Can electric buses entice more public transport use? Empirical evidence from Vietnam

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ARTICLE INFO

ABSTRACT

Greening the transport fleet is a central issue in Asian cities. Hanoi, the capital of Vietnam, recently introduced modern and comfortable electric buses along 10 routes (out of more than 110 routes). Using the Technology Acceptance Model as a departing point, this study investigates young people's intention to use this new technology. We employ primary survey data from more than 800 university students, which we model through structural equations. The results suggest that most students are intent on using e-buses. Those who are more innovative and more environmentally aware are more likely to plan on using e-buses. However, the environmental merits of e-buses are not the decisive factor. Students are also interested in the safety, security, and innovation aspects of this mode in addition to its environmental friendliness. A key lesson is that, in Vietnam and similar settings, e-bus launches should be accompanied by a package of measures that highlight *all* the benefits of this mode. E-buses should be framed as fundamentally different to the conventional buses of old.

1. Introduction

Greening the transport fleet – in other words, electrifying it – is a central issue in Asian cities and farther afield (Ajanovic and Haas, 2016; Featherman et al., 2021). Sadly, the uptake of electric vehicles for personal use is much lower in poorer cities where purchase and operation costs are high relative to local incomes (Lutsey et al., 2015; Rajper and Albrecht, 2020). Higher hopes for improvement are pegged on the electrification of (currently much polluting) urban bus fleets (Pojani and Stead, 2015; Wu et al., 2015) – the bus being the backbone of the public transport systems in those cities that lack rail-based transit (Nguyen and Pojani, 2018). China is the unquestionable leader of the e-bus market with a fleet of nearly 400,000 in 2018 (He et al., 2022; IES-Synergy 2021). Shenzhen is the first city in the world to have fully switched to e-buses (Mao et al., 2020). Most other cities around the globe still run either conventional buses or a mix of conventional and e-buses.

So far, little is known about users' attitudes and beliefs around this new technology. Can it entice more people to use public transport? This study investigates whether youth (i.e., university students) intend to use e-buses in the capital of Vietnam. Hanoi recently introduced electric buses along 10 routes (out of more than 110 routes).[1] Not only are the

new e-vehicles zero-emission, but they are also equipped with driver behavior monitoring systems, surveillance cameras, announcement screens, free Wi-Fi and USB charging ports, and LCD entertainment screens (Sustainable Bus, 2021) (see Fig. 1). A mobile app is available which shows the real-time position of e-buses. On conventional buses, these features are often broken or missing entirely.

The e-bus routes run in urban districts connecting the main destinations and points of interest (except for one route which connects the city center and the international airport). The terminals are located in residential areas or VinFast department stores and have innovative designs. The operational schedules of e-buses are quite similar to conventional buses, with 10–20 min headways. Most e-bus routes share the same infrastructure as conventional buses, meaning that they have no dedicated paths on the road. Therefore, the e-bus speeds and temporal reliability are the same as for conventional buses. However, the comfort and convenience of e-bus services is far superior while the fare is the same. E-bus passengers can pay with a contactless credit/debit card; this method is unavailable in conventional vehicles.

While normally passengers (or potential passengers) are unfamiliar with the powertrains of buses, in this case it is immediately clear that e-buses are "special" and "novel" because their exterior and interior

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[1] The e-bus program was launched in the second half of 2021; pilots ran for a few months prior.

Fig. 1. Electric buses (right) compared to conventional buses (left). Photos by authors.

design is quite different to conventional buses. The municipality has launched the e-buses with much fanfare and touted them as smarter, safer, quieter, and cleaner, as well as more innovative, secure, comfortable, and reliable than conventional buses. E-buses have been presented as evidence of the transport authorities' commitment to sustainability and innovation (People's Committee of Hanoi, 2016).

The problem is that Hanoi is not a bus-oriented city. Here motorcycles are the dominant travel mode, accounting for over 80% of daily trips (Huynh and Gomez-Ibañez, 2017). Buses are used in only 8–9% of trips; the rest of people mainly ride motorcycles. University students are the main bus patrons, accounting for nearly two thirds of passengers (Manh et al., 2021). This is not unusual: students everywhere tend to rely on buses to get around (Chen, 2012; Danaf et al., 2014; Duarte et al., 2016; Hafezi et al., 2018). Hence, examining students' perceptions and behaviors in relation to public transportation is critical.

In Hanoi, a special focus on students' intention to use electric buses is particularly important because the Vietnamese capital is a megacity of 8 million inhabitants and a higher education hub within the country. More 600,000 students attend about 80 universities and colleges (Hanoi Statistics Office, 2019). It would be a major achievement if electric buses lured even a portion of the student population away from motorcycles. At the same time, one must keep in mind that the current e-bus fleet (about 100 vehicles) might not be able to service Hanoi's entire student population.

The study employs primary survey data collected by the authors, which are modelled through structural equations. We apply a tailored framework which incorporates elements of the Technology Acceptance Model. Below we review existing studies of students' actual or potential use of public transport to highlight the gap which our study seeks to fill. Then we present the theoretical framework, followed by the methodology and analysis.

2. Literature review

As university attendance grows, so does research into the public transport-based travel patterns of university students (Table 1).

However, many gaps and uncertainties remain. For example, some studies lump together students and staff (Daniels and Mulley, 2013; Ribeiro et al., 2020), although the travel behavior of the latter's is distinct (Khattak et al., 2011). Most studies rely on observable variables (e.g., socio-demographics, university-home distance, weather, living area) employing regression analyses, which have limited power (Danaf et al., 2014; Nguyen-Phuoc et al., 2018; Obregón Biosca, 2020; Whalen et al., 2013; Zhou, 2012). While several studies integrate latent variables (Duarte et al., 2016; Nordfjærn et al., 2019; Shaaban and Kim, 2016), they are based on general theories such as the Theory Planned Behavior or Goal-Directed Behavior (Heath and Gifford, 2002; Jomnonkwao et al., 2016; Nayum and Nordfjærn, 2021). Also, they apply covariance-based structural equation modeling (CB-SEM) (De Vos et al., 2020; Wang et al., 2016, 2020), which requires large sample sizes and normal data distributions (Astrachan et al., 2014) and is poorly suited to exploratory research (Hair et al., 2017). Nearly all the existing research

in this space targets conventional public transport modes; we could identify a single study (Fu et al. 2022) which focused on a novel technology (shared autonomous vehicles). And all prior studies have been carried out before Covid-19 pandemic. No studies have considered students' intention to ride e-buses – an emerging travel mode in middle-income countries in the pandemic period.

3. Theoretical framework

The model which we have built for this study is illustrated in Fig. 2. As seen, its 10 constructs are connected by 15 paths or hypotheses (H 1–15). The main outcome, shown in the center of the diagram, is the *behavioral intention* to use electric buses. Details on the constructs that affect the behavioral intention, as well as the study hypotheses, are provided below.

Two constructs – *perceived usefulness* and the *perceived ease of use* of electric buses – are borrowed from the Technology Acceptance Model. TAM is designed to predict, in a robust and parsimonious fashion, if and how much people might accept a novel and innovative technology (Venkatesh and Davis, 2000; Wang et al., 2020), including ride-hailing (Wang et al., 2020), public transit (Chen and Chao, 2011), and e-ticketing (Cheng and Huang, 2013). Much like the Theory Planned Behavior, TAM assumes that one's actual behavior is determined by one's *behavioral intention*. In the model, the *perceived ease of use* is the extent to which a person believes that employing a technology will be free of mental and physical effort (see Schaik et al., 2002; Wu et al., 2007; Mallat et al., 2009; Venkatesh and Davis, 2000; Venkatesh et al., 2003; Yi et al., 2006). *Perceived usefulness* is the extent to which a person believes that the new technology will boost performance (Chau and Hu, 2002; Nguyen and Armoogum, 2020; Yi et al., 2006). These two constructs are connected: people believe that a technology will be more useful when it is seen as easier to use (Chau and Hu, 2002; Venkatesh and Davis, 2000).[2] Based on the original TAM model, we hypothesize that our TAM-derived constructs are linked in the following manner:

H1: Perceived ease of use is positively associated with perceived usefulness.
H2: Perceived ease of use is positively associated with behavioral intention.

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[2] The original TAM contained an additional construct, called attitude, which mediated the effect of perceived ease of use and perceived usefulness on behavioral intention (Holden and Karsh, 2010). In recent studies TAM-based studies, this construct has been usually ignored (Brown et al., 2002; Cheng and Huang, 2013; Gefen et al., 2003; Lee and Lehto, 2013; Mallat et al., 2009; Nguyen et al., 2023b; Nguyen Thi et al., 2022; Park et al., 2014; Venkatesh and Davis, 2000; Wang et al., 2020) because it does not affect the overall variance by much (Teo and Noyes, 2011) whereas the perceived ease of use and perceived usefulness are much stronger constructs (Wu and Wang, 2005). Accordingly, we have dropped attitude, and retained only the two latter constructs, as well as three paths or hypotheses (H 1–3).

Table 1
Previous studies on public transport use among university students.

Authors	Sample/setting	Target modes	Analysis	Theory/methods
Heath and Gifford (2002)	175/Canada	Bus	Intention	Theory of Planned Behaviour/Factor analysis/Hierarchical multiple regression
Zhou (2012)	769/USA	Public transport, walk, cycle, car, carpool, telework	Mode choice	Multinomial logit regression
Whalen et al. (2013)	1,385/Canada	Public transport, walk, cycle, car	Mode choice	Multinomial logit regression
Danaf et al. (2014)	594/Lebanon	Public transport, car, jitney	Mode choice	Nested logit regression
Van et al. (2014)	716/China, Thailand, Indonesia, Vietnam, Philippines	Public transport, car	Intention	Factor analysis/Multinomial logit regression
Duarte et al. (2016)	786/Colombia 653/Brazil	Bus, walk, cycle, car	Mode choice	Factor analysis/clustering (k-means)
Shaaban and Kim (2016)	330/Qatar	Bus, car	Mode choice	SEM
Jomnonkwao et al. (2016)	387/Thailand	Bus	Intention	Theory of Planned Behaviour/Structural Equation Modelling
Nguyen-Phuoc et al. (2018)	503/Vietnam	Public transport, walk, cycle, car	Mode choice	Multinomial logit regression
Nordfjærn et al. (2019)	441/Norway	Public transport, active transport, car	Mode choice	Factor analysis/Linear mixed model
Obregón Biosca (2020)	594/Mexico	Bus, active modes, car	Mode choice	Binary logit regression
Nayum and Nordfjærn (2021)	424/Norway	Public transport	Intention	Theory of Planned Behaviour/Structural Equation Modelling
Fu et al. (2022)	424/USA	Shared autonomous vehicles	Willingness to pay	Ordered logit regression

H3: Perceived usefulness is positively associated with behavioral intention.

We do not model actual behavior because the technology that we examine – electric buses – is still novel in Hanoi and the data are scarce. Other elements in our model include:

Two constructs suggested by the extant literature (Wang et al., 2020): *environmental awareness* and *personal innovativeness.*

One construct on the *perceived risk of Covid-19 infection,* which is topical given the ongoing pandemic. One additional construct resulted from this: non-pharmaceutical *self-protection measures* against Covid-19 infection.

One construct on the *perceived risk of theft* and another on the *perceived risk of sexual harassment,* which were based on our understanding of the Vietnamese context and the typical concerns of bus riders here. One additional construct resulted from these two perceived crime risks: *security measures* to protect oneself from crime.

A short discussion of these constructs follows below.

3.1. Personal innovativeness

A key variable in the new technology adoption process, *personal innovativeness* is the extent to which a person is willing to try new things (Thakur et al., 2016). Innovative people tend to focus on the advantages of a novel technology rather than the drawbacks (Cheng and Huang, 2013) and are more confident when using new technologies (Lewis et al., 2003). Earlier research in transport has demonstrated that personal innovativeness positively and strongly influences perceived ease of use and perceived usefulness (Tan et al., 2014; Wang et al., 2020). Transport studies have also shown that personal innovativeness drives the adoption of electric cars (Liao et al., 2017) and ride-hailing services (Wang et al., 2020). On this basis, we hypothesize that:

H4: Personal innovativeness is positively associated with perceived ease of use.

H5: Personal innovativeness is positively associated with perceived usefulness.
H6: Personal innovativeness is positively associated with behavioral intention.

3.2. Environmental awareness

Environmental awareness is the extent to which people are conscious and concerned about environmental threats (Arı and Yılmaz, 2017) – including the pollution produced by human activities such as car driving or motorcycle riding (Liu et al., 2014). Extensive empirical studies have shown that environmental awareness promotes pro-environmental behavior intention (Chan, 2001; Nguyen, 2021). In the transportation domain, environmental awareness is known to positively affect the uptake of ride-hailing services (Wang et al., 2020), public transport (Pojani et al., 2018), and electric cars (Kim et al., 2014; Wang et al., 2017). Therefore, our hypothesis is that:

H7: Environmental awareness is positively associated with behavioral intention.

3.3. Perceived risk of theft (and security measures)

Risk is the probability of some type of loss – financial, physical, social, psychological, and so forth (Featherman et al., 2021). Perceived risk is the belief around potential harm (Darker, 2013). Using any transport technology involves some risk. For example, driving a car carries the risk of injury or death. App-based ride-hailing services are at risk of cyberattack (Wang et al., 2020). E-ticketing can produce delays and payment errors (Cheng and Huang, 2013). Some risks newly occur when a novel technology is adopted whereas others are carried over from the old technology replacing the new. In the case of electric buses, these pose no new risks for potential users. However, passengers may be exposed to the same risk of theft (pickpocketing) as in conventional buses (Smith, 2008). *Perceived risk of theft* is a known impediment to public transport usage (Delbosc and Currie, 2012; Nguyen and Pojani,
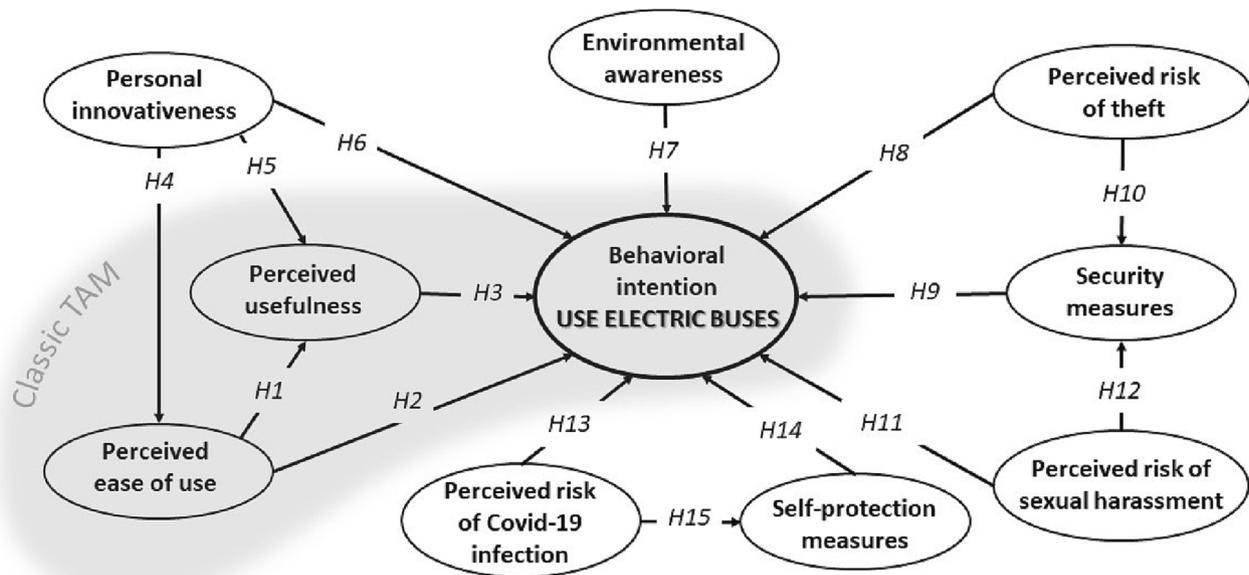
Fig. 2. Theoretical framework.

2022; Smith, 2008), particularly among youth (Currie et al., 2013). It forces passengers to take *security measures* throughout their journey (Nguyen-Phuoc et al., 2021), such as being on high alert and securing a well-lit spot to sit or stand, possibly close to bus staff. With this background in mind, we hypothesize that:

H8: Perceived risk of theft is negatively associated with behavioral intention.
H9: Security measures are positively associated with behavioral intention.
H10: Perceived risk of theft is positively associated with security measures.

3.4. Perceived risk of sexual harassment (and security measures)

Another common crime related to transit, which affects younger women in particular, is sexual harassment (Ceccato and Loukaitou-Sideris, 2021; Pojani, 2014). This can occur at any point during a trip (Orozco-Fontalvo et al., 2019), and is endemic in Vietnamese cities. In response to a *perceived risk of sexual harassment*, people may shun public transport altogether (Quinones, 2020). Where passengers are aware of *security measures* such as staff, surveillance cameras, and bright lighting, the perceived risk of sexual harassment is mitigated (Loukaitou-Sideris and Ceccato, 2022; Orozco-Fontalvo et al., 2019). Our hypotheses are that:

H11: Perceived risk of sexual harassment is negatively associated with behavioral intention.
H12: Perceived risk of sexual harassment is positively associated with security measures.

Because theft and sexual harassment are typical crimes occurring on public transport, the construct *security measures* is the same for both.

3.5. Perceived risk of Covid-19 infection (and self-protection measures)

As of this writing, in mid-2021, the pandemic is considered as ongoing and the *perceived risk of Covid-19 infection* is pervasive (Dryhurst et al., 2020). In some cities, it has decimated public transport usage (Barbieri et al., 2021; Hu and Chen, 2021). At the same time, it has

motivated remaining (and prospective) passengers to take *self-protection measures* (Yıldırım et al., 2021), such as wearing face masks, disinfecting hands, and maintaining physical distance with others while travelling around the city (Das and Tiwari, 2021; Machida et al., 2020; Manh et al., 2021; Nguyen et al., 2022; Tran et al., 2022).[3] Given these circumstances, our hypotheses are the following:

H13: Perceived risk of Covid-19 infection is negatively associated with behavioral intention.
H14: Self-protection measures are positively associated with behavioral intention.
H15: Perceived risk of Covid-19 infection is positively associated with self-protection measures.

4. Methodology

The following sections discuss the data collection and analysis process.

4.1. Data collection

This study relies on a survey of university students in Hanoi. The data were collected in May 2021 as Hanoi experienced the fourth Covid-19 wave, and the city went into lockdown; universities had just shunted to online learning.[4] In other cities, the results of a study conducted during a Covid-19 lockdown could not be generalized to other periods because the behavioral intention to use e-buses would be confounded by people's reluctance to use buses in general (Tirachini and Cats, 2020). However, in Hanoi, the pandemic has not decimated bus ridership. Three relatively minor Covid-19 waves have been successfully contained while still maintaining regular bus operations most of the time (Nguyen and Pojani, 2021).

The survey was conducted online through Google Forms, with all the

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[3] A Covid-19 vaccination program had begun in Vietnam at the time of the survey but we did not collect data on inoculation rates among our respondents.
[4] The first lockdown occurred in April 2020 (Nguyen et al., 2021a).

questions marked as mandatory to avoid receiving incomplete responses.[5] The initial link was sent to the authors' colleagues in seven universities, with a request to distribute to their students and ask respondents to pass it on to other students. (The questionnaire was piloted with 20 students before being shared broadly.).

We selected universities based on their geographical location, seeking to cover as much of the urban area as possible. We also included different types of universities (in terms of faculties and majors). The targeted universities were: Hanoi University of Mining and Geology (HUMG), National University of Civil Engineering (NUCE), University of Transport and Communications (UTC), Hanoi Architectural University (HAU), Phuong Dong University (PDU), Hanoi University of Industry (HAUI), and Hanoi College of Commerce and Tourism (HCCT). All but PDU are public institutions. HUMG, HAU, and HAUI are located close to the urban edge while the rest are in central areas (Fig. 3).

The questionnaire was in two parts. The first part collected sociodemographic information about the participants, including gender, age, year of studies, employment status, living area, living status, household income, home-university distance, motorized vehicle ownership,[6] and commute mode (pre- and post-lockdown). The second and most important part of the questionnaire comprised 36 attitudinal statements used to (a) find out whether students intend using e-buses and (b) test the extended TAM proposed for this study. Before answering the survey questions, the respondents were provided a description of the characteristics of e-buses, including their service coverage. The surveyors showed the respondents a map of the ten e-bus routes as well as several pictures of the exterior and interior of an e-bus. The full list of these statements, grouped by construct, is provided in Appendix 1. Most statements were adapted from existing studies on new transport technologies (Wang et al., 2020), Covid-19 risk perceptions (Dryhurst et al., 2020; Nguyen et al., 2020), transit-related theft (Smith, 2008), and the sexual harassment of women on public transport (Quinones, 2020). A few statements were created anew by the authors to account for the local context. All statements were measured on a 7-point Likert scale.

4.2. Sample characteristics

In total, 862 responses were received. Of these, 29 were eliminated as unreliable.[7] The final sample consisted of 833 responses. While this sample is large and representative, it is not random.[8] Snowball samples carry unavoidable biases. However, snowballing is a common sampling method in studies of students' travel mode choice where the entire population cannot be easily reached (Duarte et al., 2016; Fu et al., 2022; Nayum and Nordfjærn, 2021; Nordfjærn et al., 2019; Obregón Biosca, 2020; Whalen et al., 2013).

Table 2 presents the socio-demographic characteristics of the study participants. As seen, the gender distribution was nearly equal reflecting the overall student population in Hanoi. The sample slightly over-represented freshers and sophomores while underrepresenting juniors and seniors. The survey sample reflected the fact that many students come to the capital from other Vietnamese cities to attend university: most respondents lived in urban districts within Hanoi's border and

rented a place with roommates, relatively close to their university, rather than living with their relatives. Home-university distances were short for a city of Hanoi's size. Household incomes were relatively low, as expected of students, although many respondents had a part-time job.

With regard to transport: Motorcycle ownership and use was widespread, whereas car use was minuscule. Only about a fifth of the respondents used active transport to commute to their university, and about a third took the bus. Overall in Hanoi, buses are used by only 8–9% of the population (TRAMOC, 2019, pre-Covid-19 data). This highlights the fact that students are a key market segment for public transport. However, their contribution has declined substantially due to the pandemic. More than a third of our survey respondents were former bus users who had quit this mode in the Covid-19 era (switching to a motorcycle for the most part). Only 29% of the respondents had never commuted by bus.

4.3. Analytical tools

In this study, we applied Structural Equation Modelling (SEM) to test the complex relationships set forth in the theoretical framework. SEM is an advanced multivariate analytical technique which combines linear modeling procedures, such as regressions (Sarstedt et al., 2016). It is employed estimate causal relationships among variables, as opposed to simple links. The SEM variables can be directly or indirectly observable (Sarstedt et al., 2016). The newest version of SEM, Partial Least Squares Structural Equation Modelling (PLS-SEM) has gained prominence in travel behavior studies (Ngoc et al., 2023; Nguyen et al., 2022; Nguyen-Phuoc et al., 2021; Si et al., 2022; Tran Thi Phuong et al., 2022).

PLS-SEM follows a regression-based ordinary least squares estimation procedure with a focus on explaining the variance of the latent constructs (Astrachan et al., 2014). It can effectively estimate complex models with many constructs and paths (including extensions of existing models) even where the datasets are relatively small and not normally distributed (Hair et al., 2019; Sarstedt et al., 2016). Hence our selection of PLS-SEM as our main analytical tool.[9]

Applying PLS-SEM involves estimating a structural equation model and measurement models, which can be formative or reflective (Hair et al., 2017). The structural equation model reveals the relationships between the latent variables (i.e., inner model). The measurement model reveals the relationships between the latent variables and their measures (i.e., outer models). This study used a reflective measurement model in which the direction of causality flows from the construct to the indicators; in other words, all of the indicators of a construct are assumed to be caused by that construct. Each indicator has an error term that is independent of other error terms.

An important step in structural equation models is the analysis of path coefficients or effects (Ringle et al., 2020). Paths (represented as arrows in Fig. 2) link constructs together, reflecting the hypotheses. Where the β coefficient of a path is statistically significant, the corresponding hypothesis is accepted; otherwise, it is rejected.[10] Three types of effects are estimated: direct effects, indirect effects, and total effects, as follows.

A direct effect is the path from an exogenous construct to an endogenous construct; for example, the effect of 'environmental awareness' on 'behavioral intention' or the effect of 'perceived ease of use' on 'perceived usefulness'. The calculation of direct effects is also referred to as hypothesis testing. In this case, we had 15 hypotheses and therefore estimated 15 direct effects.

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[5] Incomplete responses are normally eliminated from the analysis, reducing the sample size.

[6] We only inquired about motorcycle ownership; car ownership was expected to be minuscule among students.

[7] The respondents had provided the same value for all attitudinal statements suggesting disengagement with the survey.

[8] The total population of students in Hanoi is about 600,000, as noted in the Introduction. A sample size of 833 is considered as representative of this population number, assuming a 95% confidence level and a 3–4% margin of error. Collecting a random sample of students would have been impossible because, for privacy reasons, universities in Hanoi do not release the full lists of students enrolled to third parties. Therefore, we relied on snowball sampling.

[9] The analysis was performed in SmartPLS professional 3.3.3 software.

[10] The statistical significance and relevance of the path coefficients (β) is determined based on the results generated by a bootstrap process wherein sub-datasets (e.g., 500 as the initial value in SmartPLS) are randomly drawn from the original data with replacement to perform non-parametric inference and modeling (Nitzl et al., 2016).
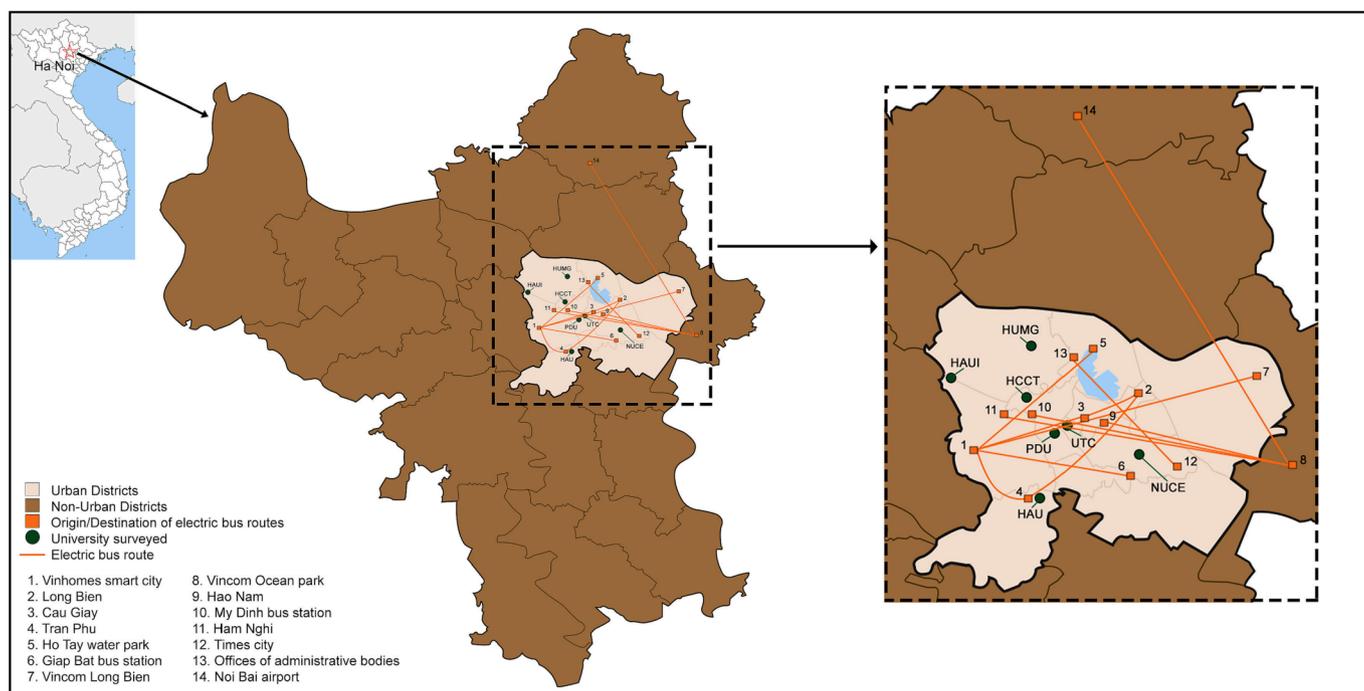
Fig. 3. Research area in Hanoi.

Table 2
Sample characteristics (N = 833).

Variable		Frequency	Percent
Gender	male	406	49
	female	427	51
Year of studies	1st year	240	29
	2nd year	213	26
	3rd year	199	24
	4th year	181	22
Household income	< 550 USD[11]	685	82
	≥ 550 USD	148	18
Living area	urban district	510	61
	non-urban district	330	39
Living status	rent house	650	78
	live with family/relatives	183	22
Motorcycle ownership	yes	441	53
	no	392	47
Part-time job	yes	476	57
	no	357	43
Home-university distance	short (<2 km)	241	29
	medium (2–5 km)	330	40
	long (>5 km)	262	32
University commute mode	walking	114	14
	bicycle	38	5
	motorcycle	382	46
	car	13	2
	bus	286	34
Former bus users		308	37
Current bus users		286	34
Non-bus users		239	29

[11]To determine what constitutes a 'lower income' at the household level, we reasoned that: most university students in Hanoi come from other provinces and rent rooms in shared houses; the Student Associations of several universities surveyed indicate that, typically, students room in groups of four and students' individual monthly income is less than US$140 on average; on this basis, a student household of four has a monthly income of about US$550–560 on average; it follows that a household income of less than US$550 is lower than average.

An indirect effect is the path from an exogenous construct to an endogenous construct through at least one mediator; for example, the effect of 'perceived risk of theft' on 'behavioral intention' is mediated by 'security measures'. Our theoretical framework depicts 8 such indirect effects.

The total effect is the sum of the direct and indirect effects on the

outcome of interest (behavioral intention in this case). Note that two constructs can be linked by a direct path and one or more indirect paths. For example, the effect of 'personal innovativeness' on 'behavioral intention' can be direct and indirect, mediated either by 'perceived usefulness' or 'perceived ease of use' and then 'perceived usefulness'. Environmental awareness only has a direct effect on behavioral

Table 3

Predictive capacity of the models.

Endogenous construct	Male respondents				Female respondents			
	R^2	SSO	SSE	Q^2	R^2	SSO	SSE	Q^2
Behavioral Intention	0.53	1218	770.060	0.368	0.598	1281	722.141	0.436
Security Measures	0.25	2030	1697.861	0.164	0.519	2135	1381.026	0.353
Perceived Ease of Use	0.22	1218	1042.321	0.144	0.345	1281	958.796	0.252
Perceived Usefulness	0.32	2436	2042.282	0.162	0.402	2562	1907.827	0.255
Self-Protection Measures	0.27	1218	965.913	0.207	0.361	1281	927.649	0.276

$Q^2 = 1\text{-SSE/SSO}$ [recommended value greater than 0].

SSO: Sum of Square Observations.

SSE: Sum of Squared prediction Errors.

intention. In this study, we computed total effects on behavioral intention for 4 constructs (see later).

For all effects, the threshold of significance was set at $p < 0.05$.

4.4. Modelling by gender

Many transport studies employing SEM report combine results for all genders. However, the transport literature suggests that men and women perceive various risks differently, with women generally being more risk adverse (Ceccato and Loukaitou-Sideris, 2021; Nguyen-Phuoc et al., 2021). Fearfulness is based on reality and not simply on gender socialization. Women are far more likely to be sexually harassed, robbed, or victimized in other ways while travelling (May et al., 2010; Pojani, 2014; Smith, 2008). Perhaps because they tend to be responsible for their family's health and wellbeing, women are more aware of, and concerned about, environmental issues than men (Lee, 2009). For the same reason, women are more concerned about the risk of contracting Covid-19 (Nguyen and Armoogum, 2021; Das and Tiwari, 2021), and more likely to adhere to prevention guidelines than men (Machida et al., 2020; Rana et al., 2021). Given these known gender differences, we have modelled the behavioral intentions of men and women separately.

4.5. Modelling by experience

As seen in Table 2, our sample contained three groups: (1) former bus users; (2) current bus users; and (3) non-bus users. We estimated three linear regression models corresponding to those three groups, wherein the dependent variable was 'behavioral intention', and the independent variables included the other nine constructs in our theoretical framework (see Fig. 2). The values of the independent and dependent variables were estimated based on confirmatory factor analysis (see below). We focused on the direct effects, ignoring any indirect effects through applying linear regression. We did not apply PLS-SEM to the three groups because the sample sizes were relatively small.

4.6. Model testing

We performed two tests: one of the reflective measurement model and another of the structural equation model. The testing steps and the results are presented below.

Based on the literature, the assessment of the reflective measurement is conducted via Confirmatory Factor Analysis (Hair et al., 2017). Indicator reliability is evaluated through the Factor Loadings (FL) of items; values should be over 0.7 (Chin, 2010), or at least over 0.6 for exploratory research (Hair et al., 2017). Internal consistency reliability is ensured if Cronbach's Alpha (CA) values and the Composite Reliability (CR) values of constructs are higher than 0.7 but below 0.95 (Hair et al.,

2017). The Average Variance Extracted (AVE) is utilized to assess the convergent validity. An AVE greater than 50% is recommended (meaning that a construct explains an average of more than 50% of its items' variance) (Hair et al., 2019). Discriminant validity is assessed by the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT). According to the Fornell-Larcker criterion, the square root of the AVE value of a construct should be larger than the values of correlations between such construct and others (Bagozzi and Yi, 1988). The HTMT values should be <0.9 (Henseler et al., 2015). The results of our reliability and validity tests are presented in Appendix 1 and Appendix 2. All the parameters (FL, CA, CR, AVE, Fornell-Larcker criterion, HTMT) met the criteria. Therefore, the constructs were eligible for further structural analyses.

After analyzing path coefficients and determining whether the hypotheses were accepted or rejected (see later), we looked at the model fit, in particular two goodness-of-fit measures: the standardized root mean square residual (SRMR) and the normed fit index (NFI; also called the Bentler-Bonett index). The recommended values are: SRMR < 0.08 and NFI greater than 0.8; (Henseler et al., 2016; Hu and Bentler, 1998). Our results confirmed that the structural models fit reasonably well both the female data (SRMR = 0.04, NFI = 0.85) and the male data (SRMR = 0.0450, NFI = 0.8378).

Because structural model coefficients are estimated from a series of regression equations, we also checked for collinearity. A Variance Inflation Factor (VIF) value smaller than 3 indicates the absence of collinearity (Hair et al., 2019). In our case, all VIFs were under 3 (Appendix 3) for both male and female models; therefore, collinearity was absent.

With regard to the predictive capacity of the models, the coefficient of determination (R^2) measures the variance of endogenous constructs (Rigdon, 2012). These are constructs which are caused by other constructs in the model. The remaining constructs are 'exogenous'. The higher the R^2, the higher the predictive capacity of the model. The value of R^2 may be considered substantial at 0.75, moderate at 0.5, and weak at 0.25. However, there is no agreement as to what constitutes an "acceptable" R^2 value (Hair et al., 2019; Henseler et al., 2009). In our models, the R^2 values of all endogenous constructs, shown in Table 3, were weak to moderate (Henseler et al., 2009).

A final test involves the blindfolding-based cross-validated redundancy measure (Q^2), which is a function of observations and prediction errors. Some authors recommend that Q^2 be over zero (Hair et al., 2019), and in our case, this recommendation was met (see Table 3).

4.7. Study limitations

The following limitations should be kept in mind when perusing the results of this study:

Table 4
Intention to use electric buses.

	Male respondents			Female respondents			Total sample		
	Freq.	Intention to use electric buses		Freq.	Intention to use electric buses		Freq.	Intention to use electric buses	
		Freq.	%		Freq.	%		Freq.	%
Former bus users	166	85	51%	142	78	55%	308	163	53%
Current bus users	140	139	99%	146	143	98%	286	282	99%
Non-users	100	28	28%	139	32	23%	239	60	25%
Total	406	252	62%	427	253	59%	833	505	61%

Note: *Intention to use electric buses* combines the scores of three items used to measure behavioral intention. We considered the intention to be positive when the all three items (measured on a 7-point Likert scale) scored over 4 (the neutral option).

Table 5
Direct effects.

Hypothesis	Male respondents				Female respondents			
	β	SD	p	Decision	β	SD	p	Decision
H1: PEU → PU	0.294	0.060	0.000*	Accepted	0.233	0.062	0.000*	Accepted
H2: PEU → BI	0.060	0.056	0.286	Rejected	−0.020	0.042	0.591	Rejected
H3: PU → BI	0.392	0.070	0.000*	Accepted	0.404	0.058	0.000*	Accepted
H4: PI → PEU	0.471	0.052	0.000*	Accepted	0.585	0.043	0.000*	Accepted
H5: PI → PU	0.363	0.068	0.000*	Accepted	0.471	0.059	0.000*	Accepted
H6: PI → BI	0.115	0.052	0.024*	Accepted	0.163	0.055	0.003*	Accepted
H7: EA → BI	0.192	0.061	0.002*	Accepted	0.129	0.048	0.010*	Accepted
H8: PRT → BI	0.016	0.032	0.595	Rejected	0.015	0.034	0.640	Rejected
H9: SM → BI	0.088	0.038	0.018*	Accepted	0.132	0.053	0.016*	Accepted
*H*10: PRT → SM	0.494	0.061	0.000*	Accepted	0.289	0.058	0.000*	Accepted
*H*11: PRSH → BI	0.040	0.043	0.388	Rejected	0.035	0.044	0.390	Rejected
H12: PRSH → SM	0.048	0.052	0.398	Rejected	0.553	0.052	0.000*	Accepted
H13: PRCI → BI	0.034	0.046	0.442	Rejected	0.073	0.055	0.191	Rejected
H14: SPM → BI	0.121	0.048	0.012*	Accepted	0.139	0.052	0.006*	Accepted
H15: PRCI → SPM	0.527	0.053	0.000*	Accepted	0.603	0.048	0.000*	Accepted

BI: Behavioral Intention; SM: Security Measures; PEU: Perceived Ease of Use; PRCI: Perceived Risk of Covid-19 Infection; PRSH: Perceived Risk of Sexual Harassment; PRT: Perceived Risk of Theft; PU: Perceived Usefulness; PI: Personal Innovativeness; SPM: Self-Protection Measures; EA: Environmental Awareness.
β: path coefficient.
SD: standard deviation.
p: p-value converted from the t-values estimated from bootstrapping (500 samples).
*p < 0.05.

Table 6
Indirect effects.

Path	Male sample			Female sample		
	β	SD	p	β	SD	p
PEU → PU → BI	0.115	0.032	0.001*	0.094	0.027	0.000*
PI → PU → BI	0.142	0.036	0.000*	0.190	0.035	0.000*
PI → PEU → PU	0.139	0.035	0.000*	0.137	0.039	0.000*
PRSH → SM → BI	0.004	0.006	0.478	0.072	0.029	0.015*
PI → PEU → BI	0.028	0.027	0.300	−0.012	0.025	0.593
PRCI → SPM → BI	0.064	0.027	0.019*	0.084	0.033	0.009*
PI → PEU → PU → BI	0.055	0.017	0.003*	0.055	0.017	0.001*
PRT → SM → BI	0.044	0.020	0.033*	0.039	0.018	0.045*

BI: Behavioral Intention; SM: Security Measures; PEU: Perceived Ease of Use; PRCI: Perceived Risk of Covid-19 Infection; PRSH: Perceived Risk of Sexual Harassment; PRT: Perceived Risk of Theft; PU: Perceived Usefulness; PI: Personal Innovativeness; SPM: Self-Protection Measures.
*p < 0.1.

While the sample was large in terms of size (862 observations) and coverage (seven universities), it may not be representative of the entire student population in Hanoi. Future studies employing random samples of the entire population (not only students) would be desirable.

Our model focused on the technical characteristics of buses and the various risks perceived by users. Future studies might consider including other factors, such as social pressures (Chen, 2016; Nguyen et al., 2023a). However, more factors would make the model more complex.

Universities in Hanoi are concentrated in urban districts while the electrification of the bus fleet is in its infancy. These characteristics of

the educational and transportation contexts should be considered in comparative studies.

5. Results

Overall, most students in our sample were intent on using electric buses (Table 4). Among current bus users, the intention to use electric buses was nearly universal. Importantly, slightly more than half of former bus users also planned on returning to public transport with the advent of electric buses. And even a quarter of those who had never used

Table 7

Total effects on behavioral intention.

Path	Male respondents			Female respondents		
	β	SD	p	β	SD	p
SM → BI	0.088	0.038	0.018*	0.132	0.053	0.016*
PU → BI	0.392	0.070	0.000*	0.404	0.058	0.000*
PI → BI	0.340	0.050	0.000*	0.396	0.052	0.000*
SPM → BI	0.121	0.048	0.012*	0.139	0.052	0.006*

BI: Behavioral Intention; SM: Security Measures; PU: Perceived Usefulness.

PI: Personal Innovativeness; SPM: Self-Protection Measures.

*$p < 0.05$.

public transport intended to at least try electric buses. These findings are very encouraging in terms of transport sustainability. However, our path analysis revealed more nuanced results based on various psychological constructs and gender. Below we present the direct, indirect, and total effects that we computed. As noted, the effects were estimated separately for male and female respondents.

5.1. Direct effects

The direct effects and the results of hypothesis testing are presented in Table 5. The table shows that for both genders, perceived usefulness, personal innovativeness, environmental awareness, security measures, and self-protection measures positively affected the behavioral intention to use electric buses. On the other hand, perceived ease of use, perceived risk of sexual harassment, perceived risk of theft, and perceived risk of Covid-19 infection did not have a significant effect on behavioral intention. However, perceived risk of theft (both genders) and perceived risk of sexual harassment (women only) affected security measures. This is consistent with the cognitive stress theory which postulates that a stressor such as transit crime can activate coping mechanisms which then encourage responses to protect from the stressor (Homburg and Stolberg, 2006). Similarly, perceived risk of Covid-19 infection affected self-protection measures, and the relationship was statistically significant. This is in line with the health belief model, whereby people who are more concerned about health and sickness are more likely to take preventive measures (Laranjo, 2016). Perceived usefulness was positively affected by perceived ease of use and personal innovativeness. Overall, perceived usefulness had the largest direct effect on behavioral intention while the effects of the other constructs were much smaller.
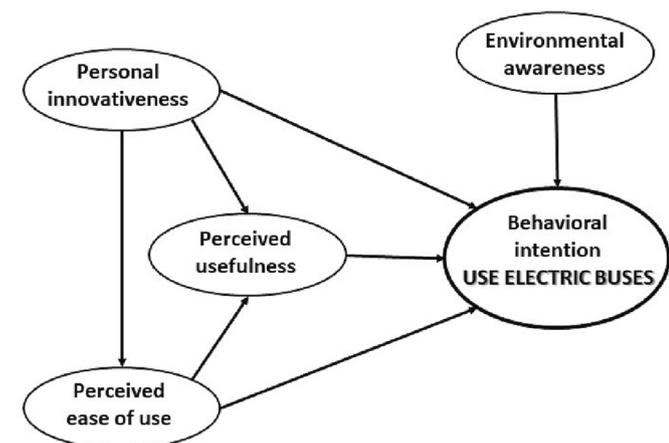
5.2. Indirect effects

Table 6 shows the indirect effects. Perceived ease of use, personal innovativeness, perceived risk of Covid-19 infection, and perceived risk of theft mediated behavioral intention for both male and female students. However, perceived risk of sexual harassment had an indirect effect on women's behavioral intention but not on men's.

5.3. Total effects

Table 7 presents the total effects (the sum of direct and indirect effects) on the outcome of interest: behavioral intention. Only 4 constructs (personal innovativeness, perceived usefulness, security measures, and self-protection measures), which have both direct and indirect effects on behavioral intention, are shown. As seen, perceived usefulness drove the behavioral intention to use electric buses, followed by personal innovativeness. In the case of environmental awareness, the total effects equaled the direct effects (this construct has no indirect effects on behavioral intention). Among male respondents, environmental awareness had a much larger (direct/total) effect on behavioral intention compared to the (total) effect of self-protection measures and security measures. In contrast, the (direct/total) effect of environmental awareness on behavioral intention was the weakest among female respondents.

5.4. Sensitivity analysis

Five of the constructs used in our model (perceived risk of Covid-19 infection; perceived risk of sexual harassment; perceived risk of theft; security measures; and self-protection measures) are connected with the behavioral intension of using electric buses but they can explain the intention to use public transport in general. To evaluate the theoretical

Fig. 4. Partial model used in the sensitivity analysis.

Table 8

Sensitivity analysis.

R^2 (Behavioral Intention)	Male respondents		Female respondents	
	Full model (10 constructs)	Partial model (5 constructs)	Full model (10 constructs)	Partial model (5 constructs)
	0.530 (53.0%)	0.503 (50.3%)	0.598 (59.8%)	0.538 (53.8%)
Difference in R^2				
	2.7%		6.0%	

Notes:

The missing constructs in the partial model were: SM: Security Measures; PRCI: Perceived Risk of Covid-19 Infection; PRSH: Perceived Risk of Sexual Harassment; PRT: Perceived Risk of Theft; SPM: Self-Protection Measures.

R^2 indicates the proportion (percentage) of variance explained by the model.

Table 9
Linear regression results.

Independent variables	Non-bus users		Current bus users		Former bus users	
	Coef.	p	Coef.	p	Coef.	p
Security measures	0.107*	0.032	0.078*	0.046	0.231**	0.006
Environmental awareness	0.204**	0.004	0.087*	0.025	0.123*	0.032
Perceived ease of use	0.086	0.130	0.079	0.105	0.029	0.550
Perceived risk of Covid-19 infection	−0.076	0.164	0.000	0.999	0.005	0.929
Perceived risk of sexual harassment	−0.021	0.665	−0.061	0.251	−0.015	0.797
Perceived risk of theft	−0.071	0.214	−0.016	0.749	−0.013	0.821
Perceived usefulness	0.346***	0.000	0.352***	0.000	0.291***	0.000
Personal innovativeness	0.126**	0.015	0.197***	0.000	0.188**	0.011
Self-protection measures	0.083*	0.047	0.098*	0.023	0.073*	0.040
Constant	−0.007	0.877	0.011	0.805	−0.008	0.851
Number of observations	239		286		308	
R^2	0.5095		0.4015		0.3723	

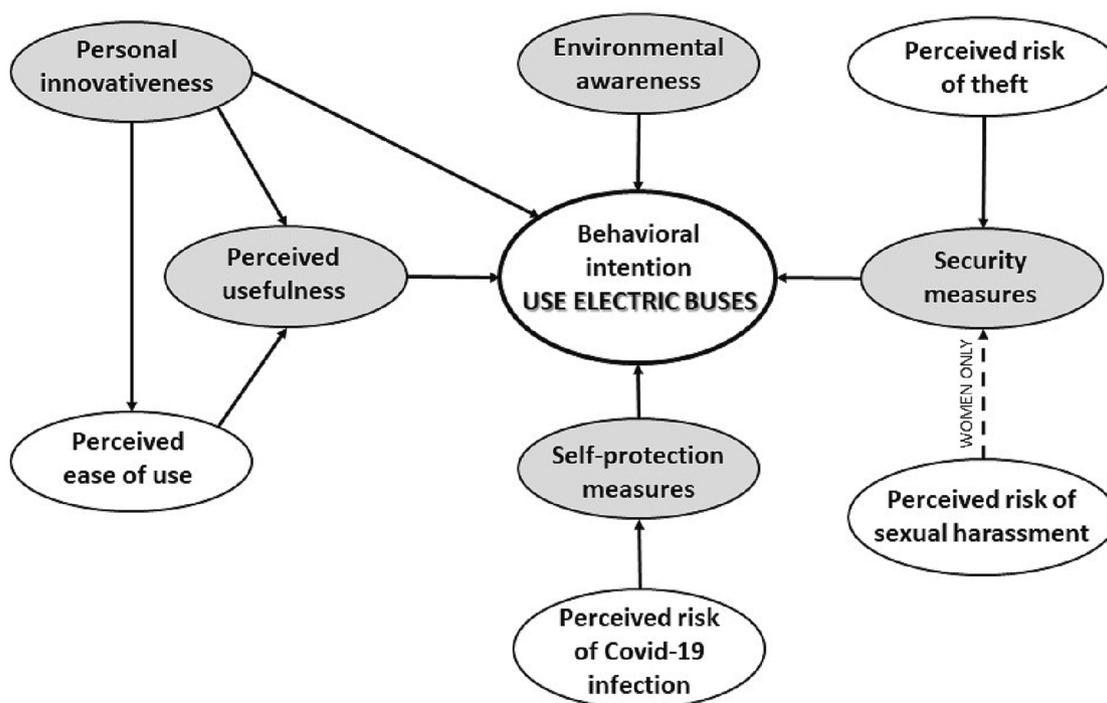Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Fig. 5. Key findings. The constructs with the strongest effects (direct and total) are shown in grey.

contribution of these five constructs, all of which are risk-related, we carried out a sensitivity analysis. This involved running the model again with the five constructs omitted (Fig. 4) and then comparing the results (Table 8).

The sensitivity analysis revealed that perceived risks have a rather weak impact on the behavioral intention (to use electric buses) relative to *personal innovativeness, environmental awareness*, the two constructs included in the classic TAM (*perceived ease of use* and *perceived usefulness*). For the male sample, the difference in the explanatory power of the full model vs the partial model was minimal (<3%). However, the perceived risks were more important to female respondents (a 6% difference in in the explanatory power of the full model vs the partial model). Therefore, we recommend retaining the five risk-related variables in future studies that focus on gender differences in transport.

5.5. Predictors by group

Table 9 shows that for all three groups (former bus users; current bus users; and non-bus users) constructs such as security measures, perceived usefulness, personal innovativeness, environmental awareness and self-protection measures are correlated to the intention to use e-buses. Overall, the strongest factor is 'perceived usefulness'. However, the effects vary across groups. For non-users, 'perceived usefulness' together with 'environmental awareness' are the key determinants, whereas for current and former users, 'perceived usefulness' and 'personal innovativeness' are more important.

6. Discussion

The key findings of this study on the factors that determine students' intention to use e-buses in Hanoi are illustrated in Fig. 5.

The study shows that the two constructs derived from TAM, in particular *perceived usefulness,* are valid. *Perceived ease of use* only had an indirect effect here because e-buses are no different to conventional buses in terms of use. We recommend retaining this construct in studies involving public transport technologies – such as BRT or LRT – which operate in a different manner to conventional buses and require some adjustment on part of users.

More importantly, the study demonstrates the relevance of the other constructs we added to the model: *environmental awareness* and *personal innovativeness* (Wang et al., 2020). In addition, constructs such as *security measures* (to protect from transit crime), and non-pharmaceutical *self-protection measures* against Covid-19 infection are relevant to women. Various perceived risks - of theft, sexual harassment, and disease - had an indirect effect on the intention to use e-buses. These findings mean that the extended version of TAM has theoretical value and can be used (and further refined) in future studies.

In plain language, our research shows that Hanoi students who are more innovative and more environmentally conscious are more intent on using electric buses in the future. Other studies set elsewhere (examining new technologies rather than e-buses in particular) have reached a similar conclusion (Cheng and Huang, 2013; Kim et al., 2014; Wang et al., 2016, 2020). While this finding may sound obvious, it is quite important in the case of Hanoi. Here, bus ridership is generally low, and the municipality is keen on shifting travelers from motorcycles to public transport in order to deal with the heavily congested and chaotic traffic. If even a portion of students were willing to use buses more than motorcycles, it would be a major achievement in terms of transportation planning. To this end, the novelty aspects of e-buses should be highlighted in promotional materials.

Overall, environmental awareness did not emerge as a strong factor in our study. It is more important among men – whereas among women this is not what drives the intention to use electric buses. Prior studies have pointed to young women as a main target group for green products, owing to their higher environmental concern and responsibility (Lee, 2009). Our study also suggests that environmental awareness is a stronger motivator for non-riders compared to current or former bus riders. It could be that non-users feel some level of guilt for using polluting transport modes and wish to reduce their environmental footprint by shifting to e-buses.

Students of all genders need to be convinced that electric buses offer real utility over conventional buses or other transport modes. This is also consistent with the extant literature on new technologies (Cheng and Huang, 2013; Wang et al., 2020; Yi et al., 2006). An obvious policy recommendation here is to highlight the usefulness of electric buses in promotional messages – in particular as compared to private cars and motorcycles.

Concerningly, our findings suggest the presence of crime in public transport, especially sexual harassment, which, as elsewhere, targets primarily female passengers (Ceccato and Loukaitou-Sideris, 2021; Smith, 2008). Further studies are needed to explore this problem and find ways to mitigate it. If ignored, transit crime may discourage the (re-)use of transit (Delbosc and Currie, 2012; Nguyen-Phuoc et al., 2021). However, we also found that those who proactively take measures to mitigate the risk of theft and sexual harassment on public transport are more likely to plan on using electric buses. To lure others to use this mode, better security measures should be introduced on electric buses compared to conventional buses.

Fortunately, fear of catching Covid-19 is not particularly strong (and is, in any case, mitigated by self-protection measures) because contagion has been relatively well-contained in Hanoi, the wearing of masks is mandated on buses, and mortality is much lower among younger cohorts such as students (Nguyen et al., 2021b; Stang et al., 2020). In other settings, fear of Covid-19 has had much more adverse impacts on public transport use (Barbieri et al., 2021; Beck et al., 2020; Hu and Chen, 2021). However, to assuage any concerns, it is important to keep enforcing measures such as face masks on electric buses and offer free hand sanitizer on board.

7. Conclusion

This study has implications for both theory and practice. In terms of *theory*, the major contribution is in elucidating young people's intention to use electric buses in a middle-income country (as opposed to highly developed countries where most prior research has been conducted). The most encouraging finding is that a majority of students are intent on using electric buses. This includes not only current bus users but also those who had quit using buses due to the pandemic and those who have never used public transport. In addition, the study has proposed a much-extended version of the Technology Acceptance Model, which has proven valid. Our model includes several constructs around the risks and benefits associated with bus travel, which appear to concern young people a great deal. The risk of sexual harassment is particularly salient for female riders and overrides the desire to embrace a green mode. We recommend that risk-related constructs (apart from the Covid-19 infection risk) be retained in future studies of bus ridership regardless of whether the buses are electric or conventional. Unlike other studies, fear of contracting Covid-19 did not emerge as a barrier to using public transport in Hanoi. Therefore, the results pertaining to infection risk may not be generalizable to other places that have been devastated by the pandemic. But this also means that our findings will remain valid in the post-pandemic period.

Not all intention will translate into actual behavior. To ensure concrete rather than hypothetical ridership, we recommend a number of *policy* interventions. It is vital that students be given an opportunity to try an e-bus as soon as possible – before the novelty wears off. To make the initial experience as positive as possible, and ensure return passengers, free services could be provided within a limited period (for example, the first month), beyond which students could obtain discounted bus passes. At the same time, the electric bus fleet should be expanded to meet student demand. (This is feasible as e-buses are domestically produced in Vietnam.) Where public transport offers quality and utility in addition to environmental friendliness, familiarity with this mode may breed habit rather than contempt. A key lesson is that, in Vietnam and similar settings, e-bus launches should be accompanied by a package of measures which highlight the safety, security, and innovativeness of this mode in addition to its environmental friendliness. E-buses should be framed as fundamentally different to the conventional buses of old. Once this mode is no longer a novelty, usage among university students and other youth should continue to be monitored in order to formulate supporting policies. More efforts need to be invested to increase the real utility and prevent crime, especially the sexual harassment of female riders. Marketing strategies should be tailored to different groups (including non-riders) rather than follow a one-size-fits-all approach.

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.

Acknowledgement

Appendix 1. Factor Loadings (FL) Cronbach's Alpha (CA), Composite reliability (CR), and average variance Extracted (AVE).

Constructs and the respective attitudinal statements	Male respondents				Female respondents			
	FL	CA	CR	AVE	FL	CA	CR	AVE
Behavioral intention (BI)		0.804	0.885	0.719		0.835	0.901	0.752
BI_1: I am willing to use electric buses in the future	0.887				0.877			
BI_2: I intend to use electric buses in the future	0.813				0.840			
BI_3: I will attempt to use electric buses in the future	0.842				0.883			
Security measures (SM)		0.894	0.921	0.701		0.888	0.917	0.690
SM_1: Ticket conductors of electric buses are responsible for protecting passengers	0.814				0.801			
SM_2: Video cameras are available on electric buses that capture all positions on board	0.832				0.845			
SM_3: Video cameras are available in many electric bus stops	0.854				0.859			
SM_4: Lightning is adequate on board of electric buses	0.831				0.831			
SM_5: Lightning is adequate at electric bus stations	0.856				0.816			
Environmental awareness (EA)		0.768	0.851	0.589		0.828	0.886	0.663
EA_1: I consider the potential environmental impact of my activities when making my decisions	0.705				0.831			
EA_2: I am concerned about climate change	0.860				0.844			
EA_3: I consider myself as environmentally responsible	0.789				0.895			
EA_4: I am willing to be inconvenienced in it means being more environmentally friendly	0.706				0.669			
Perceived ease of use (PEU)		0.769	0.867	0.685		0.822	0.893	0.736
PEU_1: If I want to use electric buses, this will be easy for me	0.867				0.883			
PEU_2: If I want to use electric buses, this will be simple for me	0.809				0.864			
PEU_3: If I want to use electric buses, I will not run into any problems	0.805				0.826			
Perceived risk of Covid-19 infection (PRCI)		0.819	0.892	0.734		0.857	0.913	0.777
PC_1: I see Covid-19 as a dangerous disease	0.886				0.899			
PC_2: Covid-19 can easily spread on buses	0.829				0.882			
PC_3: Contracting Covid-19 is scary	0.854				0.864			
Perceived risk of sexual harassment (PRSH)		0.831	0.885	0.723		0.873	0.922	0.798
PSHR_1: I am concerned about the risk of sexual harassment at bus stops	0.703				0.882			
PSHR_2: I am concerned about the risk of sexual harassment while getting on and off buses	0.893				0.897			
PSHR_3: I am concerned about the risk of sexual harassment aboard buses	0.937				0.900			
Perceived risk of theft (PRT)		0.802	0.882	0.713		0.843	0.905	0.761
PTR_1: I am concerned about the risk of theft at bus stops	0.864				0.887			
PTR_2: I am concerned about the risk of theft while getting on and off buses	0.849				0.868			
PTR_3: I am concerned about the risk of theft aboard buses	0.820				0.863			
Perceived usefulness (PU)		0.821	0.870	0.527		0.892	0.917	0.649
PU_1: Using electrical buses would make me more relaxed during my trip	0.718				0.765			
PU_2: Using electric buses would reduce noise	0.716				0.786			
PU_3: Using electric buses would reduce greenhouse gasses	0.765				0.839			
PU_4: Electric buses help people with disabilities be more mobile	0.711				0.773			
PU_5: Electric buses will contribute to the smart city concept	0.741				0.832			
PU_6: Electric buses will help reduce traffic congestion	0.705				0.837			
Personal innovativeness (PI)		0.757	0.861	0.673		0.807	0.886	0.721
PI_1: I look for ways to experiment with new technologies	0.831				0.856			
PI_2: I am usually a pioneer in trying new things/technology	0.817				0.844			
PI_3: I like to experience new things/technology	0.813				0.846			
Self-protection measures (SPM)		0.850	0.909	0.769		0.856	0.912	0.776
SPM_1: I regularly use my face mask onboard	0.896				0.904			
SPM_2: I limit physical contact and communication with others onboard	0.846				0.853			
SPM_3: I keep away from those with Covid-19 symptoms onboard	0.889				0.885			

*Legend*FL: Factor Loading [recommended value > 0.6]

  CA: Cronbach's Alpha [recommended value > 0.7]

  CR: Composite Reliability [0.95 > recommended value > 0.7]

  AVE: Average Variance Extracted [recommended value > 50%]

Appendix 2. Discriminant validity.

Con–struct	Fornell-Larcker Criterion										Heterotrait-Monotrait Ratio (HTMT)									
	SM	EA	PEU	PRCI	PRSH	PRT	PU	PI	SPM	SM	SM	EA	PEU	PRCI	PRSH	PRT	PU	PI	SPM	SM
Male respondents																				
BI	**0.848**																			
SM	0.269	**0.837**									0.469									
EA	0.546	0.218	**0.767**								0.668	0.314								
PEU	0.432	0.301	0.285	**0.827**							0.511	0.358	0.455							
PRCI	0.271	0.155	0.249	0.179	**0.857**						0.450	0.151	0.434	0.274						
PRSH	0.116	0.068	0.118	0.061	0.132	**0.850**					0.321	0.761	0.241	0.227	0.103					
PRT	0.212	0.494	0.234	0.120	0.129	0.049	**0.845**				0.454	0.598	0.448	0.316	0.269	0.488				
PU	0.648	0.171	0.543	0.458	0.175	0.077	0.162	**0.726**			0.796	0.319	0.688	0.586	0.328	0.186	0.348			
PI	0.481	0.201	0.425	0.465	0.208	0.027	0.124	0.501	**0.820**		0.696	0.401	0.592	0.719	0.283	0.216	0.391	0.713		
SPM	0.387	0.108	0.306	0.380	0.524	0.063	0.116	0.316	0.240	**0.877**	0.538	0.295	0.415	0.256	0.699	0.165	0.393	0.381	0.339	
Female respondents																				
BI	**0.867**																			
SM	0.407	**0.831**									0.315									
EA	0.569	0.271	**0.814**								0.678	0.248								
PEU	0.427	0.306	0.379	**0.858**							0.548	0.359	0.367							
PRCI	0.381	0.135	0.376	0.233	**0.882**						0.333	0.181	0.317	0.223						
PRSH	0.275	0.673	0.197	0.193	0.090	**0.893**					0.114	0.076	0.147	0.086	0.158					
PRT	0.381	0.517	0.379	0.263	0.230	0.420	**0.872**				0.249	0.566	0.287	0.147	0.160	0.079				
PU	0.687	0.284	0.599	0.507	0.287	0.164	0.303	**0.806**			0.792	0.202	0.669	0.574	0.209	0.083	0.191			
PI	0.572	0.339	0.488	0.588	0.236	0.182	0.324	0.606	**0.849**		0.617	0.242	0.549	0.608	0.261	0.044	0.158	0.634		
SPM	0.453	0.257	0.363	0.217	0.601	0.142	0.333	0.332	0.280	**0.881**	0.469	0.122	0.374	0.468	0.625	0.069	0.139	0.376	0.300	

Notes.

Fornell-Larcker criterion: the square root of the AVE value of a construct > values of correlations between such construct and others. Values in bold are the square root of the AVE value of the construct. The AVE values are shown in Appendix 1.

HTMT recommended value < 0.9.

BI: Behavioral Intention SM: Security Measures;

PEU: Perceived Ease of Use PRCI: Perceived Risk of Covid-19 Infection;

PRSH: Perceived Risk of Sexual Harassment PRT: Perceived Risk of Theft.

PU: Perceived Usefulness PI: Personal Innovativeness.

SPM: Self-Protection Measures EA: Environmental Awareness.

Appendix 3. Collinearity among constructs.

Construct	Variance Inflation Factor (VIF)																			
	SM	EA	PEU	PRCI	PRSH	PRT	PU	PI	SPM	SM	SM	EA	PEU	PRCI	PRSH	PRT	PU	PI	SPM	SM
	Male Respondents										Female Respondents									
BI																				
SM	1.463										2.238									
EA	1.593										1.817									
PEU	1.614							1.275			1.655							1.528		
PRCI	1.448									1.000	1.660									1.000
PRSH	1.031	1.002									1.878	1.214								
PRT	1.367	1.002									1.562	1.214								
PU	1.780										2.059									
PI	1.559			1.000				1.275			2.007			1.000				1.528		
SPM	1.626										1.742									

Notes.

VIF recommended value < 3.

BI: Behavioral Intention.

SM: Security Measures;

EA: Environmental Awareness.

PEU: Perceived Ease of Use.

PRCI: Perceived Risk of Covid-19 Infection;

PRSH: Perceived Risk of Sexual Harassment.

PRT: Perceived Risk of Theft.

PU: Perceived Usefulness.

PI: Personal Innovativeness.

SPM: Self-Protection Measures.

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