. Although a larger sample size could be better in a quantitative analysis, especially if one would generalize the outputs beyond a specific studied neighborhood. However, as in any survey design and recruitment processes, we balance between a larger sample size beyond the study area, the length of the questionnaire, and the ability to retain the respondents across three different survey waves, to fulfill the purpose of this study.

The questions in the survey focused mainly on four elements: socio-demographics, travel mode used, knowledge and expectation of the ABs, and adoption and perception of the ABs. With the socio-demographic questions, the characteristics of each participant were captured. Participants who joined in all three waves of the surveys only needed to answer the socio-demographic part of the survey in wave 1, and they could then fill in their assigned unique ID in waves 2 and 3.

In the part related to travel modes used, participants answered questions on what transport modes they used, the purpose, frequency and satisfaction. Following the model framework in Fig. 1, in the data collection periods, usage and experience of other travel modes are repetitively collected from the respondents in each wave so that the variance that may be caused by the continuously changing built environment can be captured.

In the part on knowledge about and perception of ABs, questions on pre-knowledge of ABs (existence, technology related), willingness to use ABs and intentions were asked. In the part on adoption and perception of ABs, questions on first time of use, perceived operation, safety, comfort, travel time were asked. In all surveys, questions followed the five-point Likert-scale.

4.1. Descriptive analysis

The respondents' socio-demographic characteristics in all three waves are shown in Table 1. The numbers show the percentage of the total number of respondents in each wave. The sum of answers to "Live or work in the neighborhood" is greater than 100% because

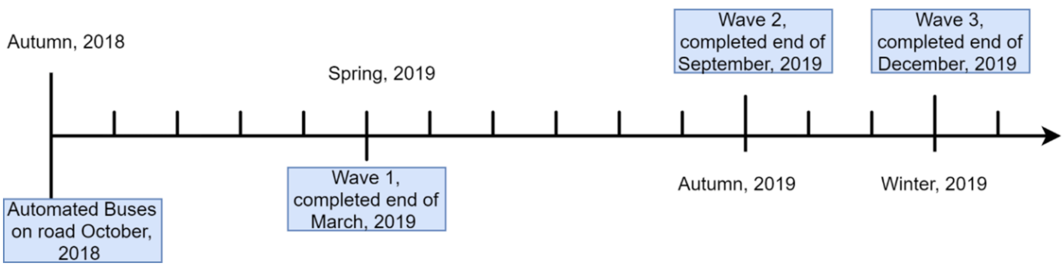


Fig. 4. Longitudinal data collections conducted in different time periods.

a respondent can both live and work in the neighborhood. The sum of answers to "How do you usually commute?" is also greater than 100% as a respondent can chose all commute modes that he/she usually uses, which can enable the check of multimodal travel behaviors.

In Table 1, a relatively consistent pattern can be seen along the three waves, meaning that, although with drop-out and new add-ins on waves 2 and 3, the distribution of each of the socio-demographic characteristics was similar within each wave. This is beneficial when comparing each wave to investigate how adoption and perception change over time. In wave 1, 811 participants were recruited for the survey. In waves 2 and 3, 128 and 147 new participants, respectively, were recruited for the survey. There were 519,573, and 584 respondents, respectively, in waves 1, 2 and 3, of which 393 respondents participated in all three waves. These respondents well represented the target population since most of the socio-demographic characteristics are relatively balanced. However, it has a bias that most respondents have a higher education (Master's degree) and are tech-savvy.

The specific question that was designed to measure the dependent variable $UA_{n,t}$ was: *Have you taken an autonomous bus ride?* Table 2 summarizes the usage frequency through the three waves. In the data process of the responses, each choice (1–5 times, 6–10 times, 11–15 times, more than 15 times, never took) was first assigned as 1,2,3,4,5, and then binary number 0 (not use), 1 (have used) for the dependent variable.

4.2. Change of factors influencing individuals' adoption of ABs

Table 3 lists the specific variables forming each latent variable and the related code. Based on the correlation of the variables

Table 1
The respondents' socio-demographic characteristics in all three waves (in %).

Attributes	Wave 1 ($n = 519$)	Wave 2 ($n = 573$)	Wave 3 ($n = 584$)	All waves ($n = 393$)
Gender				
Male	44.7	44.5	43.2	44.8
Age (years)				
0–14	0	0	0.3	0
15–24	6.6	6.3	7.0	4.1
25–34	32.4	34.0	34.4	30.5
35–44	27.0	27.0	27.1	28.8
45–54	13.5	13.5	13.4	14.5
55–64	8.7	8.2	8.2	9.2
Above 65	11.9	10.9	9.6	13.0
Employment status				
Full-time employed	72.3	74.7	71.4	71.0
Self-employed	3.7	2.8	3.1	3.3
Student	6.9	7.0	8.2	7.1
Other (pension, parental leave)	17.1	15.4	16.8	18.6
Education status				
Primary school	2.9	3.0	2.7	2.5
Upper secondary school	27.7	28.5	28.3	25.4
Bachelor's degree	16.8	15.4	17.8	16.5
Master's degree	51.3	51.5	49.1	53.7
Doctoral degree	1.3	1.6	1.5	1.8
Household gross yearly income in Swedish Kronor (SEK) (before tax)				
Below 100,000 SEK	1.7	1.6	1.7	1.5
100,000–299,000 SEK	10.2	10.3	9.1	9.9
300,000–499,000 SEK	24.5	26.8	27.1	21.4
500,000–699,000 SEK	20.8	19.1	18.7	21.1
700,000–899,000 SEK	12.7	12.3	11.5	14.2
Above 900,000 SEK	9.1	7.9	7.7	10.2
Do not want to specify	21.0	22.1	24.0	21.6
Live or work in the neighborhood				
Yes, live in the neighborhood	91.7	91.3	89.9	93.9
Yes, work in the neighborhood	9.1	9.4	9.2	7.6
Neither	3.7	3.5	4.6	3.3
Car ownership				
Yes	75.0	68.1	64	75.9
No	25.0	31.9	35.3	24.1
Do you consider yourself a tech-savvy person?				
Yes	87.2	87.1	72.8	89.0
No	12.8	12.9	9.8	11.0
How do you usually commute?				
Walk	17.2	16.6	16.8	18.2
Cycle	15.1	14.4	14.2	16.9
By bus	49.1	51.5	53.3	46.8
By Metro	32.1	31.5	32.5	32.7
By Train	48.7	48.9	50.2	52.9
By Car	38.3	34.3	31.7	35.8

Table 2
The respondents' usage frequency through three waves (in %).

Attributes	Wave 1 (n = 519)	Wave 2 (n = 573)	Wave 3 (n = 584)
Have you taken an autonomous bus ride?			
Never took	76.21	71.24	67.24
1–5 times	20.70	24.72	28.08
6–10 times	1.74	2.70	2.95
11–15 times	0.58	0.22	0.87
greater than15 times	0.77	1.12	0.87

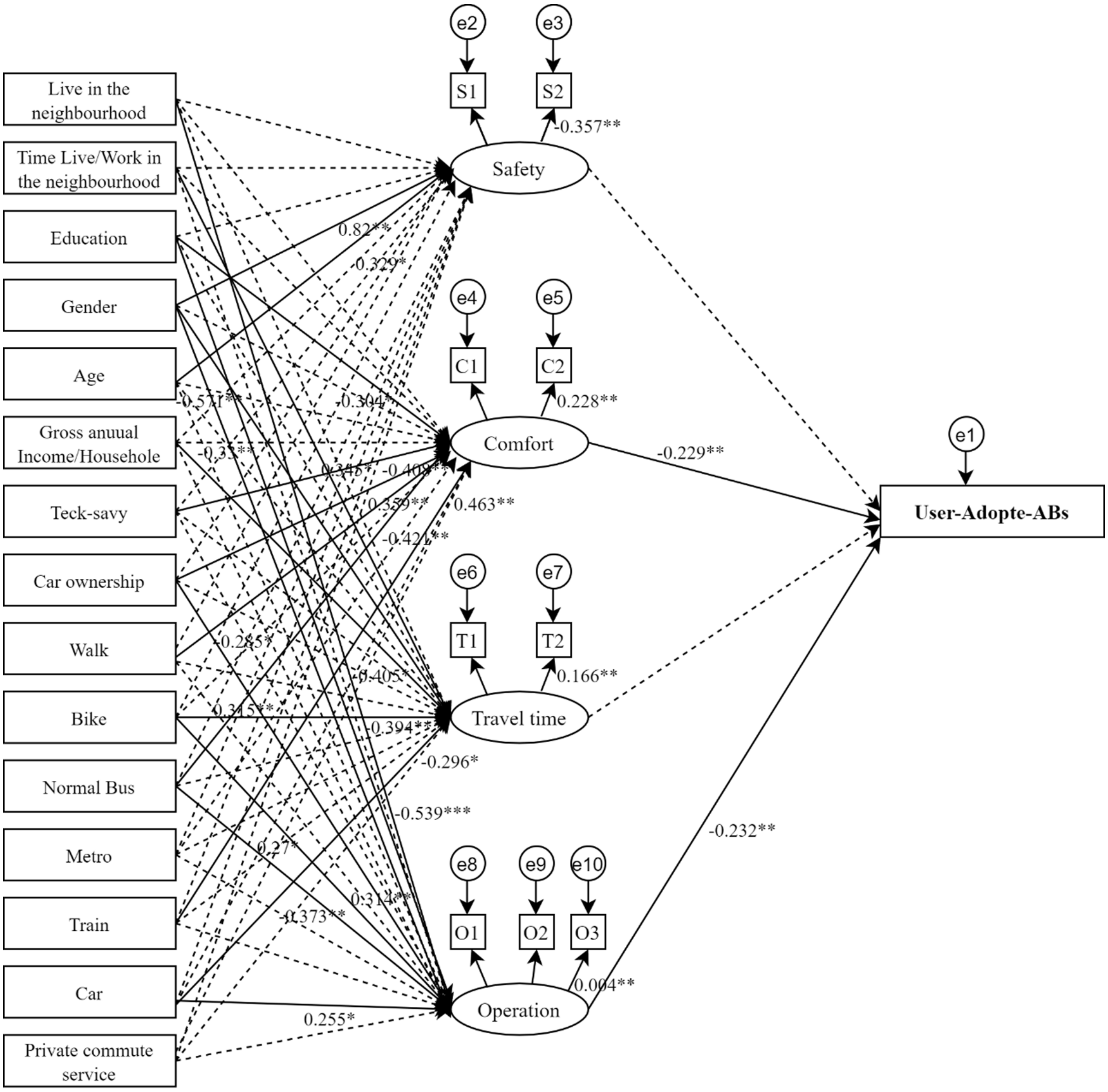
related to socio-demographic characteristics and other transport modes, not all variables are included in the model. The detail of the correlation matrix can be found in the appendix A1. Fig. 5 shows the results of the SEM according to the framework depicted in Fig. 1. SPSS AMOS 25 is used to construct the SEM and conduct the analysis.

In Fig. 5, the influences that were statistically significant are marked with solid lines, and the corresponding p-value are listed alongside; those that are statistically insignificant are marked with dash lines. In wave 1, only the latent variables of comfort and operation were statistically significant in influencing individuals to adopt the ABs service ($p < 0.05$). This may indicate that individuals are more encouraged to use the service if the ride experience was comfortable and the operation was well conducted. Given the requirement of the current policy, a steward must be onboard while the ABs are in service. Individuals may therefore not have much concern about safety. Moreover, since the ABs run at a speed of around 15 km/h, individuals who used the service were prepared for the travel time being different to traditional buses, which may lead to the fact that, in our results, the travel time did not have a statistically significant influence on individuals adopting the ABs.

As for the effects of socio-demographic characteristics, older people place significantly more value on safety. People who have a higher education view comfort and operation as more important for a ride. Individuals with a higher gross annual income put a higher value on the latent variable of travel time, while those who have good technology awareness put a higher value on the latent variable of comfort. Employment status is found to be insignificant and therefore is not illustrated in Fig. 5. Car owners were more influenced by

Table 3
Description of variables and code used in the latent variables.

Variable	Code	Description	Scale
Safety			
Steward onboard	S1	I felt ____ because the steward was on the autonomous bus.	Extremely unsafe
Steward not onboard	S2	I would feel ____ if the steward was not on the autonomous bus.	Unsafe
			The same
			Safe
			Extremely safe
Comfort			
Comfort of the overall ride	C1	I think or know that the current autonomous bus ride is:	Extremely uncomfortable
			Uncomfortable
			Neutral
			Comfortable
			Extremely comfortable
Comfort than normal bus	C2	I think or know that the level of on-board comfort of the autonomous bus is ___ than regular public transport service.	Much worse
			Somewhat worse
			Neutral
			Somewhat better
			Much better
Travel time			
Travel time vs. normal bus	T1	Given the same travel distance and route, I think that the travel time (including waiting time) of taking the autonomous bus ride is ___ than taking the normal bus ride	Much longer
			Longer
Travel time vs. car	T2	Given the same travel distance and route, I think that the travel time (including waiting time) of taking the autonomous bus ride is ___ than driving a car	Same
			Shorter
			Much shorter
Operation			
Frequency of the ABs	O1	I think the frequency of the autonomous bus is _____ than the frequency of the normal bus service.	Much lower
Speed of the ABs	O2	I think or know the driving speed of the current autonomous bus service is ___ than the regular public transport service.	Somewhat lower
			The same as
			Somewhat higher
			Much higher
Information of the ABs	O3	The current information provision about the autonomous bus service is_____.	Non-existent
			Not enough
			Enough
			Very informative
			Too much



Fit statistics: χ2(231) = 1143.547 (p < .05); χ2/df = 4.95; RMSEA = .1; NFI= .134; CFI= .106; GFI =.783; (Standardised estimates)
Note: p-value: *** significant at <.001; ** significant at <.05; * significant at <.1.

Fig. 5. Factors influencing individuals in adopting the ABs service.

the comfort and operation. The results also show that individuals living in the neighborhood put significant value on travel time. This could be because they have stronger motivations to use the service as an option for transport needs, rather than trying it out of curiosity, compared to individuals not living in the area. The experience of other transport modes is found crucial in influencing the perceptions of comfort, travel time and/or operation of ABs.

To check the model fit, the chi-square test was significant ($p < 0.05$). However, the chi-square test of absolute model fit could be sensitive to sample size and non-normality of the input variables (Termida, et al., 2017). The root mean square error of approximation (RMSEA), the goodness of fit index (GFI), the comparative fit index (CFI), and the normed fit index (NFI) were therefore further used to assess the overall fit of the model to the data. According to the reference value of model fit indices (Jackson et al., 2009), RMSEA is slightly above the reference value 0.08, the GFI was slightly lower than the reference value 0.9, while NFI and CFI were much lower than the reference value 0.9. However, the model result depends on sample size, number of latent variables and model complexity, and there may be unobserved heterogeneity; the reference standard should not be regarded as a golden rule (Fan and Sivo, 2007; West et al., 2012). Therefore, we accepted the model and constructed models for waves 2 and 3; detailed information can be found in Fig. 6 (enlarged version can be found in the appendix A3).

The results showed that factors that significantly influenced individuals' adoption of ABs changed over time. In wave 2, only operation was found statistically significant, while in wave 3, comfort and safety were found statistically significant. The influence

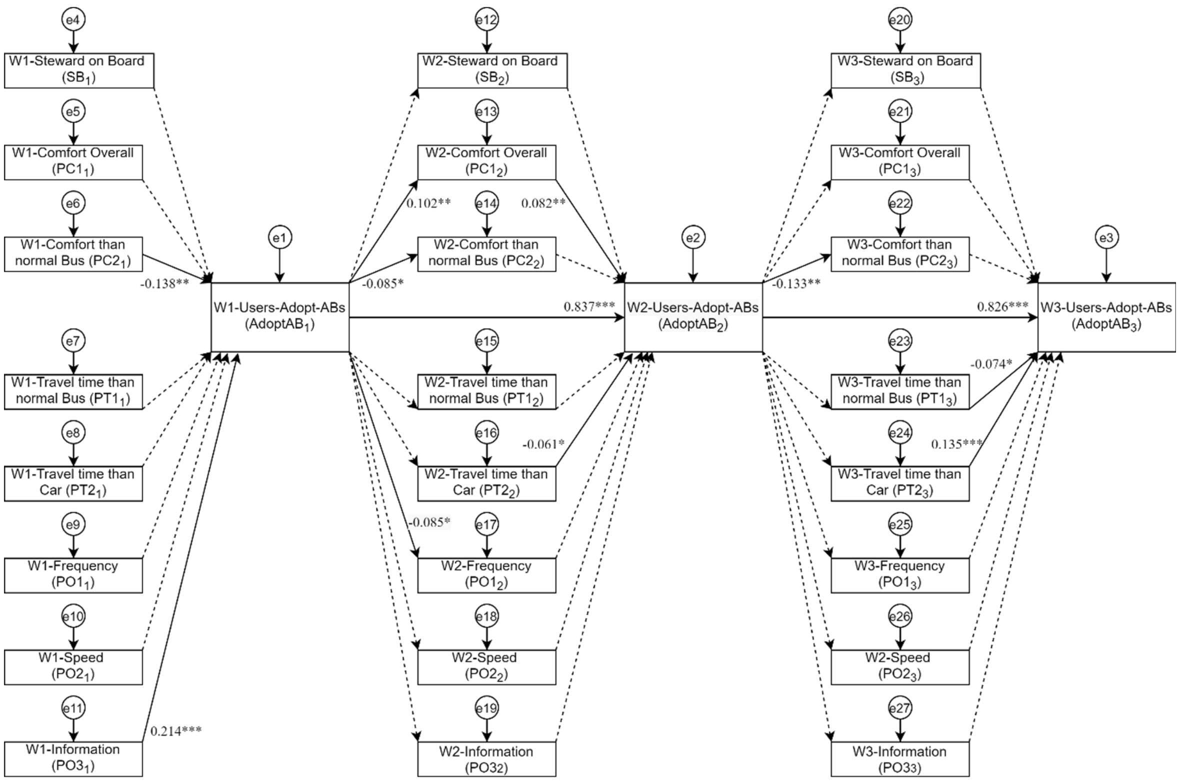
		Wave1	S.t. Estimate	S.E.	P	Sig.
Operation	<---	LiveintheNeighbourhood	-,539	,165	,001	***
TavelTime	<---	TimeLiveWorkintheNeighbourhood	,345	,082	,054	*
Comfort	<---	Education	-,304	,025	,069	*
Operation	<---	Education	,314	,039	,043	**
Safety	<---	Gender	,820	,075	,012	**
TavelTime	<---	Gender	-,571	,071	,003	**
Operation	<---	Gender	-,333	,078	,048	**
Safety	<---	Age	,329	,014	,056	*
TavelTime	<---	IncomeGrossAnnualHousehold	-,405	,020	,025	*
Comfort	<---	Tecksavy	-,408	,077	,021	**
Comfort	<---	CarOwnership	,359	,055	,036	**
Operation	<---	CarOwnership	,315	,083	,041	**
Comfort	<---	Walk	-,285	,059	,079	*
TavelTime	<---	Bike	-,394	,092	,029	**
Operation	<---	Bike	,270	,098	,081	*
Comfort	<---	NormalBus	-,421	,051	,021	**
Operation	<---	NormalBus	-,373	,076	,020	**
Comfort	<---	Train	,463	,052	,012	**
TavelTime	<---	Car	-,296	,071	,095	*
Operation	<---	Car	,255	,075	,095	*
StewardNotonBoard	<---	Safety	-,357	1,384	,014	**
ComfortthanNormalBusRide	<---	Comfort	,228	,437	,005	**
TraveltimethanCar	<---	TavelTime	,166	,294	,007	**
Information	<---	Operation	-,177	,183	,004	**
User Adopt ABs	<---	Comfort	-,229	1,645	,018	**
User Adopt ABs	<---	Operation	-,232	,942	,012	**

		Wave 2	S.t. Estimate	S.E.	P	Sig.
Operation	<---	LiveintheNeighbourhood	-,306	,166	,032	**
TavelTime	<---	LiveintheNeighbourhood	,366	,113	,062	*
Operation	<---	Education	,465	,044	,002	**
Safety	<---	Gender	,884	,083	,033	**
TavelTime	<---	Gender	-,446	,066	,066	*
Comfort	<---	Age	-,647	,020	,032	**
Comfort	<---	IncomeGrossAnnualHousehold	,495	,015	,061	*
Operation	<---	IncomeGrossAnnualHousehold	,267	,023	,066	*
TavelTime	<---	Walk	-,350	,071	,078	*
TavelTime	<---	Bike	-,414	,076	,044	**
Operation	<---	Bike	,323	,107	,025	**
Operation	<---	NormalBus	-,505	,084	***	***
Operation	<---	Car	,409	,085	,005	**
StewardNotonboard	<---	Safety	-,311	1,566	,041	**
ComfortthanNoramlBusRide	<---	Comfort	,208	,676	,032	**
TraveltimethanCar	<---	TavelTime	,156	,468	,028	**
Speed	<---	Operation	-,088	,156	,095	*
Information	<---	Operation	-,149	,145	,009	**
User Adopt ABs	<---	Operation	-,453	2,251	,068	*

		Wave 3	S.t. Estimate	S.E.	P	Sig.
Safety	<---	LiveintheNeighbourhood	,296	,189	,068	*
TavelTime	<---	Education	-,251	,034	,079	*
Safety	<---	Gender	,285	,086	,070	*
Operation	<---	Gender	-,376	,072	,010	**
TavelTime	<---	Age	,571	,026	***	***
Operation	<---	Age	,372	,026	,011	**
Comfort	<---	Tecksavy	-,506	,098	,003	**
Operation	<---	Tecksavy	-,285	,110	,043	**
Safety	<---	Walk	-,299	,117	,064	*
Comfort	<---	Walk	-,506	,083	,003	**
TavelTime	<---	Walk	-,523	,093	,001	**
Operation	<---	Walk	-,480	,101	,002	**
Safety	<---	NormalBus	-,274	,088	,081	*
Comfort	<---	NormalBus	-,396	,060	,013	**
Safety	<---	Metro	,276	,094	,080	*
TavelTime	<---	Metro	-,434	,073	,005	**
Operation	<---	Metro	-,385	,078	,009	**
Safety	<---	Train	-,272	,087	,079	*
Safety	<---	Car	-,621	,096	***	***
Comfort	<---	Car	-,417	,065	,013	**
ComfortthanNormalBusRide	<---	Comfort	,208	,289	,003	**
TraveltimethanCar	<---	TavelTime	,245	,317	***	***
Speed	<---	Operation	,240	,232	***	***
Information	<---	Operation	,102	,158	,062	*
User Adopt ABs	<---	Comfort	-,414	3,517	,072	*
User Adopt ABs	<---	Safety	,362	2,143	,083	*

Fig. 6. Factors influencing individuals in adopting the ABs service in waves 1, 2 and 3.

from the socio-demographics and transport modes to the latent variables was also identified as different among the three waves. The changes may be due to the heterogeneity of the respondents in each wave. Nevertheless, it may indicate a change of influencing factors over time since the number of new respondents added in waves 2 and 3 were rather small. The next section shows the results on the behavior change over time with the same 393 respondents.



Fit statistics: $\chi2(309) = 2707.389$ ($p < .05$); $\chi2/df = 8.76$; RMSEA = .132; NFI= .276; CFI= .292; GFI =.552; (Standardised estimates)
Note: p-value: *** significant at <.001; ** significant at <.05; * significant at <.1.

Fig. 7. The behavior change in adopting ABs of the 393 users through all three waves.

4.3. Longitudinal analysis of behavior change

In the longitudinal analysis of behavior change on individuals adopting ABs, socio-demographics and transport modes were not included, since questions related to these variables were only answered in wave 1 and were then regarded as fixed in waves 2 and 3. To avoid the complexity of introducing too many random errors in constructing latent variables, the exogenous variables used in the model are direct inputs. These variables are denoted with SB (steward onboard), PC1 (perceived comfort overall), PC2 (perceived comfort compared to normal bus), PT1 (perceived travel time vs normal bus), PT2 (perceived travel time vs car), PO1 (perceived operation of frequency), PO1 (perceived operation of speed), PO1 (perceived operation of information). Subscripts 1, 2 and 3 are used under each variable to indicate wave 1, 2, and 3. Fig. 7 illustrates behavior change of the 393 users in adopting ABs from the antecedent behavior at $t-1$ to the current behavior at t.

The results indicate that previous experience affects current behavior in adopting ABs. According to the estimated coefficients from wave 1 to wave 2 (0.837***) and from wave 2 to wave 3 (0.826***), the more individuals used the AB service in the previous time period ($t-1$), the more they would continue to use the service in the current time period (t). Five months after the introduction of the AB service, individuals who reported that they perceived the comfort of the AB was worse than a normal bus ($PC2_1$) and perceived that the information provided in the service operation was sufficient ($PO3_1$) were those who adopted the AB service ($AdoptAB_1$). However, the influence of the perceived information ($PO3_2$ and $PO3_3$) was not significant to individuals adopting ABs either less or more in waves 2 or 3 ($AdoptAB_2$ or $AdoptAB_3$). This was probably because once individuals had tried the AB service, the knowledge of the timetable, stops and other operational information was understood, and did not show significant influence on the choice of adopting the service.

The perception of travel time in using the AB service compared to using a car ($PT2_n$) consistently affects users adopting the ABs in waves 2 and 3 ($AdoptAB_2$ and $AdoptAB_3$), but the influence was the opposite. The negative influence means that individuals who perceived that the AB service took longer than taking the car were those who adopted the new service less at the time. The positive influence means that individuals who perceived that the AB service was faster than taking the car were those who adopted the new service more at the time. Particularly, 13 months after the service had been in use, individuals who perceived the travel time of the ABs as being longer than a normal bus ($PT1_3$) adopted the AB service less ($AdoptAB_3$).

On an individual basis, the perceived comfort of the AB service compared to a normal bus constantly changed over time. The significant values of the adoption behavior from a previous time ($AdoptAB_{n-1}$) to the current perceived comfort vs normal bus ($PC2_n$) indicate that individuals adjusted their perceptions based on their previous experiences. This finding may indicate that individuals who continuously adopted the ABs service considered it as a commonly used option of public transport, instead of a new experience just out of curiosity.

It was also noted that five months after the AB service was launched, previous adoption of the new service ($AdoptAB_1$) would influence individuals to have a better perception on the overall comfort of the AB ride ($PC1_2$), but a worse perception on comfort vs a normal bus ($PC2_2$) and operation frequency ($PO1_2$). This may be because after individuals had experienced the service, they put a high expectation on good overall comfort in the subsequent use of ABs, but did not expect a positive change in the comfort compared to normal buses or an increase in frequency. The positive value of $PC1_2$ further indicates that people who had a good perception on the overall comfort were those who used the AB services more at the time ($AdoptAB_2$), while the influence from $PC2_2$ and $PO1_2$ were not significant. These findings are inconsistent with Termida et al. (2017) and Jensen et al. (2013), where both studies found that individuals would use their previous experience to reevaluate the preferences and choices for a new option of transport service.

The model fit results show that the model did not fit the data well according to the reference value of the model fit indices (Jackson et al., 2009). This was anticipated, since the sample size was relatively small and the relationships between the endogenous and exogenous variables is relatively complex. The GFI (0.552), CFI (0.292) and NFI (0.276) were lower than the reference value 0.9, but RMSEA (0.132) was above the reference value 0.08. Considering the complexity of the model, the model fit cannot be the only standard to interpret the model being insufficient in checking the dynamic changes of individuals' behavior in adopting the ABs service.

Endogeneity could occur because of omitted variables and could bias the cause-effect relationships. Although the covariance of the variables were checked in the analysis (Appendix 1), finding an instrumental variable that is related to independent variables but unrelated to the disturbance term could be beneficial. However, finding an instrument is difficult given that it not only needs to be theoretically justified but also needs to be empirically verified. The current survey data could not provide sufficient information for empirical verification. If possible, the partial least squares structural equation modeling could be tested to address such problem (Hult et al., 2018). Nevertheless, the interpretation of the model and the discussion of the results should be approached with caution.

5. Conclusion

This paper contributes by adding knowledge on user acceptance of automated buses (ABs) in public transport based on a longitudinal study of empirical evidence in a real-life scenario. The relationships between socio-demographic variables, travel experience variables, and attitude variables are modeled using structural equation modeling (SEM).

Factors that influence experienced users to continue adopting the service were found to change over time. Initially, people were attracted to use the service if they perceived the information of the service to be sufficient, but they were demotivated to continue using the service if the comfort of the ABs was worse than normal buses. Low frequency of the AB service also demotivated people for continuous use since their travel needs cannot be fulfilled. Travel time is also found to be influential for people to continue using the ABs service since people perceived travel time longer because of waiting, due to the lower frequency of the ABs service.

The longitudinal analysis also shows that the previous experience of adopting the ABs had different effects on the attitude variables.

One finding is that user adoption of ABs in the previous wave had a significant negative influence on the perception of the ABs' comfort than a normal bus. This may indicate that the more users adopt the ABs, the more they would regard the service as a regular public bus service and, therefore, expect a higher level of service experience. These dynamic changes were also captured in the separate SEM models, although the heterogeneity pattern of respondents in the separate models showed that individuals tend to re-evaluate their preferences and choices over time with increased travel experiences of the service. The model fit was not ideal due to the low sample size and complex relationship between the endogenous and exogenous variables. Further calibrations may be needed to improve the model performance and partial least squares structural equation modeling could be used to address the endogeneity problem. However, we argue that the results can assist to achieve the aim of capturing the dynamic changes of users' acceptance of a new automated bus service and to give insights on which factors should be focused on to attract more users and better meet their travel needs.

There are three main takeaways to promote individuals adopting the ABs.

First, it is necessary to enhance the comfort of the ABs, to make the travel experience be at least equally comfortable as or more comfortable than taking a normal bus.

Second, the dynamic changes of the influence factors may also mean that individuals are still in an experiencing, learning and adjusting process; a continuous follow-up of the users would be beneficial to provide knowledge on evolved changes.

Third, public transport authorities and operators should work closely together to increase the frequency of the services.

It requires time for an individual to change travel behavior when a new transport service is introduced, especially with technology uncertainties and vague regulations. Providing certain types of incentives may be a strategy to attract new adopters and maintain existing ones in using the automated bus service.

As for future work, more data from the empirical evidence would be useful to investigate the changes. Variables such as the suitability of the route characteristics in serving individuals' daily needs, willingness to pay on customized services, willingness to use ABs on higher cruising without a steward, and other variables that relate to special demand and safety issues, are also important to investigate. By uncovering more hidden factors, better guidance for making strategies in promoting people adopting AB services can be provided.

CRediT authorship contribution statement

Xiaoyun Zhao: Writing – original draft, Conceptualization, Methodology, Writing – review & editing. **Yusak O. Susilo:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Anna Pernestål:** Writing – review & editing, Funding acquisition.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2021.10.021.

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