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When and why do people choose automated buses over conventional buses? Results of a context-dependent stated choice experiment

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ABSTRACT

The sustainable and continuous development of public transport systems is crucial to ensuring robust and resilient transport and economic activity whilst improving the urban environment. Through technological improvement, cities can increase the competitiveness of public transport, promote equality and pursue a multi-modal shift to greener solutions. The introduction of vehicle automation technology into existing public transport systems has potential impacts on mobility behaviours and may replace conventional bus service in the future. This study examines travellers' preferences for automated buses versus conventional buses, using a context-dependent stated choice experiment. This experiment measured the effects of context variables (such as trip purpose, travel distance, time of day, weather conditions and travel companion) on the choice of automated buses versus conventional buses. The results were analysed using mixed logit models, and the findings indicate that, in general, choice behaviours do not diverge much between the choice of automated bus and conventional bus. However, individuals' choices are more elastic towards the changes in automated bus service levels compared to conventional bus service. The results show that poor weather conditions may lower the quality and reliability of public transport service, and the probability of choosing an automated bus over a conventional bus is reduced due to such disruptions. In addition, passengers travelling for work purposes, covering long distances, or travelling with companions are more likely to choose conventional buses than automated buses.

1. Introduction

The number of private cars on the roads has increased rapidly in recent decades. The growth of private car use leads to various problems, such as air pollution and greenhouse gas emissions, traffic congestion, and poor traffic safety (Abbass, Kumar, & El-Gendy, 2020; Gärling & Schuitema, 2007; Greene & Wegener, 1997; Jou & Chen, 2014; Millard-Ball & Schipper, 2011; Power, 2012). As a means to deal with this problem, public transportation offers a safe, affordable, and convenient alternative to the private motorised transport and improves mobility in urban areas (Chapman, 2007; Chen & Jou, 2019; Han, 2010; Holmgren, 2007; Ibrahim, 2003; Redman, Friman, Garling, & Hartig, 2013; Steg & Gifford, 2005).

In recent years, vehicle automation technology has received increasing interest. The introduction of vehicle automation technology into the current transport system is expected to generate social and economic benefits and has great potential to change future mobility in the coming decades. The potential benefits of fully automated vehicles include reduced traffic accidents caused by human error (Chehri & Mouftah, 2019; Howard & Dai, 2014), decreased traffic congestion (Bansal, Kockelman, & Singh, 2016; Chehri & Mouftah, 2019; Fagnant & Kockelman, 2015; Sohrabi, Khreis, & Lord, 2020), increased effective road capacity (Fagnant & Kockelman, 2015; Litman, 2015) and reduced fuel consumption and lowered CO_2 emissions (Chehri & Mouftah, 2019; Howard & Dai, 2014; Litman, 2015). The implementation of partially or fully automated buses within automated bus systems offers similar benefits. In particular, automated public transport systems can lower bus fares due to reduced driver costs. Moreover, automated buses, even in mixed traffic with non-automated vehicles might also increase the capacity utilization of the existing road network and enhance traffic

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efficiency (Abe, 2019; Piao et al., 2016; Tirachini & Antoniou, 2020; Winter et al., 2019).

The development of automated buses is still in its early stages. Although several automated bus pilot programs have been carried out on the open and mixed public roads, a transition to fully automated buses is only possible if this technology is accepted and used by the public. In past decades, progress has been made in investigating public perception and acceptance of this technology, as well as exploring the factors affecting use preference for automated and conventional buses (Chee, Susilo, & Wong, 2020; Chee, Susilo, Pernestål, & Wong, 2020; Dong, Discenna, & Guerra, 2019; Guo, Susilo, Antoniou, & Pernestål, 2020; Nordhoff et al., 2017; Piao et al., 2016; Salonen, 2018; Wicki, Guidon, Becker, Axhausen, & Bernauer, 2019). Although state-of-the-art research studies are very compelling, in reality, we know very little about what will actually happen when self-driving vehicles are deployed. Many recent studies have questioned whether the assumptions and approaches of such acceptance and preference studies are realistic (e.g., Guo et al., 2020; Soteropoulos, Berger, & Ciari, 2019); this line of critique has highlighted the unpredictability of individual responses and questioned whether the assumptions and approaches in earlier studies are realistic (e.g., Hoogendoorn, van Arem, & Hoogendoorn, 2014; Milakis, van Arem, & van Wee, 2017).

When deployed as a complementary service within conventional bus systems, automation public transport service is expected to meet the diversification of passenger demands and profoundly change current bus service. However, to the best of the authors' knowledge, only a few studies have examined travellers' preferences for automated buses versus conventional buses, in particular after they are being exposed to automated bus service on a daily basis over a long period of time. The most recent reviews on automated vehicle studies (e.g., Becker & Axhausen, 2017; Gkartzonikas & Gkritza, 2019; Narayanan, Chaniotakis, & Antoniou, 2020) have noted that most studies focused on people who have not taken automated buses before, and rarely on people who have experience to take the buses. Whilst the successful implementation of automated bus service depends on people's actual adoption rate of the service (Bansal et al., 2016), it is reasonable to expect that travellers' acceptance and willingness to adopt a technology changes after they are exposed to that technology for a considerable amount of time (Chee, Susilo, Pernestål et al., 2020; Chee, Susilo, Wong et al., 2020; Susilo, Darwish, Pernestål, & Chee, 2021). To address this research gap, in this study we developed a discrete choice model to investigate preferences for new automated buses versus conventional buses after passengers had an opportunity to use them.

The stated choice approach is based on random utility theory and assumes that rational decisionmakers maximise their expected utility and choose the most preferred alternative. At the same time, a growing body of research has demonstrated that every decision process is made within a choice context. Choice criteria for individuals' choices and decisions may vary depending on the decision context (Bertram, Meyerhoff, Rehdanz, & Wüstemann, 2017; Bos, Van der Heijden, Molin, & Timmermans, 2004; Jaeger & Rose, 2008; Kim & Park, 2017; Sharma, Hickman, & Nassir, 2019). In the context of vehicle automation technology, one issue that has yet to be studied—the understanding of which the present work therefore contributes to—is whether the choice of the new bus system is context-dependent. This study seeks to fill this research gap by conducting a context-dependent stated choice experiment, hoping to shed light on how contextual characteristics influence users' choice of automated buses or conventional buses.

The following section briefly reviews the literature related to this study. Section 3 then describes the survey design, data collection process and descriptive statistics. In section 4, we propose a context-dependent mixed logit model to investigate the effects of context on bus choice. Section 5 presents and discusses the model estimation results. The final section summarises our major findings and discusses future research directions.

2. Literature review

2.1. Acceptance and use of automated buses

The development of automated buses offers potential benefits to existing public transportation systems, such as reducing labour costs for operation and maintenance, improving labour productivity in the bus industry, increasing road safety, increasing reliability and punctuality, increasing road capacity and service frequency, and eventually enhancing public transit accessibility (Abe, 2019; Alessandrini et al., 2017; Dong et al., 2019; López-Lambas & Alonso, 2019; Lutin & Kornhauser, 2014; Piao et al., 2016; Strathman, Kimpel, Dueker, Gerhart, & Callas, 2002; Winter et al., 2019). In recent years, a growing body of literature has examined public perception, acceptance and willingness to use this new transport mode (see Chee, Susilo, Pernestål et al., 2020; Chee, Susilo, Wong et al., 2020; Dong et al., 2019; Guo et al., 2020; Herrenkind, Brendel, Nastjuk, Greve, & Kolbe, 2019; Kassens-Noor, Kotval-Karamchandani, & Cai, 2020; Nordhoff, de Winter, Payre, van Arem, & Happee, 2019; Salonen & Haavisto, 2019; Wicki et al., 2019).

Prior studies have shown that factors such as service frequency, ride comfort and perceived safety would influence public acceptance and usage of automated buses. For example, Dong et al. (2019) used a mixed logit model to examine which types of transit users would be willing to use driverless buses. Their results showed that bus frequency, the presence and responsibility of bus operators and concern about riding in driverless buses had significant impacts on users' willingness to ride driverless buses. Wicki et al. (2019) conducted a stated choice experiment examining individuals' willingness to use a self-driving bus service. The results showed that longer travel times and waiting times, higher costs and denser bus occupancy lowered the probability of choosing to use a self-driving shuttle. In an online survey of Stockholm residents in March 2019, Guo et al. (2020) investigated public perceptions of the city's fully operational automated public transportation service, which operates in a mixed-traffic environment on public roads. The authors found that attitudinal factors such as perceptions of safety, driving speed, reliability and convenience have a significant influence on acceptance of the new bus system.

As a new transport mode, automated buses have to complement or compete with other existing transport modes. Although previous studies have assessed public opinions about driverless buses, little is known about people's intention to use automated buses compared to conventional buses. There are a few exceptions; for example, Piao et al. (2016) examined public opinions towards the implementation of automated vehicles in urban areas, finding that about two-thirds of respondents stated they would like to take automated buses if both human-driven and automated buses were available on routes, with only about one-third stating a preference for conventional buses. Alessandrini et al. (2017) investigated users' attitudes towards automated buses and conventional buses in a stated preference study conducted in four European cities, finding that people stated a preference to use automated buses over conventional buses. Using a mixed logit model, Winter et al. (2019) found that self-driving buses were preferred over regular buses for shorter trips, while regular buses were preferred for longer trips. More recently, during trials of automated buses in Stockholm in 2018, Chee, Susilo, Pernestål et al. (2020), Chee, Susilo, Wong et al. (2020) investigated how public perceptions and expectations of the new bus service would influence people's willingness to use the automated buses. The results indicated that people's willingness to use the service was greatly increased when the service frequency of automated buses was comparable to conventional buses. For further extensive reviews of the plausible impacts of automated vehicles, Milakis, Snelder, van Wee, Van Wee, & Homem De Almeida Rodriguez Correia (2016)); McGehee, Brewer, Schwarz, & Smith (2016)) and Innamaa et al. (2017) provided a comprehensive description of plausible societal impacts and policy implementation challenges. Hoogendoorn et al. (2014) discussed the roles of human factors and expected traffic impacts, while Nordhoff et al. (2019) and Chee, Susilo, Wong et al. (2020) looked at automated vehicle technology acceptance for daily travel, and Le-Anh and De Koster (2006) studied the design and control of automated vehicle systems. More recently, Soteropoulos et al. (2019) provided a systematic overview of different modelling approaches that have been used to explain the impacts of automated vehicles on travel behaviour and land-use characteristics.

Although all these studies to date are very compelling, in reality, we know very little about what will actually happen when self-driving vehicles are deployed. Most of the literature on use cases for self-driving vehicles is heavily biased towards transport systems based on autonomous taxis and their performance compared to private car usage (e.g., Chen & Kockelman, 2016; Meyer, Becker, Bösch, & Axhausen, 2017; OECD International Transport Forum, 2015). Based on the great uncertainties mentioned above, we believe it is extremely important for researchers to reflect on observations from real-world deployments of this technology.

Furthermore, although a growing body of literature has investigated individual preferences for automated buses compared to conventional ones, the majority of these studies assume that the decision-making mechanisms do not vary according to different choice contexts. In reality, individual decisions often dependent a great deal on choice contexts. Hence, the effects of context on transport mode decisions should be taken into consideration.

2.2. Contextual influences

Understanding individuals' choice behaviour plays an important role in marketing success. Traditional behavioural research on decision-making assumes that decisionmakers are intentionally rational and choose the alternative with the maximum utility. At the same time, however, a growing body of research suggests that every choice is made within a decision context. Customer choice criteria may vary depending on such decision contexts (Bettman, Luce, & Payne, 1998). Over the years, the behavioural literature on decisions has studied such contextual effects in a wide range of areas, including marketing and retailing, tourism and leisure and recreation (Bertram et al., 2017; Cohen & Babey, 2012; Dhar, Nowlis, & Sherman, 2000; Kim & Park, 2017; Rooderkerk, Van Heerde, & Bijmolt, 2011).

In recent decades, several studies of transport mode choice have explored contextual effects on those choices. Bos et al. (2004) adopted a stated preference approach to investigate the determinants of park and ride (P&R) choices. The study found that drivers with heavy luggage were more likely to use P&R facilities than car drivers without luggage. Moreover, drivers travelling to work were less likely to use P&R than drivers travelling for recreational purposes. Molin and Timmermans (2010) estimated contextual effects on train-riders' choice of transport mode to reach their final destination after exiting the train. They found that context variables such as travel purpose, time of day, weather, travel companion, amount of luggage, distance and route knowledge had significant impacts on riders' choice of post-train transport mode. Arentze, Feng, Timmermans, & Robroeks (2012)) conducted a choice experiment to examine truck drivers' route choices, with distance to destination, truck size, time of day, time since resting and amount of time available as contextual factors. The results indicated that truck size, in particular, had an influence on route choice, with truck drivers preferring to avoid local roads when driving heavier trucks. In addition, highway routes were less attractive when time constraints did not allow for potential delays. In a study which incorporated the contextual effects of activity schedule to predict activity location choice, Arentze, Ettema, & Timmermans (2013)) found that the schedule context had a significant effect on that decision.

More recently, based on data collected from thirty public transport users from Melbourne, Australia, Nguyen-Phuoc, Currie, De Gruyter, & Young (2018)) conducted a qualitative study to examine the factors influencing public transport users' shift to passenger vehicles when public transport ceased. Their results indicated that contextual variables such as travel distance, travel time, travel cost, trip destination, weather and flexibility had impacts on public transport users' change in transport mode. In another study, Charoniti, Kim, Rasouli, & Timmermans (2020)) investigated stated preference for car sharing in the context of travel mode choice, under conditions of uncertain travel times. Using a context-dependent latent class model, the study focused on heterogeneity in the decision-making process due to different activity- and travel-related contexts such as time pressure, activity duration and uncertain travel times. The authors found that activity- and travel-related contexts played important roles in accounting for the heterogeneity of decision rules.

Although contextual effects on decisions have been widely studied in recent decades, to the best of our knowledge, only a few studies have examined the roles of internal and external contexts (e.g., personal time pressure and weather conditions) on relative preferences for automated buses compared to conventional buses. This study aims to investigate contextual effects on choice preferences for automated buses as a means to address this research gap.

3. Survey and data collection

3.1. Experimental design

This study used a context-dependent stated choice experiment to estimate people's choice preferences for automated buses or conventional buses as influenced by various choice contexts. The stated choice experimental approach has advantages when studying the influence of contextual factors on various choice behaviours. Compared to the revealed preference approach, which uses choices observed in real-world situations, the stated choice experiments can demonstrate sufficient context variables, making this approach more appropriate for the aim of this study.

The stated choice experiment used in this study involved two alternatives: automated buses and conventional buses. Table 1 gives an overview of the attributes and their levels of used in the stated choice experiment. Based on the existing literature, driving speed, access and egress time (the time it takes to get from home to the start point, and the time it takes to get from the alighting point to the final destination), bus frequency, availability of seats, and use of an exclusive bus lane or not were chosen as factors influencing transport mode choice (see Abdul Aziz et al., 2018; Cherry & Cervero, 2007; Cullinane & Toy, 2000; Krygsman, Dijst, & Arentze, 2004; Limtanakool, Dijst, & Schwanen, 2006; Hensher & Rose, 2007; Stradling, Carreno, Rye, & Noble, 2007; Su, Schmöcker, & Bell, 2009; Li & Hensher, 2011; Tirachini, Hensher, & Rose, 2013; Vij, Carrel, & Walker, 2013; Tiwari, Jain, & Rao, 2016; Wong, Szeto, Yang, Li, & Wong, 2018; Ton, Duives, Cats, Hoogendoorn-Lanser, & Hoogendoorn, 2019).

Table 1
Attributes and attribute levels of automated and conventional buses.

Attributes	Levels
Travel characteristics	
Speed	15 km/h, 30 km/h
Has exclusive bus lane or not	Has exclusive bus lane, Shared with other vehicles
Seats available or not	Have enough seats, Crowded (2 out of 5 times must stand for whole journey)
Frequency	Every 5 min., 10 min., 15 min., 20 min
Access and egress time	5 min., 10 min., 15 min., 20 min
Contextual variable	
Trip purpose	Work, Recreation or leisure activity
Distance to destination	1 km, 5 km
Weather conditions	Sunny, Rainy or snowy
Time of day	Rush hour, Off-peak hour
Companion	Travel with friends, family members or co-workers, Travel alone

Apart from the traffic characteristic variables, five contextual variables were used to understand how such contextual variables would influence transport mode choice, including trip purpose, distance to destination, time of day, weather conditions and travel companion. Trip purpose was defined according to two categories: subsistence or mandatory activity (work and work-related) and recreation activity (e.g., visiting friends, eating at restaurants, going to the movies, visiting museums, sporting activities, sightseeing, etc.). Work and work-related activity is a compulsory or mandatory activity performed by individuals and is considered to have predetermined or fixed spatial and temporal characteristics (Pendyala, Kitamura, & Reddy, 1998). Within a given time window, it is assumed that service reliability – such as reliability of waiting times and arrival times – has an impact on preference for conventional buses or automated buses. Distance to the destination was also selected as a contextual factor and divided into two categories: a relatively short trip (1 km) versus a relatively long trip (5 km). It was expected that travel distance would influence transport mode choice. Time of day refers to the sense of traffic safety and punctuality (Mehran & Nakamura, 2009) and divided into two categories: travel during rush hour (weekdays from 6:30 to 9:00 and 16:00 to 18:30) and travel during other times (weekdays before 6:30, from 9:00 to 16:00, and after 18:30 plus weekends and holidays). Traffic volume and density on the road is higher during rush hour than during off-peak hours. It was assumed that people would prefer conventional buses over automated buses during rush hour due to a lack of trust in the vehicle automation technology. Travelling with companions was assumed to make the journey more pleasant, challenging and interesting. Travel companion was therefore selected as a contextual factor and assumed to influence mode decisions. Travel companion was divided into two categories: travel with friends, family members or co-workers and travel alone. The final contextual variable is weather conditions, categorised as good weather (a sunny day) or adverse weather (a rainy or snowy day). Adverse weather conditions are known to increase the risk of traffic accidents and could be expected to influence the reliability and convenience of a transport service (Liu, Susilo, & Karlström, 2015, 2016, 2017; Markolf, Hoehne, Fraser, Chester, & Underwood, 2019; Miao, Welch, & Sriraj, 2019; Strong, Ye, & Shi, 2010;).

The choice sets were constructed based on an orthogonal fractional factorial design with 128 choice profiles, which were blocked into sixteen blocks. Choice sets were randomly selected from among the profiles and assigned to respondents. Each participant was given eight choice scenarios. An example of the stated choice experiment is shown in Fig. 1.

3.2. Data

The data were collected in Barkabystaden, a housing development in Stockholm, Sweden (one of the largest in northern Europe), which has been developed to incorporate the most sustainable and modern public transport solutions. Automated buses have been operated in Barkabystaden along a fixed route on a public road since October 2018. Currently, the automated buses travel at 12–15 km/h, a speed that is expected to increase to 18 km/h. The route length is 2.5 km, and a length that was expected to double in 2020. The data used in this study were collected in December 2019. The recruited participants either live or work near the automated bus line. After data cleaning, 568 responses were used in this study.

Table 2 reports the respondents' main socio-demographic characteristics. The number of males and females was almost equally distributed. More than 48 % of respondents were under the age of 35 years, and another 32 % were between 36 and 55 years old. The survey participants were relatively young because the study area is a newly developed area with a relatively young population. 12.8 % of respondents had a gross annual income of less than 300,000 SEK (about 27,500 EUR), 45.6 % of respondents have a mid-level income between 300,000 SEK and 700,000 SEK (between about 27,500 EUR and 64,000 EUR) and 27 % of participants stated that they earned more than 700,000 SEK per year. The remaining 14.6 % declined to provide income information. In terms of educational level, 44.3 % of respondents held a master's or doctoral degree. Nearly two-thirds of respondents stated they own cars.

Table 3 presents participants' awareness and usage of the automated buses operated in Barkabystaden: 93.4 % stated they had seen the automated buses running, 6.3 % had heard of the automated buses but had not seen one, and only 0.3 % respondents reported that they were unaware of the existence of automated buses in Barkabystaden. Although the participants were somewhat familiar with this new mode of public transport, only about one-third of respondents reported having taken the bus previously.

4. Model formulation

This study employed a multinomial logit model and a mixed logit model to model the choice of conventional buses versus automated buses. Each participant assigns a utility to each choice and selects the alternative with the highest value. Based on random utility theory, we assumed that individual n in choice situation t would choose alternative i, denoted as U_{nit}. Following random utility theory, utility is separated into two components: a deterministic utility, V_{nit}, and a random utility, ε_{nit}.

$$U_{nit} = V_{nit} + \varepsilon_{nit} \, , \tag{1}$$

Individual choice preferences are driven by the contexts provided by choice sets. To incorporate choice context into a discrete choice model,

Table 2
Descriptive statistics for the sample.

Characteristics	Levels	Percentage (%)
Gender	Male	50.1
	Female	49.9
Age	18–35	48.2
	36–55	31.7
	> 55 years and older	20.1
Annual income (SEK)	Less than 300	12.8
	300–499	24.1
	500–699	21.5
	700–899	14.1
	More than 900	12.9
	Do not wish to answer	14.6
Educational level	Lower or upper secondary school	37.2
	Bachelor's degree	18.5
	Graduate degree	44.3
Car ownership	Own a car	71.8
	Do not own a car	28.2

Attributes	**Autonomous bus**	**Conventional bus**
Speed	30 km/h	30 km/h
Crowding	Enough seats	2 out of 5 times you have to stand for the whole journey
Bus frequency	Every 15 mins	Every 5 mins
Walking time to/from station	15 mins	5 mins
Has exclusive bus lane	Shared with other modes	Shared with other modes
Your choice (please tick)		

Fig. 1. Sample choice experiment question.

Table 3
Awareness and usage of automated buses.

Variable	Classification	Percentage (%)
Are you aware that there are automated buses (ABs) in Barkabystaden?	Yes, and I have seen it myself.	93.4
	Yes, but I have not seen it myself.	6.3
	No, I am not.	0.3
Have you ridden in an AB before?	Yes	32.8
	No	67.2

the deterministic utility is divided into a part-worth utility V^{p}_{nit} and a context-dependent utility V^{c}_{nit}. Then, the utility expression becomes

$$U_{nit} = V^{p}_{nit} + V^{c}_{nit} + \varepsilon_{nit} \ , \tag{2}$$

Both the part-worth utility and the context-dependent utility are assumed to be a linear form of observed attributes. To further explore how traffic characteristics impact bus choices in different choice contexts, interaction effects were included in the choice model. Hence, the utility function is expressed as

$$U_{nit} = \alpha_i + \boldsymbol{\beta}_n \boldsymbol{X}_{nit} + \varepsilon_{nit} \ , \tag{3}$$

where $\boldsymbol{X}_{nit}$ is the vector of characteristics of explanatory variables (i.e., traffic characteristics such as driving speed, bus frequency, access and egress time, crowding conditions, and having an exclusive bus lane or not), context variables (i.e., purpose of trip, distance to destination, weather conditions, time of day, and travel companion) and the interaction between traffic characteristics and context variables. $\boldsymbol{\beta}_n$ is the vector of coefficients of $\boldsymbol{X}_{nit}$, and α_i is the alternative-specific constant. The term ε_{nit} is an identically and independently Gumbel distributed error term. To capture heterogeneity across individuals, we selected several traffic characteristic explanatory variables as random parameters. The density function for β is denoted as $f\ (\beta\theta)$, where θ are parameters of the distribution. The choice probability is given by

$$P_{nit} = \prod_{t=1}^{T} \int \frac{\exp(\boldsymbol{\beta}_n \boldsymbol{X}_{nit})}{\sum_{i=1}^{I} \exp(\boldsymbol{\beta}_n \boldsymbol{X}_{nit})} f(\beta\theta) d\beta), \tag{4}$$

In our experiment, each respondent was requested to provide a response to a set of eight profiles. Thus, this model considers panel effects. Thus, the choice probability becomes,

$$P_{nit} = \int \prod_{t=1}^{T} \prod_{i=1}^{I} \frac{\exp(\boldsymbol{\beta}_n \boldsymbol{X}_{nit})}{\sum_{i=1}^{I} \exp(\boldsymbol{\beta}_n \boldsymbol{X}_{nit})} f(\beta\theta) d\beta). \tag{5}$$

5. Analysis and results

Before estimating the model, all attributes were effect coded using the last category as the reference category. For variables with two levels, the first level was coded as 1 and the second level as –1. For variables with four categories, the first level was coded as [1, 0, 0], the second level as [0, 1, 0], the third level as [0, 0, 1], and the last level as [-1, -1, -1].

The study specified three choice models: a multinomial logit model (MNL) and two mixed logit models. Specifically, model 1 presents the basic MNL model. Furthermore, transport mode choice may differ due to respondents' personalities and lifestyles. The study used mixed logit models to capture such heterogeneity, as these models can account for unobserved heterogeneity among individuals. We tested a variety of random variables before deciding on the final model. Normal and lognormal distributions are the most common in the literature. Other distributions, such as uniform and triangular, can also be used to define the density function (Hensher & Greene, 2001). Making different distributional assumptions with regards to the selected bus services attributes, we estimated different forms of distributions. Normal, uniform and triangular distributions led to similar improvements in model fit compared to the performance of the MNL model. The biggest improvement in model fit was obtained in the model using the normal distribution, while the lowest log-likelihood for the mixed logit was found using lognormal distribution. Thus, normal distribution was chosen to estimate the heterogeneity of the alternative-specific constant and selected bus services attributes. Only random variables with significant heterogeneity remained in the final model in model 2. Lastly, transport mode choice may depend on choice contexts. Hence, context effects were taken into consideration in model 3. The context-dependent mixed logit model considered not only the choice and context variables but also interactions among them. Only variable interactions that made a significant contribution in the preliminary analysis were included in the final model. The reported estimates are based on 500 Halton draws.

The results of the MNL, mixed logit model and context-dependent mixed logit model were consistent. Table 4 presents the results from all three models. The model fits for the mixed logit models were acceptable. The use of mixed logit models achieves an improvement in model fit (adjusted rho squared of 0.232) relative to the basic MNL model (adjusted rho squared of 0.168). By including both context variables and interactions among context variables and choice variables, model 3 performs better than the other two models. Therefore, it is the results of the context-dependent mixed logit model that will be discussed in the next section.

The marginal utilities of the traffic characteristic variables are similar between the automated bus and conventional bus choices. Table 4 shows that access and egress time has the most significant impact on the choice of both automated and conventional bus. Access and egress time/distance is defined as walking time/distance from the departure point to the bus terminal and from the alighting point to the destination. As expected, the results show that users are less likely to choose a transport mode when access and egress exceed an absolute maximum threshold (15 min, or approximately 1200 m to/from the bus terminal). Access and egress times are an important element influencing the availability and convenience of public transport service and are sensitive to urban development characteristics such as land use density and diversity. Understanding how the location and density of public transport stops influence people's willingness to use new public transport systems is critical in developing policy guidance for land use and transport planning. In addition, taking access/ egress times as a random parameter, the influence of station accessibility on bus riders' choice preference is more widely distributed for the automated bus option than it is for the conventional bus option.

Followed by access and egress time, bus frequency and driving speed are the second- and third-most-important attributes influencing the choice between automated buses and conventional buses. The findings suggest that if bus frequency decreases and falls within the range of three to four buses per hour, people are unwilling to use either automated buses or conventional buses. Moreover, these two attributes are modelled as random parameters. The results show that the standard deviations for these two parameters are significant.

Implementing exclusive bus lanes and having sufficient seats available for passengers led to a higher probability of choosing to use public transport. The results specifically indicate that implementing exclusive bus lanes plays an essential role in improving service performance and efficiency. The standard deviation for the implementation of exclusive bus lanes is statistically significant. Compared with conventional buses, the presence of separated bus lanes was shown have lower mean value and higher standard deviation associated with automated buses, which suggests that providing exclusive bus lanes on urban roads enhances the service level of buses and has a larger effect on attracting people to use conventional buses than on attracting people to use automated buses. Additionally, the proportion of available seats has a significant impact on riders' willingness to use both conventional buses and driverless

Table 4
Estimated results.

Alternatives	Attributes	Level	Model 1 Coef.		t value	p value	Model 2 Coef.		t value	p value	Model 3 Coef.		t value	p value
Random variables														
Automated bus	Speed	Low	−.283	***	−8.35	.000	−.473	***	−8.35	.000	−.483	***	−8.20	.000
		High	.283				.473				.483			
	Bus lane	Bus lane	.090	***	2.61	.009	.163	***	2.91	.004	.163	***	2.79	.000
		Shared	−.090				−.163				−.163			
	Frequency	Low	−.430	***	−6.95	.000	−.707	***	−7.26	.000	−1.097	***	−2.89	.005
		Medium 1	−.263	***	−4.44	.000	−.373	***	−4.38	.000	−1.086	***	−2.94	.003
		Medium 2	.113	*	1.95	.052	.185	**	2.18	.029	−.503		−1.32	.187
		High	.580		9.38		. 895				1.680			
	Access and egress time	Short	.811	***	13.23	.000	1.323	***	11.62	.000	1.287	***	11.07	.000
		Medium 1	.376	***	6.41	.000	.618	***	6.81	.000	.591	***	6.42	.000
		Medium 2	−.469	***	−7.92	.000	−.713	***	−8.20	.000	−.610	***	−6.74	.000
		Long	−.781				−1.228				−1.268			
	Constant		.043		1.27	.206	.060		.72	.472	.061		.71	.478
Conventional bus	Speed	Low	−.297	***	−8.63	.000	−.472	***	−8.36	.000	−.496	***	−8.38	.000
		High	.297				.472				.496			
	Bus lane	Bus lane	.291	***	8.41	.000	.478	***	8.69	.000	.419	***	7.52	.000
		Shared	−.291				−.478				−.419			
	Access and egress time	Short	.768	***	12.91	.000	1.243	***	11.48	.000	1.299	***	11.37	.000
		Medium 1	.200	***	3.40	.000	.328	***	3.82	.000	.391	***	4.38	.000
		Medium 2	−.320	***	−5.54	.000	−.500	***	−5.77	.000	−.539	***	−6.02	.000
		Long	−.648				−1.071				−1.151			
Non-random variables														
Automated bus	Seat	Have seat	.243	***	7.09	.000	.426	***	8.11	.000	.425		7.87	.000
		Crowded	−.243				−.426				−.425			
Conventional bus	Frequency	Low	−.411	***	−7.26	.000	−.724	***	−7.32	.000	−.726	***	−7.65	.000
		Medium 1	−.191	***	−3.12	.008	−.275	***	−3.11	.002	−.302	***	−3.25	.001
		Medium 2	.154	***	2.64	002	.259	***	3.08	.002	.283	***	3.20	.001
		High	.448				.740				.745			
	Seat	Have seat	.209	***	6.15	.000	.330	***	6.61	.000	.391	***	7.46	.000
		Crowed	−.209				−.330				−.391			
Social-demographic variables														
	Gender	Male	.168	***	7.06	.000	.246	***	7.12	.000	.255	***	7.26	.001
		Female	−.168				−.246				−.255			
Context variables														
	Purpose	Work									−.169	***	−3.27	.001
		Recreation									.169			
	Distance	Short									.204	***	3.80	.000
		Long									−.204			
	Weather	Sunny									.108	**	2.09	.037
		Raining or snowy									−.108			
	Time-of-day	Rush hour									−.041		−.86	.391
		Off-peak time									.041			
	Companion	With friends or family members									.272	***	5.02	.000
		Alone									−.272			
Interaction effects														
Automated bus	Speed * Weather										.108	**	1.98	.055
	Access and egress time (1) * Distance										.158	*	1.65	.098
	Access and egress time (2) * Distance										.137		1.49	.136
	Access and egress time (3) * Distance										−.097		−1.05	.294
Conventional bus	Speed* Weather										.082		1.58	.114
	Access time and egress (3) * Distance										1.810	***	3.67	.000
	Access time and egress (3) * Distance										−1.871	***	−3.92	.000
	Access time and egress (3) * Distance										−2.014	***	−4.12	.000
Standard deviation of random parameters														
Automated bus	Speed						.275	*	1.70	.089	.287		1.50	.134
	Bus lane						.505	***	4.54	.000	.518	***	4.48	.000
	Frequency (1)						.617	***	3.38	.001	.578	***	2.87	.004
	Frequency (2)						.082		.43	.169	.443	**	2.13	.033
	Frequency (3)						.318		1.38	.668	.012		.05	.957
	Access and egress time (1)						.963	***	6.95	.000	.934	***	6.83	.000
	Access and egress time (2)						.298		1.09	.274	.399	*	1.72	.086
	Access and egress time (3)						.039		.13	.899	.138		.58	.561

(continued on next page)

Table 4 (*continued*)

			Model 1				Model 2				Model 3			
Alternatives	Attributes	Level	Coef.		t value	p value	Coef.		t value	p value	Coef.		t value	p value
Conventional bus	Constant_ Automated Bus						1.644	***	13.91	.000	1.703	***	13.89	.000
	Speed						.492	***	4.77	.000	.503	***	4.60	.000
	Bus lane						.341	***	2.64	.008	.299	**	2.13	.033
	Access and egress time (1)						.676	***	3.88	.000	.679	***	3.76	.000
	Access and egress time (2)						.034		.16	.871	.011		.04	.965
	Access and egress time (3)						.075		.32	.748	.077		.31	.760
Model performance measurements														
	Sample size										568			
	LL(β)		−2602.012				−2402.305				−2353.802			
	LL(0)		−3149.661				−3149.661				−3149.661			
	ρ^2		.174				.237				.253			
	ρ^2 adjusted		.168				.232				.245			

buses. This suggests that providing sufficient seats for passengers can improve bus comfort and thus attract more people to use public transport in general.

This study also looked at socio-demographic variables. Some empirical studies have found that age, income and gender play significant roles in acceptance of vehicle automation technology (Alessandrini, Alfonsi, Site, & Stam, 2014; Bansal et al., 2016). However, we found that only gender had a significant effect on passengers' transport mode choice preference; therefore, we removed age and income from the final analysis. Empirical evidence shows that women have less-favourable attitudes towards automated vehicles than men (Haboucha, Ishaq, & Shiftan, 2017; Kyriakidis, Happee, & de Winter, 2015; Piao et al., 2016; Yap, Correia, & van Arem, 2016). In line with previous studies, our results reveal that men are more inclined to choose automated buses than women. Lastly, with respect to alternative-specific constants, although no significant effect was detected, the constant for automated buses was found to be slightly larger than for conventional buses. Additionally, our results show that the standard deviation for the alternative-specific constant is highly significant, which suggests substantial heterogeneity in people's choice preferences for such a new public transport mode.

5.1. Context effects on bus choice

Choice behaviour is highly adaptive and context dependent. The choice model takes into consideration not only choice variables but also context variables. As shown in model 3, travel companion appears to be the most important context variable. The results suggest that passengers travelling with companions are more likely to use automated buses over conventional buses. One possible explanation is that users travelling alone feel more comfortable with conventional buses compared to automated buses.

Travel distance plays an important role in influencing the choice of public transport mode. The results indicate that short-distance travellers prefer automated buses, while long-distance travellers prefer conventional buses. We further investigate the interaction between access and egress time and travel distance. When travel distance is short, increased access and egress time is associated with negative utility, which suggests that passengers avoid long access and egress times when the travel distance is relatively short.

Travellers pursuing different activities have different degrees of flexibility in terms of space and time and also value travel time differently (Wang, 2015). In our results for travel purpose, people travelling for work stated a preference for conventional buses over automated buses. This might be explained by the fact that commuting activities are more time- and space sensitive, and commuters have a greater need for reliability. The majority of respondents believed that the reliability of the automated bus service, as an emerging and innovative transport mode, would be the same or worse than the reliability of conventional bus service (Guo et al., 2020). Thus, due to the relatively lower perceptions of automated bus reliability, passengers travelling for work purposes are more likely to state a preference for conventional buses than automated buses.

Lastly, our results show that the choice of public transport mode depends on weather conditions. In rainy and snowy weather, travellers were less likely to prefer automated buses than they were conventional buses. This could be explained by perceived certainty and reliability – one of most concerning issues for automated buses, especially during poor weather conditions. Additionally, we found a significant interaction effect between driving speed and weather conditions. When people were presented with a high-speed bus scenario, they assigned negative utility to poor weather conditions. This may mean that as vehicle speed increases, travellers are less inclined to choose public transport, especially during adverse weather conditions.

6. Conclusions and discussions

Public transport provides various benefits to modern transport systems. As a sustainable transport mode, bus systems have an irreplaceable role in alleviating the pressure of private transport and improving citizens' quality of life. By introducing vehicle automation technology into existing public transport systems, automated buses can replace or complement the conventional buses. Using a context-dependent mixed logit model, we explored the heterogeneity of the decision-making process in light of different activity and travel contexts, such as time pressure, activity duration and uncertain travel times. This knowledge is important if we are to understand automated public transport systems' real potential to address the diversification of passenger demand and to profoundly change current bus service, keeping user needs and interests as the centre.

This paper provides important insights into the mechanisms behind users' choice to use automated buses. First, the results indicate that the influence of choice attributes does not vary much when choosing to use automated buses or choosing to use conventional buses. Additionally, individuals' choices are more elastic towards differences in automated bus service levels compared to choices under differing conventional bus service levels; this indicates that people are more sensitive to changes in service levels for vehicle automation systems and will increase their use of automated buses over conventional ones. Access and egress time/distance determines the availability and convenience of public transport systems, and this factor was shown to be the most important attribute influencing a choice preference for both automated and conventional buses. Adjusting and optimising the location and density of bus stops could improve the quality of public transport systems and increase market share for both automated and conventional bus modes. Second, to promote a new transport mode that is both competitive and market-oriented, it is necessary to identify users' travel needs. This study examines the effects of context variables—such as trip purpose, distance to destination, time of day, weather conditions, and travel companion—on the choice to use automated buses and conventional buses. The results indicate that people are more likely to use automated buses for short trips and leisure purposes. Moreover, automated bus users are more inclined to travel in good weather and less inclined to use this transport mode in adverse weather, and they have a stronger preference to use this mode when travelling with companions than they do when travelling alone.

This study also provides directions for future research. First, the study shows that transport mode choice decisions are context dependent. Safety and security concerns and pro-technology attitudes are issues that will shape the acceptance and usage of vehicle automation technology. Thus, further investigations should examine motivational and attitudinal influences on intent-to-use for automated buses. Second, this study examines travellers' preferences for automated buses compared to conventional buses. As vehicle automation technology matures, automated bus service quality will be improved. As a complementary service to conventional buses, it would be interesting to know how this new bus modes will compete with other transport modes, such as private cars, car sharing, e-scooters, walking, cycling. As an extension to the current study, city planners and bus companies should seek to understand travellers' demands and to create efficient marketing strategies that reflect these demands. Third, a large body of literature reports the impacts of land use on travel behaviour and vice versa (Boarnet & Crane, 2001; Boarnet, 2011; Cervero & Kockelman, 1997; van Acker, Witlox, & van Wee, 2007; Park, Ewing, Scheer, & Tian, 2018). Introducing vehicle automation technology into the market is expected to influence land-use patterns. Thus, including land-use effects in the choice decision-making process could be a natural extension of this study.

Declaration of Competing Interest

The authors declare that they have no conflict of interest to this work.

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References

Abbass, R., Kumar, P., & EI-Gendy, A. (2020). Car users exposure to particulate matter and gaseous air pollutants in Megacity Cairo. *Sustainable Cities and Society, 56*, Article 102090.

Abdul Aziz, H. M., Nagle, N., Morton, A., Hillard, M., White, D., & Stewart, R. (2018). Exploring the impact of walk-bike infrastructure, safety perception, and built-environment on active transportation mode choice: A random parameter model using New York City Commuter Data. *Transportation, Vol, 45*, 1207–1229.

Abe, R. (2019). Introducing autonomous buses and taxis: Quantifying the potential benefits in japanese transportation systems. *Transportation Research Part A, 126*, 94–113.

Alessandrini, A., Alfonsi, R., Site, P. D., & Stam, D. (2014). Users' preferences towards automated road public transport: Results from european surveys. *Transportation Research Procedia, 3*, 139–144.

Alessandrini, A., Delle Site, P., Stam, D., Gatta, V., Marcucci, E., & Zhang, Q. (2017). Using repeated-measurement stated preference data to investigate users' attitudes towards automated buses within major facilities. *Advances in Intelligent Systems and Computing, 539*, 189–199.

Arentze, T., Ettema, D., & Timmermans, H. T. P. (2013). Location choice in the context of multi-day activity-travel patterns: Model development and empirical results. *Transportmetrica A Transport Science, 9*, 107–123.

Arentze, T., Feng, T., Timmermans, H. T. P., & Robroeks, J. (2012). Context-dependent influence of road attributes and pricing policies on route choice behavior of truck drivers: Results of a conjoint choice experiment. *Transportation, 39*, 1173–1188.

Bansal, P., Kockelman, K., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: An austin perspective. *Transportation Research Part C, Emerging Technologies, 67*, 1–14.

Becker, F., & Axhausen, K. W. (2017). Predicting the use of automated vehicles. *17th Swiss Transport Research Conference*.

Bertram, C., Meyerhoff, J., Rehdanz, K., & Wüstemann, H. (2017). Differences in the recreational value of urban parks between weekdays and weekends: A discrete choice analysis. *Landscape and Urban Planning, 159*, 5–14.

Bettman, J., Luce, M., & Payne, J. (1998). Constructive consumer choice processes. *The Journal of Consumer Research, 25*, 187–217.

Boarnet, M. (2011). A broader context for land use and travel behavior, and a research agenda. *Journal of the American Planning Association, 77*, 197–213.

Boarnet, M., & Crane, R. (2001). The influence of land use on travel behavior: Specification and estimation strategies. *Transportation Research Part A, 35*, 823–845.

Bos, I., Van der Heijden, R., Molin, E., & Timmermans, H. J. P. (2004). The choice of park and ride facilities: An analysis using a context-dependent hierarchical choice experiment. *Environment & Planning A, 36*, 1673–1686.

Cervero, R., & Kockelman, K. M. (1997). Travel demand and the three Ds.: Density, diversity and design. *Transportation Research Part D, Transport and Environment, 2*, 199–219.

Chapman, L. (2007). Transport and climate change: A review. *Journal of Transport Geography, 15*, 354–367.

Charoniti, E., Kim, J., Rasouli, S., & Timmermans, H. J. P. (2020). Intrapersonal heterogeneity in car-sharing decision-making processes by activity-travel contexts: A context-dependent latent class random utility-random regret model. *International Journal of Sustainable Transportation*.

Chee, P., Susilo, Y., Pernestål, A., & Wong, Y. (2020). Which factors affect willingness-to-pay for automated vehicle services? Evidence from public road deployment in Stockholm. *Sweden. European Transport Research Review*, 12.

Chee, P., Susilo, Y., & Wong, Y. (2020). Determinants of intention-to-use first-/last-mile automated bus service. *Transportation Research Part A, 139*, 350–375.

Chehri, A., & Mouftah, H. (2019). Autonomous vehicles in the sustainable cities, the beginning of a green adventure. *Sustainable Cities and Society, 51*, Article 101751.

Chen, T. Y., & Jou, R. (2019). Using HLM to investigate the relationship between traffic accident risk of private vehicles and public transportation. *Transportation Research Part A, 119*, 148–161.

Chen, T. D., & Kockelman, K. M. (2016). Management of a shared autonomous electric vehicle fleet: Implications of pricing schemes. *Transportation Research Record: Journal of the Transportation Research Board, 2572*, 37–46.

Cherry, C., & Cervero, R. (2007). Use characteristics and mode choice behavior of electric bike users in China. *Transport Policy, 14*, 247–257.

Cohen, D. A., & Babey, S. H. (2012). Contextual influences on eating behaviours: Heuristic processing and dietary choices. *Obesity Reviews, 13*, 766–779.

Cullinane, K., & Toy, N. (2000). Identifying influential attributes in freight route/mode choice decisions: A content analysis. *Transportation Research Part E, 36*, 41–53.

Dhar, R., Nowlis, S., & Sherman, S. (2000). Trying hard or hardly trying: An analysis of context effects in choice. *Journal of Consumer Psychology, 9*, 189–200.

Dong, X., Discenna, M., & Guerra, E. (2019). Transit user perceptions of driverless buses. *Transportation, 46*, 35–50.

Fagnant, D., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. *Transportation Research Part A, 77*, 167–181.

Gärling, T., & Schuitema, G. (2007). Travel demand management targeting reduced private Car use: Effectiveness, public acceptability and political feasibility. *The Journal of Social Issues, 63*, 139–153.

Gkartzonikas, C., & Gkritza, K. (2019). What have we learned? A review of stated preference and choice studies on autonomous vehicles. *Transportation Research Part C, Emerging Technologies, 98*, 323–337.

Greene, D. L., & Wegener, M. (1997). Sustainable transport. *Journal of Transport Geography, 5*, 177–190.

Guo, J., Susilo, Y., Antoniou, C., & Pernestål, A. (2020). Influence of individual perceptions on the decision to adopt automated bus services. *Sustainability, 12*, 6484.

Haboucha, C. J., Ishaq, R., & Shiftan, Y. (2017). User preferences regarding autonomous vehicles. *Transportation Research Part C, Emerging Technologies, 78*, 37–49.

Han, S. S. (2010). Managing motorization in sustainable transport planning: The Singapore experience. *Journal of Transport Geography, 18*, 314–321.

Hensher, D., & Greene, W. (2001). *The mixed logit model: The state of practice and warnings for the unwary. Working paper (Institute of transport studies)*, 02-01, ISSN 1440-3501.

Hensher, D., & Rose, J. (2007). Development of commuter and non-commuter mode choice models for the assessment of new public transport infrastructure projects: A case study. *Transportation Research Part A, 41*, 428–443.

Herrenkind, B., Brendel, A., Nastjuk, I., Greve, M., & Kolbe, L. (2019). Investigating end-user acceptance of autonomous electric buses to accelerate diffusion. *Transportation Research Part D, Transport and Environment, 74*, 255–276.

Holmgren, J. (2007). Meta-analysis of public transport demand. *Transportation Research Part A, 41*, 1021–1035.

Hoogendoorn, R., van Arem, B., & Hoogendoorn, S. (2014). Automated driving, traffic flow efficiency, and human factors: Literature review. *The Transportation Research Record: Journal of Transportation Research Board, 2422*, 113–120.

Howard, D., & Dai, D. (2014). Public perceptions of self-driving cars: The case of Berkeley, California. *93rd Annual Meeting of the Transportation Research Board*.

Ibrahim, M. F. (2003). Improvements and integration of a public transport system: The case of Singapore. *Cities, 20*, 205–216.

Innamaa, S., Smith, S., Barnard, Y., Rainville, L., Rakoff, H., Horiguchi, R., et al. (2017). *Trilateral_IA_Framework*. https://connectedautomateddriving.eu/wp-content/uploads/2018/03/Trilateral_IA_Framework_April2018.pdf.

Jaeger, S., & Rose, J. (2008). Stated choice experimentation, contextual influences and food choice: A case study. *Food Quality and Preference, 19*, 539–564.

Jou, R. C., & Chen, T. Y. (2014). Factors affecting public transportation, Car, and motorcycle usage. *Transportation Research Part A, 61*, 186–198.

Kassens-Noor, N., Kotval-Karamchandani, Z., & Cai, M. (2020). Willingness to ride and perceptions of autonomous public transit. *Transportation Research Part A, 138*, 92–104.

Kim, D., & Park, B. (2017). The moderating role of context in the effects of choice attributes on hotel choice: A discrete choice experiment. *Tourism Management, 63*, 439–451.

Krygsman, S., Dijst, M., & Arentze, T. (2004). Multimodal public transport: An analysis of travel time elements and the interconnectivity ratio. *Transport Policy, 11*, 265–275.

Kyriakidis, M., Happee, R., & de Winter, J. C. F. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F, Traffic Psychology and Behaviour, 32*, 127–140.

Le-Anh, T., & De Koster, M. B. M. (2006). A review of design and control of automated guided vehicle systems. *European Journal of Operational Research, 171*, 1–23.

Li, Z., & Hensher, D. (2011). Crowding and public transport: A review of willingness to pay evidence and its relevance in project appraisal. *Transport Policy, 18*, 880–887.

Limtanakool, N., Dijst, M., & Schwanen, T. (2006). The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium and longer-distance trips. *Journal of Transport Geography, 14*, 327–341.

Litman, T. (2015). Autonomous vehicle implementation predictions: Implications for transport planning. *94th Annual Meeting of the Transportation Research Board*.

Liu, C., Susilo, Y. O., & Karlström, A. (2015). Investigating the impacts of weather variability on individual's daily activity-travel patterns: A comparison between commuters and non-commuters in Sweden. *Transportation Research part A, 82*, 47–64.

Liu, C., Susilo, Y. O., & Karlström, A. (2016). Measuring the impacts of weather variability on individuals' trip chain complexity: A focus on spatial heterogeneity. *Transportation, 43*, 843–867.

Liu, C., Susilo, Y. O., & Karlström, A. (2017). Weather variability and travel behaviour - what do we know and what do we not know. *Transport Reviews, 37*, 715–741.

López-Lambas, M. E., & Alonso, A. (2019). The driverless bus: An analysis of public perceptions and acceptability. *Sustainability, 11*, 4986.

Lutin, J. M., & Kornhauser, A. L. (2014). Application of autonomous driving technology to transit-functional capabilities for safety and capacity. *Transportation Research Record*, 14-0207.

Markolf, S., Hoehne, C., Fraser, A., Chester, M., & Underwood, B. S. (2019). Transportation resilience to climate change and extreme weather events – Beyond risk and robustness. *Transport Policy, 74*, 174–186.

McGehee, D. V., Brewer, M., Schwarz, C., & Smith, B. W. (2016). *Review of automated vehicle technology: Policy and implementation implications*. Iowa Dept of Transportation, University of Iowa. IADOT_RB28_015_UIPPC_McGehee_Review_Automated_Vehicle_Technology_Policy_Implementation_Implications_V1_2016.pdf.

Mehran, B., & Nakamura, H. (2009). Considering travel time reliability and safety for evaluation of congestion relief schemes on expressway segments. *IATSS Research, 33*, 55–70.

Meyer, J., Becker, H., Bösch, P., & Axhausen, K. W. (2017). Autonomous Vehicles: The Next Jump in Accessibilities? *Research in Transportation Economics, 62*, 80–91.

Miao, Q., Welch, E., & Sriraj, P. (2019). Extreme weather, public transport ridership and moderating effect of bus stop shelters. *Journal of Transport Geography, 74*, 125–133.

Milakis, D., Snelder, M., van Wee, B., Van Wee, G. P., & Homem De Almeida Rodriguez Correia, G. (2016). Scenarios about development and implications of automated vehicles in the Netherlands. *Transportation Research Board 95th Annual Meeting*.

Milakis, D., van Arem, B., & van Wee, B. (2017). Policy and society related implications of automated driving: A review of literature and directions for future research. *Journal of Intelligent Transportation Systems Technology Planning and Operations, 21*, 324–348.

Millard-Ball, A., & Schipper, L. (2011). Are we reaching peak travel? Trends in passenger transport in eight industrialized countries. *Transport Reviews, 31*(3), 357–378.

Molin, E., & Timmermans, H. T. P. (2010). Context dependent stated choice experiments: The case of train egress mode choice. *Journal of Choice Modelling, 3*, 39–56.

Narayanan, S., Chaniotakis, E., & Antoniou, C. (2020). Shared autonomous vehicle services: A comprehensive review. *Transportation Research Part C, Emerging Technologies, 111*, 255–293.

Nguyen-Phuoc, D., Currie, G., De Gruyter, C., & Young, W. (2018). How do public transport users adjust their travel behavior if public transport ceases? A qualitative study. *Transportation Research Part F, Traffic Psychology and Behaviour, 54*, 1–14.

Nordhoff, S., de Winter, J., Payre, W., van Arem, B., & Happee, R. (2019). What impressions do users have after a ride in an automated shuttle? An interview study. *Transportation Research Part F, Traffic Psychology and Behaviour, 63*, 252–269.

Nordhoff, S., van Arem, B., Merat, N., Madigan, R., Ruhrort, L., Knie, A., et al. (2017). User acceptance of driverless shuttles running in an Open and mixed traffic environment. *12th ITS European Congress*.

OECD International Transport Forum. (2015). *Urban mobility system upgrade - how shared self-driving cars could change city traffic*. https://www.itfoecd.org/sites/default/files/docs/15cpb_self-drivingcars.pdf.

Park, K., Ewing, R., Scheer, B., & Tian, G. (2018). The impacts of built environment characteristics of rail station areas on household travel behavior. *Cities, 74*, 277–283.

Pendyala, R. M., Kitamura, R., & Reddy, D. V. G. P. (1998). Application of an activity-based travel-demand model incorporating a rule-based algorithm. *Environment and Planning B, 25*, 753–772.

Piao, J., McDonald, M., Hounsell, N., Graindorge, M., Graindorge, T., & Malhene, N. (2016). Public views towards implementation of automated vehicles in urban areas. *Transportation Research Procedia, 14*, 2168–2177.

Power, A. (2012). Social inequality, disadvantaged neighbourhoods and transport deprivation: An assessment of the historical influence of housing policies. *Journal of Transport Geography, 21*, 39–48.

Redman, L., Friman, M., Garling, T., & Hartig, T. (2013). Quality attributes of public transport that attract Car users: A research review. *Transport Policy, 25*, 119–127.

Rooderkerk, R., Van Heerde, H., & Bijmolt, T. (2011). Incorporating context effects into a choice model. *Journal of Marketing Research XLVIII*, 767–780.

Salonen, A. (2018). Passenger's subjective traffic safety, in-vehicle security and emergency management in the driverless shuttle bus in Finland. *Transport Policy, 61*, 106–110.

Salonen, A., & Haavisto, N. (2019). Towards autonomous transportation. passengers' experiences, perceptions and feelings in a driverless shuttle bus in Finland. *Sustainability, 11*, 588.

Sharma, B., Hickman, M., & Nassir, N. (2019). Park-and-ride lot choice model using random utility maximization and random regret minimization. *Transportation, 46*, 217–232.

Sohrabi, S., Khreis, H., & Lord, D. (2020). Impacts of autonomous vehicles on public health: A conceptual model and policy recommendations. *Sustainable Cities and Society*. https://doi.org/10.1016/j.scs.2020.102457, 102457.

Soteropoulos, A., Berger, M., & Ciari, F. (2019). Impacts of automated vehicles on travel behaviour and land use: An international review of modelling studies. *Transport Reviews, 39*, 29–49.

Steg, L., & Gifford, R. (2005). Sustainable transportation and quality of life. *Journal of Transport Geography, 13*, 59–69.

Stradling, S., Carreno, M., Rye, T., & Noble, A. (2007). Passenger perceptions and the ideal urban bus journey experience. *Transport Policy, 14*, 283–292.

Strathman, J., Kimpel, T., Dueker, K., Gerhart, R., & Callas, S. (2002). Evaluation of transit operations: Data applications of tri-met's automated bus dispatching system. *Transportation, 29*, 321–345.

Strong, C., Ye, Z., & Shi, X. (2010). Safety effects of winter weather: The state of knowledge and remaining challenges. *Transport Review, 30*, 677–699.

Su, F., Schmöcker, J., & Bell, M. (2009). Mode choice of older people before and after shopping. *Journal of Transport and Land Use, 2*, 29–46.

Susilo, Y. O., Darwish, R., Pernestål, A., & Chee, P. N. (2021). *Lessons from the deployment of the world first automated bus service on a mixed public road in Stockholm. Forthcoming in transport in human scale cities, ed: Toivonen, Mladenovic, Willberg, karst geurs, edward elgar*.

Tirachini, A., & Antoniou, C. (2020). The economics of automated public transport: Effects on operator cost, travel time, fare and subsidy. *Research in Transportation Economics, 21*, Article 100151.

Tirachini, A., Hensher, D., & Rose, J. (2013). Crowding in public transport systems: Effects on users, operation and implications for the estimation of demand. *Transportation Research Part A, 53*, 36–52.

Tiwari, G., Jain, D., & Rao, K. (2016). Impact of public transport and non-motorized transport infrastructure on travel mode shares, energy, emissions and safety: Case of indian cities. *Transportation Research Part D, Transport and Environment, 44*, 277–291.

Ton, D., Duives, D., Cats, O., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2019). Cycling or walking? Determinants of mode choice in the Netherlands. *Transportation Research Part A, 123*, 7–23.

van Acker, V., Witlox, F., & van Wee, B. (2007). The effects of the land use system on travel behavior: A structural equation modeling approach. *Transportation Planning and Technology, 30*, 331–353.

Vij, A., Carrel, A., & Walker, J. (2013). Incorporating the influence of latent modal preferences on travel mode choice behavior. *Transportation Research Part A, 54*, 164–178.

Wang, D. (2015). Place, context and activity-travel behavior: Introduction to the special section on geographies of activity-travel behavior. *Journal of Transport Geography, 47*, 84–89.

Wicki, M., Guidon, S., Becker, F., Axhausen, K., & Bernauer, T. (2019). How technology commitment affects mode choice for a self-driving shuttle service. *Transportation Business and Management, 32*, Article 100458.

Winter, K., Wien, J., Molin, E., Cats, O., Morsink, P., & van Arem, B. (2019). Taking the automated bus: A user choice experiment. *Conference: 2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*.

Wong, R. C. P., Szeto, W. Y., Yang, L., Li, Y. C., & Wong, S. C. (2018). Public transport policy measures for improving elderly mobility. *Transport Policy, 63*, 73–79.

Yap, M. D., Correia, G., & van Arem, B. (2016). Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. *Transportation Research Part A, 94*, 1–16.