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Demographic and social differences in autonomous vehicle technology acceptance in Hungary

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ABSTRACT

Progress in automation has resulted in a growing number of autonomous vehicles (AVs). However, demographic and social differences behind the acceptance of AV technology are an emerging topic in the East-Central European region. These countries (e.g., Poland, Slovakia, Romania) move on a similar technological development path, and the social and economic conditions are alike; thus, Hungary represents this region well. This study contributes to fill this niche. We used quantitative research methods (factor analysis, Kruskal-Wallis H test, Pearson-correlation) to analyze with a snowball (non-probability) sampling. The Hungarian respondents (N=949) selected in the sample were interviewed through a face-to-face and online quantitative questionnaire. The results show that gender and age influence mostly the acceptance; residence and occupation have only partial influence. The propensity to take risks is significantly differentiated in almost all demographic segments. The results facilitate differentiation of users based on their demographic characteristics in AV adoption. Furthermore, the integration of risk propensity into the analysis helps to identify which potential user groups are more likely to overcome any fears of novelty or which clusters are more likely to adopt the current framework of safe transport without driver control. The outcomes are of interest to engineers, manufacturers and policy-makers who can adapt their products, services and taking measures to meet the mobility needs of potential users and introduce effective incentives to increase public acceptance of AVs.

1. Introduction

The term 'mobility' covers several types of human movements with different frequency, distance, and motivations (Muir et al., 2014; Vance et al., 2016). In our research we focused on a transportation-related interpretation, namely the relatively frequent movement of people over relatively short distances. In this context, we considered the following interpretation of mobility: transportation processes derived from spatial attributes of human needs (toward material goods, intellectual properties, and services) and activities. It covers the movement of people and information, such as passenger transportation and information communication processes. In passenger transportation, vehicles and their operation are increasingly automatized. Accordingly, we turned our attention to autonomous vehicles (AVs) and the demographic and social differences of their acceptance.

AVs, or driverless or self-driving vehicles, are not controlled by a human controller but by a robotic system (Paden et al., 2016). We

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are not talking about automatic but rather self-driving technology; automatic systems are usually applied in the case of fixed-track transport (Miskolczi et al., 2021). AV technology is developing rapidly. Several levels of automation can be distinguished (Kaur and Rampersad, 2018). According to the Society of Automotive Engineers (Society of Automotive Engineers (SAE), 2018), there are vehicles with conditional automation (Level 3), high automation (Level 4), and full automation (Level 5). Previous studies have examined the topic of automation in the context of technology acceptance models (Payre et al., 2014; Nees, 2016; Chen and Yan, 2019; Jászberényi et al., 2022; Kenesei et al., 2022); however, the impact of demographic variables on AV technology acceptance has been still promising research area and the transportation engineering implications have been a research niche.

It is becoming increasingly important to learn about the barriers that can hinder consumer acceptance of self-driving technology (Kyriakidis et al., 2015; Io et al., 2022; Krizsik and Sipos, 2023). These may be related to infrastructural, economic, or social elements. We focus on the latter, where we not only examine lifestyle and attitude factors (risk, perceived simplicity, trust, intention, etc.) but also try to find the characteristics of each segment based on its sociodemographic background. It is not just a question of how one factor relates to another or the degree of security perception, privacy risk, risk-taking, and perceived simplicity that should be addressed (Fagnant and Kockelman, 2015), but also which factors are more different according to the sociodemographic characteristics of individuals. Individual situations and conditions are also different, within the framework of which the consumer will decide on the use of the technology. Some authors have proposed that moderating variables, such as gender, age, driving experience, and voluntary use, could be incorporated in future studies (Osswald et al., 2012; Nastjuk et al., 2020). Technology acceptance is a very complex issue; it is influenced by many factors, such as attitude; perception; motivation, preference, demographics, mobility needs, relevant business models, and social, cultural, economic, and political environments (Milakis et al., 2017; Li et al., 2023).

Our research topic is especially relevant in the East-Central European region (e.g., Poland, Slovakia, Czech Republic, Romania), where the automotive industry's share within the entire economy is significant (around 10% of GDP), and thus, these countries' economic success depends on it (RSM Global, 2023). The automotive and related industries have significantly developed in these countries in the last decades. There were and are several investments in car manufactories by European and Asian investors (e.g., France, Germany, Japan, China). In many cases, these countries compete with each other for investors. More and more research and innovation actions are now associated with production and assembly processes. Hungary represents the East-Central European region well because the trends in the automotive industry and the socioeconomic processes are similar in the mentioned countries.

In Hungary, several initiatives have boosted research, development, and innovation. The so-called national laboratories manage and support the most relevant research activities in this field (Autonomous Systems National Laboratory, 2023). Besides, the ZalaZONE test track (ZalaZONE, 2023) has been established in the last few years to attract companies, universities, and research labs from all over the world, especially Europe, to test their innovative solutions.

The key motorization indicators in Hungary provided by the Central Statistical Office (KSH – Hungarian Central Statistical Office, 2023) also confirm the topic's relevance. The motorization rate has recently exceeded 400 passenger cars/1000 inhabitants and shows an accelerated rate. The average age of cars is already above 15 years in early 2024, which is also increasing. Besides, worrying social processes can be observed; the population is decreasing (10 million inhabitants in 1980 while 9.7 million inhabitants in 2023) and ageing (average age is 36.2 years in 1980 and 43.2 years in 2023) simultaneously. Accordingly, accepting and using AVs could be an efficient solution for the mentioned worrisome trends. Thus, the mobility of older people and the high age of cars can also be solved.

Based on this approach, our research examined the sociodemographic differences in the main factors most encountered when using an AV. We examined perceived ease of use, intention to use, perceived safety risk, perceived privacy risk, and risk aversion (as an inverse factor of risk propensity). Along these factors, we examined differences by gender, age, occupation, education, and place of residence.

The research questions are as follows:

1. Do gender and age as variables show a significant relationship with the examined factors?
2. Which factors are affected by educational background, place of residence, and occupation?

We consider and study a future mobility system where predominantly AVs with the highest automation level (SAE5) are used as private cars or in public mobility services. However, SAE 3/4/5 will co-exist with only a few vehicles today. Accordingly, the respondents participating in the survey answered the questions based on their current knowledge about AVs with the highest automation level, regardless of whether these vehicles are ready for implementation. Their stated preferences were investigated, and the statements about the envisaged future mobility system when the SAE5 level becomes a reality (Krizsik and Sipos, 2023).

To motivate travelers to use AVs and AV-based mobility services, it is necessary to understand their attitudes and concerns by revealing deeper correspondences (Lukovics et al., 2023). Public or 'user' acceptance is a crucial factor for the successful implementation of AV-based services and, potentially, a more significant barrier than the novelty of the technology to the adoption of AVs. Many of the benefits depend on the critical mass of a product or service. The future mobility system elements and their capacities should be determined according to the demands. Travel demand primarily derives from social and economic structures and land use. Their alteration influences the volume and spatial-temporal attributes of the demand and the modal-share among transportation modes. If the transportation system cannot provide a satisfactory service (in terms of both quantitative and qualitative aspects), some mobility needs do not appear as travel demands.

The rest of this paper is organized as follows: In Section 2, we present the theoretical background. In Section 3, we introduce the research methodology with measurements and data analysis steps and present and discuss the results, along with their limitations. In Section 4, we summarize the transportation engineering implications. In Section 5, we discuss the results. Section 6 concludes and summarizes the key findings and the future research directions.

2. Theoretical framework

Perceived usefulness and perceived ease of use are the main factors in the acceptance of new technologies (Chen, 2019). Perceived use is derived from the Technology Acceptance Model (TAM) and expresses the extent to which a technology improves operation or performance (Venkatesh and Davis, 2000; Venkatesh et al., 2003). Perceived ease of use expresses the degree of decrease in required effort when the technology is used (Davis et al., 1989). Zhang et al. (2019) assessed how new technology is beneficial. Its interpretation is very close to the performance expectancy factor that appeared in the Unified Theory of Acceptance and Use of Technology (UTAUT) model. Perceived ease of use refers to how much physical and/or mental effort is required to use the new technology and how easy it is to understand how to use it (Venkatesh and Davis, 2000; Venkatesh et al., 2003 Acheampong and Cugurullo, 2019). Featherman and Pavlou (2003) defined perceived ease of use as the level of effort decrease that is expected by a user. At the same time, the factor can be interpreted as the opposite of perceived difficulty (Chen, 2019). Perceived ease of use is interpreted as the convenience of using the technology (Amin et al., 2014). In the Theory of Planned Behavior (TPB) model, the perceived behavioral control (Ajzen, 1991) and effort expectancy factors in UTAUT (Venkatesh et al., 2003; Xu et al., 2018) have a similar sense, meaning the degree of ease of use of the technology (Oh and Yoon, 2014).

Behavioral intention has a direct impact on the actual use of technology (i.e., it shows how much an individual will use the technology). It is a measure of the strength of one's intention to perform a focused behavior (Al-Emran and Granić, 2021). This definition is also used by the Theory of Reasoned Action (TRA) model and TAM (Oh and Yoon, 2014). TAM highlights the stable relationship between behavioral intention and attitude, which suggests that those who are positive about new technologies also have a stronger behavioral intention to use them (Zhang et al., 2019). Behavior theory also confirms that behavior is preceded by intention and that behavioral intention is linked to three factors: attitude toward behavior, perceived behavioral control, and subjective norm (Acheampong and Cugurullo, 2019).

Risk propensity mostly refers to a person's risk aversion or intention (Cho and Lee, 2006). Early authors tended to link the levels of risk-taking to personality type (Fischhoff et al., 1981), but later in the 1990 s, it was more closely linked to individual behavior (Sitkin and Pablo, 1992; Taylor et al., 1996). Risk propensity is the level of risk-taking an individual considers to be useful to maximize the chances of gaining a potential benefit (Kusumasondjaja, 2015). This is related to the fact that the more likely a person is to take risks, the less likely they are to perceive a risk (Cho and Lee, 2006). This is why it is sometimes a problem that company managers and CEOs tend to be more risk-taking, which can lead to the company falling into over-risk-taking (Boustanifar et al., 2022). Individuals perceive the risk of a given situation differently, a perception that can significantly determine their risk-taking intention (Baz et al., 1999). This perception determines whether a given risk is considered too high or acceptable by the subjects. This disposition can influence risk perception because it can induce bias or relativization (Brockhaus, 1980). It is all a matter of weighing who gives what probability to positive and negative outcomes (Wang et al., 2015). However, Wang et al. (2015) showed that increased risk-taking intention decreases the degree of risk perception. The degree of risk-taking also depends on trustworthiness, i.e. the more trustworthy something is, the more likely individuals are to take risks (Alarcon and Jessup, 2023).

In classical decision theory, risk is generally seen as a risk that reflects the probability and distribution of subjective values of possible outcomes (Mitchell, 1999). Bauer (1960, 1967, 24) first mentioned perceived risk as a factor that influences customer decision-making, which he defined as follows: "Consumer behavior is a risk in the sense that any action by a consumer will result in consequences that (s)he cannot predict with some approximate certainty, some of which are likely to be unpleasant".

Perceived fears and anxieties as latent variables are relevant to safety for prospective users (Acheampong and Cugurullo, 2019). Safety risk is most typical for AV passengers and other road users. Security risk is the most common cause of anxiety regarding the use of AVs (Zmud et al., 2016); it is primarily the risk of system and equipment failure (Zhang et al., 2019). Osswald et al. (2012) link behavioral anxiety to the operation of the system, as the passenger in the AV might lose control of the car. Safety risk indicates possibilities that the product could malfunction or work improperly, thereby failing to achieve the expected benefits (Grewal et al., 1994; Featherman and Pavlou, 2003), so it is closely tied to performance. Osswald et al. (2012) also approached the concept from the perspective of perceived safety, which is the individual's perception of the use of the system, i.e., their own driving abilities and feelings of safety vis-à-vis other drivers.

Perceived privacy risk is associated with losing control of personal data. That occurs when personal information is used and/or shared without permission (Featherman and Pavlou, 2003); when it is passed on to government, vehicle developers, insurance companies, or third parties without prior notice or consent from users; or when the data is used negatively against users (Zhang et al., 2019).

We considered the following sociodemographic variables:

- Gender
- Age
- Educational background
- Occupation
- Residence

We summarize the main contributions from the literature alongside the sociodemographic variables.

2.1. Differences based on gender

Gender as a demographic variable in connection with technology acceptance appears in most research, but its moderating effect is considered only in a few cases. Although the original TAM did not include gender as a variable, TAM 2 showed that perceived usefulness was outstanding for men, and perceived ease of use was outstanding for women (Venkatesh et al., 2003). Zhang et al. (2019) examined the acceptance of Level 3 AVs and found that men are more positive toward perceived usefulness and perceived ease of use. Acheampong and Cugurullo (2019) also confirmed that men perceived more benefits of AVs.

The UTAUT model supports the fact that performance expectancy does not determine behavioral intention; namely, the effect of performance expectancy is stronger for men. The effect of effort expectancy on behavioral intention is more observable for women (Venkatesh et al., 2003). Gender as a variable has a significant relationship to willingness to travel by AVs with men being more open to it (Alessandrini et al., 2014; Dong et al., 2019). In relation to robot technology, (Hudson et al., 2016) stated that men's attitude is more positive. Bansal et al. (2016) examined attitudes toward the use of automation technologies and acceptance of the use of shared AVs and found that men have a more positive attitude toward AVs. According to Saeed et al. (2020) women are less likely to adopt AVs than men. The fact that women (Plaut, 2006; Van Acker and Witlox, 2010) spend substantially less time in a car also leads to a gender gap. Payre et al. (2014) found that men are more in favor of AVs than women.

In risk-related research, Byrnes et al. (1999) found that women are more prone to risk aversion. Meertens and Lion (2008) also found a significant difference in risk propensity; namely, male students have a higher risk propensity. Some attribute the risk-taking attitude more to men (Czerwonka, 2019) or to certain cultures where the distance from power may moderate risk-taking (Antoncic et al., 2018; Syahrivar et al., 2021). Schoettle and Sivak (2014) found that men have a more favorable attitude; they consider AVs safer and more prominently perceive the benefits of reduced emissions and fuel consumption. Meanwhile, women are concerned about equipment failure, the proper handling of unforeseen situations, legal liability, and privacy issues. Men generally perceive fewer risks in new technologies (Hudson and Orviska, 2011; Zhu et al., 2022). The study by Acheampong and Cugurullo (2019) suggests that women are more skeptical about the benefits of technological development than men, and that women perceive a higher safety risk in AVs, making them less likely to adopt AVs. Safety is more important for women (Koul and Eydaghi, 2020).

H_{1a}: Perceived ease of use for AVs is higher for men.

H_{1b}: Intention to use AVs is higher for men.

H_{1c}: Risk propensity for AVs is higher for men.

H_{1d}: Risk perception (safety and privacy) of AVs is higher for women.

2.2. Differences based on age

Several studies support that perceived usefulness and perceived ease of use negatively correlate with age. The older (X generations or Baby boomers) someone is, the less useful they find the technology and its use (Yang et al., 2013). We can describe them as late adopters of AV technology (Ruggeri et al. 2018). Young people are more positive about perceived use and better perceive the benefits of AV usage (Acheampong and Cugurullo, 2019; Zhang et al., 2019). As the perception of expected benefits decreases with age, the advantages of AVs, such as engaging in other leisurely or active activities while traveling, become less important for users.

Attitude toward behavior is more prominent among young employees (Venkatesh and Davis, 2000). The UTAUT model supports that age also determines behavioral intention in performance expectancy, and the effect of performance expectancy is stronger in the case of young people. The effect of effort expectancy on behavioral intention is more observable for older (X generations or Baby boomers) employees (Venkatesh et al., 2003). Age is significantly associated with a willingness to travel (Dong et al., 2019). Younger (Z or Y generations) people are more open to travel by autonomous buses; meanwhile, elderly people are more dismissive of the subject. Older people with a certain educational background are less accepting of the use of robot technology (Hudson et al., 2016). Young people are more open and more willing to use shared AVs (Haboucha et al., 2017). Older (X generations or Baby boomers) people are fundamentally less interested in autonomous technologies, because they are generally concerned about learning to use new technologies (Bansal et al., 2016). Nomura et al. (2009) also found that a negative attitude toward the acceptance of new technologies increases with age. As older people spend significantly less time in a car (Schwanen et al., 2004), this also affects their intention to use AVs.

There is a significant association between age and risk tolerance; young people are more tolerant of risks (Mandal and Roe, 2014; Schoettle and Sivak, 2014). We can also see that younger (Z or Y generations) people have lower risk perception on the road generally (Rhodes and Pivik, 2011; Hassan and Abdel-Aty, 2013; Laiou et al., 2021). Although young people have less knowledge about genetic engineering, older (X generations or Baby boomers) people are more likely to perceive safety risks (Hudson and Orviska, 2011).

H_{2a}. Perceived ease of use for AVs is higher for younger people (Z or Y generations).

H_{2b}. Intention to use AVs is higher for younger people (Z or Y generations).

H_{2c}: Risk propensity for AVs is higher for younger people (Z or Y generations).

H_{2d}: Risk perception (safety and privacy) of AVs is higher for older people (X generations or Baby boomers).

2.3. Differences based on educational background

Several studies show that perceived usefulness and perceived ease of use positively correlate with educational background; the higher their education, the more useful they find the technology and its use (Acheampong and Cugurullo, 2019). The negative trend of those with lower education toward perceived ease of use is significant (i.e., the use of AVs is considered increasingly simple with the increase in education [Zhang et al., 2019]). A higher level of education also has a positive effect on perceived benefits and perceived ease of use (Acheampong and Cugurullo, 2019).

Knowledge of the technology strengthens willingness to travel by autonomous buses (Dong et al., 2019). People with higher education are more open and more willing to use shared AVs (Haboucha et al., 2017), and those with technological knowledge have a more positive attitude toward AVs (Bansal et al., 2016). Educational background in the context of science and technology has a positive effect on acceptance (Nomura et al., 2009). The risk aversion rate is also lower for those with higher educational background (Liu et al., 2022). Higher (tertiary) education has a positive correlation with attitudes toward technology (Acheampong and Cugurullo, 2019). People with higher education perceive less risk in new technologies (Hudson and Orviska, 2011; Liu et al., 2022; Al-Emran and Griffy-Brown, 2023).

H_{3a}. Perceived ease of use for AVs is higher for higher educated people.

H_{3b}. Intention to use AVs is higher for higher educated people.

H_{3c}. Risk propensity for AVs is higher for higher educated people.

H_{3d}. Risk perception (safety and privacy) of AVs is higher for lower educated people.

2.4. Differences based on occupation and residence

People with higher income and living in cities prefer to use AVs as an alternative means of transport (Bansal et al., 2016), because this opportunity can be easy to use for them (Yap et al., 2016). Consequently, individuals from such backgrounds are also at lower risk of being perceived (Kenesei et al., 2022). The introduction of a new technology tends to be riskier for those living in rural areas, as in many cases, its positive impact is felt only later (Hudson and Orviska, 2011).

Students are more open and more willing to use shared AVs (Haboucha et al., 2017; Arpaci et al., 2023). Furthermore, better social status (employment position, higher income, education) can also make take more risks (Deb et al., 2017). In general, employees and students also perceive the use of technology as easier (Al-Emran et al., 2021; Arpaci et al., 2023). Retirees are included in the group of people without work (and therefore we do not use the term 'unemployment' in a general sense, but refer to people without work) in our research, so based on the previous findings related to age, it can be assumed that people without work (also due to the higher average age) perceive a higher risk (Liu et al., 2022).

H_{4a}. Perceived ease of use for AVs is higher for city residents.

H_{4b}. Intention to use AVs is higher for city residents.

H_{4c}. Risk propensity for AVs is higher for city residents.

H_{4d}. Risk perception (safety and privacy) of AVs is higher for rural residents.

H_{5a}: Perceived ease of use for AVs is higher for employees and students.
H_{5b}: Intention to use AVs is higher for employees and students.
H_{5c}: Risk propensity for AVs is higher for employees and students.
H_{5d}: Risk perception (safety and privacy) of AVs is higher for people without work.

Overall, most appear to have found significant differences based on gender and age for several of the factors we also examined (Table A1). Furthermore, employment status and education are also somewhat decisive. We have identified three main research gaps during the literature synthesis. In most of the literature reviewed, demographic differences have been a subsidiary finding; deeper analysis, which primarily focuses on demographic differences, is a research gap. On the other hand, the opinion of Hungarians on autonomous vehicles is also a promising research area in the literature. Finally, both the core factors associated with TAM (perceived ease of use, intention to use AVs) and risk perception and associated sub-factors (risk propensity, perceived safety risk and perceived privacy risk) have also not been addressed in the AV literature mainly focusing on demographic differences. Our research seeks to fill these niches.

3. Methods

We used the online questionnaire with the Computer Assisted Web Interview (CAWI) technique for the analysis. Participation was voluntary in this research, so there was no fee or gift for valid responses. We want to reach a large sample for our research cost-efficiently. We used the Qualtrics system for data gathering because, in this software, the respondent can continue the questionnaire after a more extended break, too. We want to obtain a large sample to conduct the most robust statistical tests of relationships between the main demographic variables that answer our primary objectives and questions. With the online questionnaire, we can be relatively cost efficient and sustainable, and we can generate easily accessible data. We followed our ethical rules regarding the data-gathering process.

We used Pearson correlation, as well as multivariate non-parametric tests (Kruskal-Wallis test) with quantitative research analysis. We collected more than 1000 respondents with snowball sampling technic; but, at the end we had 949 valid responses. We filtered out

Table 1
Factors, statements used to assess them, and sources.

Factors	Statements	Factor weights	Total Variance Explained	Sources
Perceived ease of use	Learning to use AVs will be easy for me	0.927	0.809	Modified from Zhang et al. (2019), Xu et al. (2018), and Osswald et al. (2012)
	I will find it easy to get AVs to do what I want them to do	0.924		
	It will be easy for me to become skillful at using AVs	0.919		
	I will find AVs easy to use	0.843		
	I think an AV is easy to control	0.852		
	I think an AV is easy to learn to use	0.878		
	I think an AV is easy to understand	0.908		
	Learning how to operate the system is easy for me	0.941		
Intention to use	I predict I will use AVs in the future	0.916	0.835	Zhang et al. (2019) and Osswald et al. (2012)
	I plan to use AVs in the future	0.940		
	I will purchase an AV as my next car	0.875		
	If the AV is available, I plan to use it in the future	0.924		
Risk propensity	I prefer to avoid risks	0.730	0.515	Meertens and Lion (2008)
	Safety first	0.636		
	I do not take risks with my health	0.777		
	I take risks regularly (inverse)	0.865		
	I really dislike not knowing what is going to happen	0.450		
	I usually view risks as a challenge (inverse)	0.629		
	I view myself as a risk-taker (inverse)	0.844		
Perceived safety risk	There is a good chance that something will go wrong when using AVs	0.847	0.563	Zhang et al. (2019) and Featherman and Pavlou (2003)
	AVs may not perform well, and problems may occur during their use	0.805		
	AV use will be risky for me	0.787		
	I am concerned about the overall safety of a particular technology	0.722		
	I would worry that a mistake while using an AV would cause an accident	0.558		
Perceived privacy risk	I am concerned that AVs will collect too much personal information from me	0.838	0.785	Zhang et al. (2019) and Featherman and Pavlou (2003)
	I am concerned that AVs will use my personal information for other purposes without my authorization	0.950		
	I am concerned that AVs will share my personal information with other entities without my authorization	0.865		

respondents who gave the same score for the attitude scales throughout, those who took less than 2 minutes to complete the questionnaire, and those who gave the wrong answer to our four control questions. These methods minimized the common method bias. We used quantitative techniques (factor analysis, Kruskal-Wallis test, Pearson-correlation) because we had a large sample, and we wanted to know the statistically significant differences between individuals through demographic variables (Kim et al., 2019; Logan et al., 2019). In this section, we show first our data collection method as well as the statements and factors. to be assessed. Then, we present the sample characteristics and summarize the data analysis tools statistical test.

3.1. Data collection

Our data collection was based on an online questionnaire survey consisting of two main parts. The first part asked about demographic characteristics. In the second part, we provided the definition of Level 5 vehicles as 'When we talk about full automation, we talk about a vehicle that performs all driving tasks automatically.' Here, the questions were formulated according to the factors shown in Table 1. Based on the literature review, we applied validated scales. The factors were mostly based on some statements of the initial (TAM1, 2, 3) and revised (UTAUT1, 2) TAM theory and the theory of perceived risk, with a research focus on AVs or other similar digital technologies. Some we took from previous studies specializing in AVs, others from the theory of general perceived risk (e.g., risk propensity). Respondents rated the statements on a Likert scale from 1 to 7, where 1 strongly disagreed and 7 strongly agreed. We used the risk propensity scale in an inverse way, so a higher value means more risk averseness.

3.2. Sample characteristics

We conducted the questionnaire survey online (CAWI – Computer Assisted Web Interview) in Hungarian language through the Qualtrics system in November and December 2019 through Hungarian university students and their acquaintances. Random selection and snowball sampling were applied in three steps (Goodman, 1961). We asked university students in the first step because we had to ask over 18-year-olds for research in Hungary. After snowball sampling, we could also reach their acquaintances and others from Hungary in the second and third steps. With this filtering process, we have found representatives of the older age group through the younger age group (Browne, 2005). There was no fee or gift for the participants in our research. The demographic variables as well as the proportion of responses are summarized in Table 2.

The mean age of the respondents was 30.7 years (SD=16.6 years). The youngest respondent was 18 years old, the oldest was 75. The proportion of people living in the capital or other cities (33%-33%) as well as the proportion of people living in the county seat and village (16%–17%) were quite similar. Half of the respondents were students (56.3%), and fewer than 10% were self-employed or retired.

3.3. Data analysis

In addition to the basic descriptive statistics, we used Pearson correlation, as well as multivariate non-parametric tests, to examine the relationships between the factors and demographic variables. We used the non-parametric test (Kruskal-Wallis H test for two or more than two grouping criteria) to compare Likert-scale statements and non-metric statements. For the Kruskal-Wallis H test, we used Tomczak and Tomczak's (2014) test strength formula, and we calculated the value of the eta square (η^2). We consider Likert-scale statements as a metric element. To sort the statements into factors, we first performed exploratory factor analysis (EFA), using the Maximum Likelihood Estimation (MLE) method, with Promax rotation. The analysis was performed with IBM SPSS 25 and IBM SPSS AMOS Graphics licensed software.

4. Results

To answer the research questions, the obtained differences in relation to the factors are summarized in Tables 3 and 4. The grouping

Table 2
Sample characteristics.

Demographic variable	Value set	Frequency	Proportion (%)	Percentage of total population (%)
Gender	Male	369	38.9	48.8
	Female	580	61.1	51.2
Residence	Capital city	314	33.1	19.4
	County city	155	16.4	21.4
	Other city	313	33.0	30.6
	Village	166	17.5	28.6
Educational background	Primary	46	4.9	28.8
	Secondary	607	65.3	52.4
	Tertiary	277	29.8	18.8
Occupation	Student	517	56.3	16.9
	Employee	273	29.7	55.8
	Self-employed	66	7.2	2.1
	Retired	62	6.8	25.2

Table 3
Significant differences in relation to factors and demographic variables.

Demographic variable	Group criterion	Factors	Value of test statistics (H)	Test strength (η^2)	Average rank value	Mean
Gender (N=948)	Male	Perceived ease of use	75.589***	0.08	571.35	3.92 (0.96)
	Female				412.78	3.33 (1.04)
	Male	Perceived safety risk	10.896***	0.01	437.73	4.74 (0.99)
	Female				497.93	4.95 (0.79)
	Male	Perceived privacy risk	1.987	Not relevant	458.80	3.92 (1.19)
	Female				484.51	4.01 (1.17)
	Male	Risk propensity (inverse)	32.091**	0.03	411.40	4.33 (1.03)
	Female				514.72	4.73 (0.83)
	Male	Intention to use	7.256**	0.01	504.51	1.99 (0.96)
	Female				455.38	1.86 (0.89)
Residence (N=948)	Capital city	Perceived privacy risk	3.815	Not relevant	457.49	3.92 (1.19)
	County city				477.58	3.99 (1.17)
	Other city				486.90	4.04 (1.16)
	Village				504.89	4.09 (1.17)
	Capital city	Perceived safety risk	2.187	Not relevant	465.49	4.84 (0.90)
	County city				456.82	4.80 (0.89)
	Other city				493.35	4.95 (0.81)
	Village				480.59	4.89 (0.95)
	Capital city	Risk propensity (inverse)	10.295*	0.01	451.85	4.51 (0.93)
	County city				452.39	4.46 (1.07)
	Other city				517.44	4.71 (0.88)
	Village				489.42	4.64 (0.89)
	Capital city	Intention to use	11.799**	0.01	500.74	2.00 (0.89)
	County city				434.31	1.77 (0.98)
	Other city				465.81	1.88 (0.91)
	Village				420.22	1.72 (0.93)
	Capital city	Perceived ease of use	4.829	Not relevant	489.75	3.64 (0.99)
	County city				485.07	1.10 (1.04)
	Other city				447.55	3.44 (1.11)
	Village				451.52	3.47 (1.10)
Occupation (N=918)	Student	Intention to use	28.485***	0.03	477.20	1.97 (0.92)
	Employee				450.07	1.88 (0.95)
	Self-employed				512.26	2.09 (0.75)
	Retired				297.23	1.36 (0.80)
	Student	Perceived safety risk	4.329	Not relevant	487.08	4.90 (0.87)
	Employee				446.17	4.80 (0.91)
	Self-employed				471.17	4.85 (0.99)
	Retired				490.28	4.91 (0.79)
	Student	Perceived privacy risk	15.484**	0.02	460.61	3.92 (1.14)
	Employee				461.66	3.93 (1.21)
	Self-employed				491.26	4.10 (1.28)
	Retired				578.63	4.40 (1.17)
	Student	Risk propensity (inverse)	45.614***	0.05	422.65	4.45 (0.92)
	Employee				496.46	4.70 (0.94)
	Self-employed				424.44	4.45 (0.92)
	Retired				641.37	5.18 (0.78)
	Student	Perceived ease of use	72.171***	0.08	476.62	3.66 (0.97)
	Employee				485.89	3.67 (0.99)
	Self-employed				475.35	3.60 (1.01)
	Retired				183.71	2.24 (1.16)
Educational background (N=930)	Primary	Intention to use	0.395	Not relevant	451.24	1.91 (0.88)
	Secondary				469.35	1.92 (0.94)
	Tertiary				459.44	1.89 (0.88)
	Primary	Perceived safety risk	7.379*	0.01	455.43	4.81 (0.87)
	Secondary				482.53	4.92 (0.89)
	Tertiary				429.86	4.76 (0.85)
	Primary	Perceived privacy risk	2.604	Not relevant	524.70	4.22 (1.23)
	Secondary				465.49	3.98 (1.17)
	Tertiary				455.68	3.95 (1.22)
	Primary	Risk propensity (inverse)	2.802	Not relevant	464.28	4.59 (0.99)
	Secondary				455.35	4.54 (0.93)
	Tertiary				487.95	4.64 (0.94)
	Primary	Perceived ease of use	0.749	Not relevant	449.04	3.45 (1.25)
	Secondary				461.76	3.56 (1.05)
	Tertiary				476.43	3.59 (0.99)

Notes: ***: $p<0.001$; **: $p<0.01$. *:$p<0.05$. The standard deviations are shown in parentheses. The value of η2 by Tomczak and Tomczak (2014)

Table 4
Pearson correlation values between age and the measured factors.

	Intention to use	Perceived safety risk	Perceived privacy risk	Risk propensity (inverse)	Perceived ease of use
Age	-0.136***	0.011	0.131***	0.216***	-0.265***

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

criteria indicate the subgroups of one demographic statement in which we can find the significant differences alongside the factors.

The most relevant differentiating factors are gender (Table 3) and age (Table 4). In both cases, the biggest difference is in the perceived ease of use factor, as men and younger (Z or Y generations) people find AV technology simpler. Risk aversion is higher for women and older (X generations or Baby boomers) people. However, we found fewer significant differences in risk perception, as men have lower perceived safety risk. Regarding perceived privacy risk we did not find a gender difference, while perceived privacy risk increases with age. Men and younger (Z or Y generations) people intend to try AV technology on the roads. Yet, in the case of risk perception, less-significant differences are observed. It seems that the degree of risk-taking intention is the most significant segmenting factor, and not what risks are perceived by individuals with different sociodemographic backgrounds. This is also supported by the results; there is little difference in risk perception according to occupation, residence, and educational background (Table 3). There is no difference at all in the case of residence, while the perceived safety risk is slightly higher for those with lower education and the perceived privacy risk is higher for people without work (e.g. retired). The mean age is also high in both groups, which may moderate this result. There are no significant differences for the other factors either, but the value of risk propensity typically differs between groups.

5. Discussion

Gender is the variable that affects all five factors. Men are more open to AVs and perceive them as less risky. According to technology acceptance models, men find it more useful to introduce new technologies and are more willing to use them. Previous studies also support the fact that men are more willing to use new technologies (Hudson et al., 2016); their willingness to use (Bansal et al., 2016) and travel (Dong et al., 2019) with AVs are higher than women's. They also perceive the usability of AVs to be simpler, while women are primarily risk averse (Byrnes et al., 1999; Meertens and Lion, 2008). Women perceive privacy risk and safety risk (Acheampong and Cugurullo, 2019) much more than men. The gender gap in acceptance is also exacerbated by the fact that men typically have more knowledge about AVs and are therefore more confident. For this reason, it is important to involve women in conversations and debates about AVs, which would increase their acceptance through seeing the benefits of AV usage more clearly (KPMG, 2013). The stronger presence of ladies in AV technology communication is essential. This can help not only the acceptance of AV technology, but also the openness of a society to the widest use of AV technology. However, when exploring gender differences, it is worth noting that in many cases, some of the different reactions stem from gender roles and socialization processes arising from birth, and not specifically from biological gender differences (Lynott and McCandless, 2000). It is worthwhile examining the gender differences with consideration of the age factor, as gender differences are often only temporary (Levy, 1988).

The second most influential demographic variable is age. Young people show the highest intention to use AVs. The result is consistent with all previous research findings, showing that older (X generations or Baby boomers) people are less open to using this technology (Bansal et al., 2016), and their willingness to travel is lower than that of young people (Dong et al., 2019). In terms of perceived ease of use, we found that 21–29-year-olds perceive AVs to be the easiest to use, while those over 60 find it the least easy to use, which is also consistent with previous research (Yang and Coughlin, 2014; Acheampong and Cugurullo, 2019). Shared AVs could be an age-appropriate mobility option for older travelers, providing convenient and flexible mobility at low cost. According to our research, risk avoidance and risk perception appear stronger in those over 40. The high-risk tolerance of young people, highlighted by Mandal and Roe (2014) and Schoettle and Sivak (2014), is also supported by our present study. Respondents over 60 clearly engage in risk-averse reactions against AVs. Meanwhile, elderly people perceive a new technology as riskier and perceive its benefits to be fewer; it is more important for them to have easy access to AVs at any time. As the attitudes of men and young people are fundamentally positive, it will be worth demonstrating to women and the elderly that AVs are easy to use and offer several benefits, such as reducing congestion or increasing mobility. Perceived risk is reduced by information provision, such as what happens if an AV breaks down or data is lost, making both women and the elderly see it as less risky to use AVs, thus increasing their intention to use. These suggested measures can help older (X generations or Baby boomers) people become more involved and flexible in the use of mobility services based on AVs.

Regarding educational background, we found only one slight difference in the case of perceived safety risk. In terms of perceived ease of use, the higher the level of education, the easier the use of AVs (Acheampong and Cugurullo, 2019; Zhang et al., 2019). However, our research only partially supports this statement. Like the results of Zhang et al. (2019), we did not find a significant correlation between intention to use and educational background. However, previous research linked intention to use new technologies to higher education (Haboucha et al., 2017; Hudson et al., 2016) and knowledge of technology (Nomura et al., 2009; Bansal et al., 2016; Dong et al., 2019). The relationship among risk propensity, perceived risk, and education is a less researched area. Our study did not support the relationship between educational level and perception of safety risk, contrary to what Hudson and Orviska (2011) found. That education does not segment people can foster a greater acceptance of AVs at the level of other social structure elements.

From a demographic point of view, residence and occupation are also important factors, but these areas are quite under-researched, in terms of both technology acceptance and AV acceptance. Students and working people find it easier to use AVs, and retirees and the unemployed do not find it easy. This is partly reflected by Yang et al. (2013). On the other hand, there are sensory features in such cars that will support technology acceptance by the elderly (Yang and Coughlin, 2014). Haboucha et al. (2017) emphasize students' willingness to use, which is also supported by our findings. Our research also confirms that people without work are the most risk averse (Mandal and Roe, 2014; Schoettle and Sivak, 2014). Rural residence and the lack of working status are found to influence performance safety risk perception (Hudson and Orviska, 2011), and this was also significant in our research. We found that people living in villages were more likely to perceive the risk of AVs, which is a novel result, compared to previous studies (Ruggeri et al., 2018). Previous studies suggest that those with higher incomes (Yap et al., 2016) and those living in the city (Bansal et al., 2016) show a greater propensity to use AVs; however, our present study did not support this relationship.

6. Conclusions and limitations

To answer our two main research questions, the first question (with H_{1a}-H_{1d}) shows that men find it easier to use AVs, and their intention to use them is also significantly higher. Compared to women, men also have significantly a higher risk propensity, a lower perceived privacy risk, and a lower perceived performance safety risk. Regarding the first question about the age differences (H_{2a}-H_{2d}), the age variable, younger (Z or Y generations) people show a greater intention to use an AV, which may result from a higher risk propensity and a lower perceived privacy risk. Young people also significantly and positively agreed on perceived ease of use. In terms of the second research question, the results of the occupation variable (H_{3a}-H_{3d}), the people without work (retired) group is more risk-averse, their intention to use AVs is very low, and they consider AV technology to be challenging. In our second research question, students show the highest risk propensity and the highest intention to use AVs (H_{5a}-H_{5d}). AVs' acceptance is higher for city residents, and they have a greater intention to use it than rural residents, but there is not any significant difference between the residence place through risk perception, which is another main answer to our second research question too (H_{4a}-H_{4d}). Typically, AV use acceptance factors differentiate mainly (perceived ease of use, intention to use) from a sociodemographic point of view, while factors related to risk perception and risk-taking tend to segment better for only one group, primarily by age and gender (youth and men). We summarized the results of hypotheses testing in Appendices (A2).

Our results support describing travel willingness directly and mobility system/service specification indirectly in the specific area (Hungary). The research subject is Level 5 AVs, which are not yet widely available for testing purposes. However, several successful experiments have been performed in the ZalaZONE test track (ZalaZONE, 2023), and experts believe a mass uptake of autonomous vehicles by 2030 (Rohr et al., 2016; Miskolczi et al., 2021; Krizsik and Sipos, 2023). In the absence of experience, the attitude toward these vehicles is relatively diverse, and it is based only on respondents' existing knowledge and stated preferences. Our results support experts (e.g., manufacturers and mobility service providers) in their efforts to segment their consumers better, personalize their products and services, provide customized information, and perform targeted awareness-raising campaigns. Accordingly, vehicle design can be improved and perfected, whether an interior feature (seat position, wheel position, design, etc.), a safer crash zone, or an advanced vehicle communication and control method.

To reveal the correspondences, we supplemented previous technology acceptance models and assessed the acceptance of AVs according to five factors. Demonstrating risk propensity in the analysis is one of the main findings of our research to the topic, as it has not been included in previous research. Results from examining the degree of risk propensity are useful to segment consumers by their individual characteristics, and the possible perceived risks can be overcome accordingly. In the theory of risk perception, if someone in a specific area does not have enough information to alleviate their potential fears, the individual falls back on their general self-confidence and thus to their willingness to take risks (Meertens and Lion, 2008).

Using our results, those in critical moments who feel some danger or just do not feel easy enough to use the vehicle can also be supported. Aversions and fears can be mitigated by simplifying use, enhancing safety, offering testing opportunities for the system, or providing other warranty support. In the knowledge of social characteristics, the transportation behavior and users' decision as well as transportation modal share can be significantly influenced by providing customized and personalized mobility services. From this perspective, the concept of safe travel today may change in the future, despite the risks that some people perceive when trying out autonomous vehicles. This is because, if the use of autonomous vehicles becomes widespread, this phenomenon may also increase the degree of risk-taking, even if the existence of possible objective risks (loss of control over driving, moral dilemmas, technological failures, phenomena of anthropomorphism) is not (or not willingly) perceived by the individual. And these risk perceptions may differ across cultures, there may also be differences between developing and developed countries, especially on issues of loss of control and moral dilemmas. For this reason, the question of how each group overcomes or wants to overcome perceived or even non-perceived risk, i.e. the level of risk-taking, may be more important research fields in these differences. As Hungary strives to be at the forefront of technological research and innovation, potential users' acceptance is a critical element in the success of the entire automotive ecosystem.

Given the difficulty in accurately estimating the exact introduction of entirely autonomous vehicles (SAE level 5), it is conceivable that some current age groups will not be affected by the adoption issues of AVs (Krizsik and Sipos, 2023). There are many different scenarios in the studies, with some predicting the adoption of AVs by 2030 (Rohr et al., 2016; Miskolczi et al., 2021) and others predicting more years for the whole spread of AVs level 5 (Marletto, 2019) or even later from 2050 (Bagloee et al., 2016; Fulton, 2018). For this reason, it is challenging to estimate the expected attainment of the relevant age groups in social research. However, our research points out what Ruggeri et al. (2018) also suggest, that consulting current vehicle users and transport users can have a significant impact on the development of AVs, and that certain inconsistencies can be corrected by engineers in the current development process. In order to compensate for this, we have taken into account the differences in the attitudes and risk perceptions of certain age groups, and we have also presented these differences, so that the decision-maker can decide in the future what is relevant for him or her in the light of these detailed results. Our results are valid in such countries, where the socioeconomic conditions, the cultural background, the knowledge about autonomous vehicles as well as research, development and innovation ecosystem and the expected adoption of autonomous vehicles (Alatawneh and Török, 2023) are rather similar than that in Hungary.

Respondents do not correspond to the real population ratio for the study country. Since the majority of sample were young people, it would be worthwhile to further research the attitudes of older generations (Chen and Yan, 2019; Kökény and Kiss, 2021). In recent literature, mobility culture is also an important demographic variable (Kyriakidis et al., 2015; Hudson et al., 2016; Syahrivar et al., 2021). Accordingly, we are going to extend our survey to other countries, too. We could get better-fitting data using probability representative sampling instead of snowball sampling with filtering. However, the filtering could help us to gain a non-probability representative sample, which has similar domains as a representative sample, but it is not the same. We will also examine the impact on other factors in the immediate vicinity of TAM and the UTAUT model along demographic variables, such as trust, social influence, or support. Finally, we will compare the perceptions and demographics of those who completely reject AV technology (Ma, 2021) with our results. Life-cycle or lifestyle-based analyses are becoming more and more prominent in demographic measurement, so this type of research could be added to the results in the future. Continual research in this area is also motivated by the fact that individuals' interests in AVs are not stable over time.

CRediT authorship contribution statement

Melinda Jászberényi: Writing – review & editing, Supervision, Resources, Project administration, Conceptualization. **Katalin Ásványi:** Writing – review & editing, Resources, Investigation, Data curation, Conceptualization. **Csaba Csiszár:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization. **László Kökény:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Appendices

Table A1
Summary table of the individual research works

Author(s)	Methodology applied	Demographic differences	Measured factors in AV
Acheampong and Cugurullo (2019)	Quantitative SEM	Gender – Higher for men	*Perceived ease of use*
Zhang et al. (2019)	Quantitative SEM	Gender – Higher for men	*Perceived ease of use*
Venkatesh et al. (2003)	Quantitative SEM	Gender – Higher for women	*Perceived ease of use,*
Alessandrini et al. (2014)	Linear regression	Gender – Higher for men	*Intention to use*
Bansal et al. (2016)	Quantitative analysis	Gender – Higher for men	*Intention to use*
Dong et al. (2019)	Logit model, ANOVA	Gender – Higher for men	*Intention to use*
Hudson et al. (2016)	Quantitative analysis and regression	Gender – Higher for men	*Intention to use*
Payre et al. (2014)	Quantitative analysis	Gender – Higher for men	*Intention to use*
Plaut (2006)	Quantitative analysis	Gender – Higher for women	*Intention to use*
Saeed et al. (2020)	Quantitative modelling	Gender – Higher for men	*Intention to use*
Van Acker & Witlox (2010)	Quantitative SEM	Gender – Higher for women	*Intention to use*
Venkatesh et al. (2003)	Quantitative SEM	Gender – Higher for women	*Intention to use*
Antoncic et al. (2018)	Multinominal logistic regression	Gender – Higher for men	*Risk propensity*
Byrnes et al. (1999)	Quantitative analysis	Gender – Higher for men	*Risk propensity*
Czerwonka (2019)	Regression analysis	Gender – Higher for men	*Risk propensity*
Meertens & Lion (2008)	Quantitative analysis	Gender – Higher for men	*Risk propensity*
Acheampong and Cugurullo (2019)	Quantitative SEM	Gender – Higher for women	*Risk perception*
Hudson & Orviska (2011)	Quantitative analysis	Gender – Higher for women	*Risk perception*
Koul & Eydaghi (2020)	Multiple linear regression	Gender – Higher for women	*Risk perception*
Schoettle & Sivak (2014)	Quantitative analysis	Gender – Higher for women	*Risk perception*
Zhu et al. (2022)	Quantitative SEM	Gender – Higher for women	*Risk perception*
Acheampong and Cugurullo (2019)	Quantitative SEM	Age – Higher for younger people (Z or Y generations)	*Perceived ease of use*
Ruggeri et al. (2018)	Quantitative analysis	Age – Higher for younger people (Z or Y generations)	*Perceived ease of use*
Yang et al. (2013)	Quantitative analysis	Age – Higher for younger people (Z or Y generations)	*Perceived ease of use*
Zhang et al. (2019)	Quantitative SEM	Age – Higher for younger people (Z or Y generations)	*Perceived ease of use*
Bansal et al. (2016)	Quantitative analysis	Age – Higher for younger people (Z or Y generations)	*Intention to use*
Dong et al. (2019)	Logit model, ANOVA	Age – Higher for younger people (Z or Y generations)	*Intention to use*
Haboucha et al. (2017)	Quantitative analysis and modelling	Age – Higher for younger people (Z or Y generations)	*Intention to use*
Hudson et al. (2016)	Quantitative analysis and regression	Age – Higher for younger people (Z or Y generations)	*Intention to use*

(*continued on next page*)

Table A1 (*continued*)

Author(s)	Methodology applied	Demographic differences	Measured factors in AV
Nomura et al. (2009)	Quantitative analysis	Age – Higher for younger people (Z or Y generations)	*Intention to use*
Schwanen et al. (2004)	Quantitative analysis	Age – Higher for younger people (Z or Y generations)	*Intention to use*
Venkatesh et al. (2003)	Quantitative SEM	Age – Higher for younger people (Z or Y generations)	*Intention to use*
Venkatesh & Davis (2000)	Quantitative SEM	Age – Higher for younger people (Z or Y generations)	*Intention to use*
Hassan & Abdel-Aty (2013)	Quantitative analysis and modelling	Age – Higher for older people (X generations, Baby boomers)	*Risk perception*
Laiou et al. (2021)	Quantitative analysis	Age – Higher for older people (X generations, Baby boomers)	*Risk perception*
Mandal & Roe (2014)	Quantitative analysis and modelling	Age – Higher for younger people (Z or Y generations)	*Risk propensity*
Schoettle & Sivak (2014)	Quantitative analysis	Age – Higher for younger people (Z or Y generations)	*Risk propensity*
Hudson & Orviska (2011)	Quantitative analysis	Age – Higher for older people (X generations, Baby boomers)	*Risk perception*
Rhodes & Pivik (2011)	Regression modelling	Age – Higher for older people (X generations, Baby boomers)	*Risk perception*
Acheampong and Cugurullo (2019)	Quantitative SEM	Education – Higher for higher educated people	*Perceived ease of use*
Zhang et al. (2019)	Quantitative SEM	Education – Higher for higher educated people	*Perceived ease of use*
Acheampong and Cugurullo (2019)	Quantitative SEM	Education – Higher for higher educated people	*Intention to use*
Bansal et al. (2016)	Quantitative analysis	Education – Higher for higher educated people	*Intention to use*
Dong et al. (2019)	Logit model, ANOVA	Education – Higher for higher educated people	*Intention to use*
Haboucha et al. (2017)	Quantitative analysis and modelling	Education – Higher for higher educated people	*Intention to use*
Nomura et al. (2009)	Quantitative analysis	Education – Higher for higher educated people	*Intention to use*
Liu et al. (2022)	Quantitative SEM	Education – Higher for higher educated people	*Risk propensity*
Al-Emran & Griffy-Brown (2023)	Quantitative analysis	Education – Higher for lower educated people	*Risk perception*
Hudson & Orviska (2011)	Quantitative analysis	Education – Higher for lower educated people	*Risk perception*
Liu et al. (2022)	Quantitative SEM	Education – Higher for lower educated people	*Risk perception*
Yap et al. (2016)	Quantitative analysis and modelling	Residence – Higher for cities	*Perceived ease of use*
Bansal et al. (2016)	Quantitative analysis	Residence – Higher for cities	*Intention to use*
Deb et al. (2017)	Quantitative analysis	Residence – Higher for cities	*Risk propensity*
Hudson & Orviska (2011)	Quantitative analysis	Residence – Higher for rural areas	*Risk perception*
Kenesei et al. (2022)	Quantitative analysis	Residence – Higher for rural areas	*Risk perception*
Al-Emran et al. (2021)	Quantitative SEM	Occupation – Higher for students	*Perceived ease of use*
Arpaci et al. (2023)	Quantitative SEM	Occupation – Higher for employees	*Perceived ease of use*
Arpaci et al. (2023)	Quantitative SEM	Occupation – Higher for students	*Intention to use*
Deb et al. (2017)	Quantitative analysis	Occupation – Higher for students	*Risk propensity*
Haboucha et al. (2017)	Quantitative analysis and modelling	Occupation – Higher for students	*Risk propensity*
Liu et al. (2022)	Quantitative SEM	Occupation – Higher for people without work	*Risk perception*

Table A2
Results of hypotheses testing

Hypotheses	Accepted/Rejected
H_{1a}: Perceived ease of use for AVs is higher for men.	Accepted
H_{1b}: Intention to use AVs is higher for men.	Accepted
H_{1c}: Risk propensity for AVs is higher for men.	Accepted
H_{1d}: Risk perception (safety and privacy) of AVs is higher for women.	Partially accepted, only for perceived safety risk
H_{2a}: Perceived ease of use for AVs is higher for younger people (Z or Y generations).	Accepted
H_{2b}: Intention to use AVs is higher for younger people (Z or Y generations).	Accepted
H_{2c}: Risk propensity for AVs is higher for younger people (Z or Y generations).	Accepted
H_{2d}: Risk perception (safety and privacy) of AVs is higher for older people (X generations or Baby boomers).	Partially accepted, only for perceived privacy risk
H_{3a}: Perceived ease of use for AVs is higher for higher educated people.	Rejected
H_{3b}: Intention to use AVs is higher for higher educated people.	Rejected
H_{3c}: Risk propensity for AVs is higher for higher educated people.	Rejected
H_{3d}: Risk perception (safety and privacy) of AVs is higher for lower educated people.	Partially accepted, only for perceived safety risk
H_{4a}: Perceived ease of use for AVs is higher for city residents.	Rejected
H_{4b}: Intention to use AVs is higher for city residents.	Accepted
H_{4c}: Risk propensity for AVs is higher for city residents.	Accepted
H_{4d}: Risk perception (safety and privacy) of AVs is higher for rural residents.	Rejected
H_{5a}: Perceived ease of use for AVs is higher for employees and students.	Accepted
H_{5b}: Intention to use AVs is higher for employees and students.	Accepted
H_{5c}: Risk propensity for AVs is higher for employees and students.	Accepted
H_{5d}: Risk perception (safety and privacy) of AVs is higher for people without work.	Partially accepted, only for perceived privacy risk

References

Acheampong, R.A., Cugurullo, F., 2019. Capturing the behavioral determinants behind the adoption of autonomous vehicles: conceptual frameworks and measurement models to predict public transport, sharing and ownership trends of self-driving cars. Transp. Res. Part F Traffic Psychol. Behav. 62, 349–375. https://doi.org/10.1016/j.trf.2019.01.009.

Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50, 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Alarcon, G.M., Jessup, S.A., 2023. Propensity to trust and risk aversion: differential roles in the trust process. J. Res. Pers. 103, 104349 https://doi.org/10.1016/j.jrp.2023.104349.

Alatawneh, A., & Török, Á. , 2023. Examining the impact of hysteresis on the projected adoption of autonomous vehicles. Promet 3 Traffic&Transportation. 35(5): 607-620. https://doi.org/10.7307/ptt.v35i5.278.

Alessandrini, A., Alfonsi, R., Delle Site, P., Stam, D., 2014. Users' preferences towards automated road public transport: results from European surveys. Transp. Res. Procedia 3, 139–144. https://doi.org/10.1016/j.trpro.2014.10.099.

Al-Emran, M., & Granić, A., 2021. Is it still valid or outdated? A bibliometric analysis of the technology acceptance model and its applications from 2010 to 2020. In: M. Al-Emran & K. Shaalan (Edit), Recent Advances in Technology Acceptance Models and Theories (Issue. 335, o. 1–12). Springer International Publishing. https://doi.org/10.1007/978-3-030-64987-6_1.

Al-Emran, M., Granić, A., Al-Sharafi, M.A., Ameen, N., Sarrab, M., 2021. Examining the roles of students' beliefs and security concerns for using smartwatches in higher education. J. Enterp. Inf. Manag. 34 (4), 1229–1251. https://doi.org/10.1108/JEIM-02-2020-0052.

Al-Emran, M., Griffy-Brown, C., 2023. The role of technology adoption in sustainable development: overview, opportunities, challenges, and future research agendas. Technol. Soc. 73, 102240 https://doi.org/10.1016/j.techsoc.2023.102240.

Amin, M., Rezaei, S., Abolghasemi, M., 2014. User satisfaction with mobile websites: the impact of perceived usefulness (PU), perceived ease of use (PEOU) and trust. Nankai Bus. Rev. Int. 5 (3), 258–274. https://doi.org/10.1108/NBRI-01-2014-0005.

Antoncic, J.A., Antoncic, B., Gantar, M., Hisrich, R.D., Marks, L.J., Bachkirov, A.A., Kakkonen, M.L., 2018. Risk-taking propensity and entrepreneurship: the role of power distance. J. Enterprising Cult. 26 (01), 1–26. https://doi.org/10.1142/S0218495818500012.

Arpaci, I., Masrek, M.N., Al-Sharafi, M.A., Al-Emran, M., 2023. Evaluating the actual use of cloud computing in higher education through information management factors: a cross-cultural comparison. Educ. Inf. Technol. https://doi.org/10.1007/s10639-023-11594-y.

Autonomous Systems National Laboratory, 2023. Autonomous Systems do Watch, Decide, Produce, Drive, and Even Fly. https://autonom.nemzetilabor.hu/.

Bagloee, S.A., Tavana, M., Asadi, M., Oliver, T., 2016. Autonomous vehicles: Challenges, opportunities, and future implications for transportation policies. J. mod. transp. 24 (4), 284–303. https://doi.org/10.1007/s40534-016-0117-3.

Bansal, P., Kockelman, K.M., Singh, A., 2016. Assessing public opinions of and interest in new vehicle technologies: an Austin perspective. Transp. Res. Part C Emerg. Technol. 67, 1–14. https://doi.org/10.1016/j.trc.2016.01.019.

Bauer, R.A., 1960. Consumer behavior as risk taking. dynamic marketing for a changing world, R. S. Handcock, Chicago, AMA Proceedings, 389–398.

Bauer, R.A. , 1967. Consumer behavior as risk taking. In: D. F. Cox (Ed.), Risk Taking and Information Handling in Consumer Behavior (pp. 23–33). Divison of Research, Graduate School of Business Administration.

Baz, J., Briys, E., Bronnenberg, B.J., Cohen, M., Kast, R., Viala, P., Wertenbroch, K., 1999. Risk perception in the short run and in the long run. Mark. Lett. 10 (3), 267–283. https://link.springer.com/article/10.1023/A:1008193420722.

Boustanifar, H., Zajac, E.J., Zilja, F., 2022. Taking chances? The effect of CEO risk propensity on firms' risky internationalization decisions. J. Int. Bus. Stud. 53 (2), 302–325. https://doi.org/10.1057/s41267-021-00480-9.

Brockhaus Sr, R.H., 1980. Risk taking propensity of entrepreneurs. Acad. Manag. J. 23 (3), 509–520. https://doi.org/10.5465/255515.

Browne, K., 2005. Snowball sampling: using social networks to research non-heterosexual women. Int. J. Soc. Res. Methodol. *8* (1), 47–60. https://doi.org/10.1080/1364557032000081663.

Byrnes, J.P., Miller, D.C., Schafer, W.D., 1999. Gender differences in risk taking: a meta-analysis. Psychol. Bull. 125 (3), 367–383. https://doi.org/10.1037/0033-2909.125.3.367.

Chen, C.-F., 2019. Factors affecting the decision to use autonomous shuttle services: evidence from a scooter-dominant urban context. Transp. Res. Part F Traffic Psychol. Behav. 67, 195–204. https://doi.org/10.1016/j.trf.2019.10.016.

Chen, H.K., Yan, D.W., 2019. Interrelationships between influential factors and behavioral intention with regard to autonomous vehicles. Int. J. Sustain. Transp. 13 (7), 511–527. https://doi.org/10.1080/15568318.2018.1488021.

Cho, J., Lee, J., 2006. An integrated model of risk and risk-reducing strategies. J. Bus. Res. 59 (1), 112–120. https://doi.org/10.1016/j.jbusres.2005.03.006.

Czerwonka, M., 2019. Cultural, cognitive and personality traits in risk-taking behaviour: evidence from Poland and the United States of America. Econ. Res. Èkon. istraživanja 32 (1), 894–908. https://doi.org/10.1080/1331677X.2019.1588766.

Davis, F.D., Bagozzi, R.P., Warshaw, P.R., 1989. User acceptance of computer technology: a comparison of two theoretical models. Manag. Sci. 35 (8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982.

Deb, S., Strawderman, L., Carruth, D.W., DuBien, J., Smith, B., Garrison, T.M., 2017. Development and validation of a questionnaire to assess pedestrian receptivity toward fully autonomous vehicles. Transp. Res. Part C Emerg. Technol. 84, 178–195. https://doi.org/10.1016/j.trc.2017.08.029.

Dong, X., Di Scenna, M., Guerra, E., 2019. Transit user perceptions of driverless buses. Transportation 46, 35–50. https://doi.org/10.1007/s11116-017-9786-y.

Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transp. Res. Part A Policy Pract. 77, 167–181. https://doi.org/10.1016/j.tra.2015.04.003.

Featherman, M.S., Pavlou, P.A., 2003. Predicting E-services adoption: a perceived risk facets perspective. Int. J. Hum. Comput. Stud. 59 (4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3.

Fischhoff, B., Lichtenstein, S., Slovic, P., Derby, S.L., Keeney, R.L., 1981. Acceptable Risk. Cambridge University Press, New York, NY, 1981.

Fulton, L.M., 2018. Three Revolutions in Urban Passenger Travel. Joule 2 (4), 575–578. https://doi.org/10.1016/j.joule.2018.03.005.

Goodman, L.A., 1961. Snowball sampling. Ann. Math. Stat. 32 (1), 148–170. https://doi.org/10.1214/aoms/1177705148.

Grewal, D., Gotlieb, J., Marmorstein, H., 1994. The moderating effects of message framing and source credibility on the price-perceived risk relationship. J. Consum. Res. 21 (1), 145. https://doi.org/10.1086/209388.

Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. Transp. Res. Part C Emerg. Technol. 78, 37–49. https://doi.org/10.1016/j.trc.2017.01.010.

Hassan, H.M., Abdel-Aty, M.A., 2013. Exploring the safety implications of young drivers' behavior, attitudes and perceptions. Accid. Anal. Prev. 50, 361–370. https://doi.org/10.1016/j.aap.2012.05.003.

Hudson, J., Orviska, M., 2011. European attitudes to gene therapy and pharmacogenetics. Drug Discov. Today 16, 843–847. https://doi.org/10.1016/j.drudis.2011.06.008.

Hudson, J., Orviska, M., Hunady, J., 2016. People's attitudes to robots in caring for the elderly. Int. J. Soc. Robot. 9 (2), 199–210. https://doi.org/10.1007/s12369-016-0384-5.

Io, H.N., Lee, C.B., Lian, Z., 2022. Sentiments about autonomous vehicles. J. Eng. Technol. Manag. 66, 101717. https://doi.org/10.1016/j.jengtecman.2022.101717.

Jászberényi, M., Miskolczi, M., Munkácsy, A., Földes, D., 2022. What drives tourists to adopt self-driving cars? Transp. Res. Part F Traffic Psychol. Behav. 89, 407–422. https://doi.org/10.1016/j.trf.2022.07.013.

Kaur, K., Rampersad, G., 2018. Trust in driverless cars: investigating key factors influencing the adoption of driverless cars. J. Eng. Technol. Manag. 48, 87–96. https://doi.org/10.1016/j.jengtecman.2018.04.006.

Kenesei, Z., Ásványi, K., Kökény, L., Jászberényi, M., Miskolczi, M., Gyulavári, T., Syahrivar, J., 2022. Trust and perceived risk: how different manifestations affect the adoption of autonomous vehicles. Transp. Res. Part A Policy Pract. 164, 379–393. https://doi.org/10.1016/j.tra.2022.08.022.

Kim, M.-K., Park, J.-H., Oh, J., Lee, W.-S., Chung, D., 2019. Identifying and prioritizing the benefits and concerns of connected and autonomous vehicles: a comparison of individual and expert perceptions. Res. Transp. Bus. Manag. 32, 100438 https://doi.org/10.1016/j.rtbm.2020.100438.
Kökény, L., Kiss, K., 2021. There is a time and a place for everything (and for everyone): examining main socio-demographic and territorial differences in use of leisure time. Reg. Stat. 11 (2), 136–164. https://doi.org/10.15196/rs110206.
Koul, S., Eydaghi, A., 2020. The impact of social influence, technophobia, and perceived safety on autonomous vehicle technology adoption. Period. Polytech. Transp. Eng. 48 (2), 133–142. https://doi.org/10.3311/PPtr.11332.
KSH – Hungarian Central Statistical Office, 2023. Number of Road Vehicles by County and Region IN Hungary, 31 December 24.1.2.2. ⟨https://www.ksh.hu/stadat_files/sza/hu/sza0040.html⟩.
Kusumasondjaja, S., 2015. Information quality, homophily, and risk propensity: consumer responses to online hotel reviews. J. Econ. Bus. Account. Ventur. *18* (2), 241. https://doi.org/10.14414/jebav.v18i2.451.
KPMG Self-driving Cars: Are We Ready? 2013. http://www.kpmg.com/US/en/IssuesAndInsights/ArticlesPublications/Documents/self-driving-cars-are-we-ready.pdf.
Krizsik, N., Sipos, T., 2023. Social perception of autonomous vehicles. Period. Polytech. Transp. Eng. 51 (2), 133–139. https://doi.org/10.3311/PPtr.20228.
Kyriakidis, M., Happee, R., De Winter, J.C.F., 2015. Public opinion on automated driving: results of an international questionnaire among 5000 respondents. Transp. Res. Part F Traffic Psychol. Behav. 32, 127–140. https://doi.org/10.1016/j.trf.2015.04.014.
Laiou, A., Theofilatos, A., Yannis, G., Meesmann, U., Torfs, K., 2021. An exploration of European road users' safety attitudes towards speeding. J. Transp. Saf. Secur. 13 (5), 552–573. https://doi.org/10.1080/19439962.2019.1650144.
Levy, J.A., 1988. Intersactions of gender and aging. Sociol. Q. 29 (4), 479–486.
Li, X., Zhang, L., Cao, J., 2023. Research on the mechanism of sustainable business model innovation driven by the digital platform ecosystem. J. Eng. Technol. Manag. 68, 101738 https://doi.org/10.1016/j.jengtecman.2023.101738.
Liu, P., Du, M., Xu, Z., Chu, Y., 2022. People with more misconceptions about automated vehicles might be more positive toward them. Transp. Res. Part F Traffic Psychol. Behav. 87, 264–278. https://doi.org/10.1016/j.trf.2022.04.010.
Logan, E., Kaye, S.-A., Lewis, I., 2019. The influence of the revised reinforcement sensitivity theory on risk perception and intentions to speed in young male and female drivers. Accid. Anal. Prev. 132, 105291 https://doi.org/10.1016/j.aap.2019.105291.
Lynott, P.P., McCandless, N.J., 2000. The impact of age vs. life experiences on the gender role attitudes of women in different cohorts. J. Women Aging 12 (2), 5–21. https://doi.org/10.1300/J074v12n01_02.
Lukovics, M., Prónay, S., Majó-Petri, Z., Kovács, P., Ujházi, T., Volosin, M., Palatinus, Z., Keszey, T., 2023. Combining survey-based and neuroscience measurements in customer acceptance of self-driving technology. Transp. Res. Part F Traffic Psychol. Behav. 95, 46–58. https://doi.org/10.1016/j.trf.2023.03.016.
Ma, L., 2021. Understanding non-adopters' intention to use internet pharmacy: revisiting the roles of trustworthiness, perceived risk and consumer traits. J. Eng. Technol. Manag. 59, 101613 https://doi.org/10.1016/j.jengtecman.2021.101613.
Mandal, B., Roe, B.E., 2014. Risk tolerance among National Longitudinal Survey of Youth participants: the effects of age and cognitive skills. Economica 81, 522–543. https://doi.org/10.1111/ecca.12088.
Marletto, G., 2019. Who will drive the transition to self-driving? A socio-technical analysis of the future impact of automated vehicles. Technol. Forecast. Soc. Change. 139, 221–234. https://doi.org/10.1016/j.techfore.2018.10.023.
Meertens, R.M., Lion, R., 2008. Measuring an individual's tendency to take risks: the risk propensity scale. J. Appl. Soc. Psychol. 38 (6), 1506–1520. https://doi.org/10.1111/j.1559-1816.2008.00357.x.
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. J. Intell. Transp. Syst. 21 (4), 324–348. https://doi.org/10.1080/15472450.2017.1291351.
Miskolczi, M., Földes, D., Munkácsy, A., Jászberényi, M., 2021. Urban mobility scenarios until the 2030s. Sustain. Cities Soc. 72, 103029 https://doi.org/10.1016/j.scs.2021.103029.
Mitchell, V., 1999. Consumer perceived risk: conceptualisations and models. European Journal of Marketing 33 (1/2):163-195. https://doi.org/10.2753/JEC1086-4415130402.
Muir, M., Wallace, M., McMurray, D., 2014. Women on the move: the self-initiated expatriate in China. J. Glob. Mobil. 2 (2), 234–254. https://doi.org/10.1108/JGM-06-2013-0045.
Nastjuk, I., Herrenkind, B., Brendel, A.B., Kolbe, L.M., 2020. What drives the acceptance of autonomous driving? An investigation of acceptance factors from an end-user's perspective. Technol. Forecast. Soc. Change 161, 120319. https://doi.org/10.1016/j.techfore.2020.120319.
Nees, M.A., 2016. Acceptance of self-driving cars: an examination of idealized versus realistic portrayals with a self-driving car acceptance scale. In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Vol. 60, No. 1. Sage CA: Los Angeles, CA: SAGE Publications. pp. 1449–1453.
Nomura, T., Kanda, T., Suzuki, T., Kato, K., 2009. Age differences and images of robots: social survey in Japan. Interact. Stud. 10 (3), 374–391. https://doi.org/10.1075/is.10.3.05nom.
Oh, J.C., Yoon, S.J., 2014. Predicting the use of online information services based on a modified UTAUT model. Behav. Inf. Technol. 33 (7), 716–729. https://doi.org/10.1080/0144929X.2013.872187.
Osswald, S., Wurhofer, D., Trösterer, S., Beck, E., & Tscheligi, M., 2012. Predicting information technology usage in the car: towards a car technology acceptance model. Inproceedings. In: Proceedings of the 4th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, PP. 51–58. AutomotiveUI'12. New York, NY, USA: ACM. https://doi.org/10.1145/2390256.2390264.
Paden, B., Cap, M., Yong, S.Z., Yershov, D., Frazzoli, E., 2016. A survey of motion planning and control techniques for self-driving urban vehicles. IEEE Trans. Intell. Veh. 1 (1), 33–55. https://doi.org/10.1109/TIV.2016.2578706.
Payre, W., Cestac, J., Delhomme, P., 2014. Intention to use a fully automated car: attitudes and a priori acceptability. Transp. Res. Part F Traffic Psychol. Behav. 27, 252–263. https://doi.org/10.1016/j.trf.2014.04.009.
Plaut, P.O., 2006. The intra-household choices regarding commuting and housing. Transp. Res. Part A Policy Pract. 40 (7), 561–571. https://doi.org/10.1016/j.tra.2005.10.001.
Rhodes, N., Pivik, K., 2011. Age and gender differences in risky driving: the roles of positive affect and risk perception. Accid. Anal. Prev. 43 (3), 923–931. https://doi.org/10.1016/j.aap.2010.11.015.
RSM Global, 2023. Automotive Industry in Central and Eastern Europe. ⟨https://www.rsm.global/poland/en/insights/doing-business-poland/automotive-industry-central-and-eastern-europe⟩.
Ruggeri, K., Kácha, O., Menezes, I.G., Kos, M., Franklin, M., Parma, L., Langdon, P., Matthews, B., Miles, J., 2018. In with the new? Generational differences shape population technology adoption patterns in the age of self-driving vehicles. J. Eng. Technol. Manag. 50, 39–44. https://doi.org/10.1016/j.jengtecman.2018.09.001.
Saeed, T.U., Burris, M.W., Labi, S., Sinha, K.C., 2020. An empirical discourse on forecasting the use of autonomous vehicles using consumers' preferences. Technol. Forecast. Soc. Change 158, 120130. https://doi.org/10.1016/j.techfore.2020.120130.
Schoettle, B., & Sivak, M., 2014. A Survey of Public Opinion about Autonomous and Self-Driving Vehicles in the U.S., the U.K., and Australia, Michigan, USA. ⟨https://deepblue.lib.umich.edu/bitstream/handle/2027.42/108384/103024.pdf?sequence=1&isAllowed=y⟩.
Schwanen, T., Dijst, M., Dieleman, F.M., 2004. Policies for urban form and their impact on travel: the Netherlands experience. Urban Stud. 41 (3), 579–603. https://doi.org/10.1080/0042098042000178690.
Sitkin, S.B., Pablo, A.L., 1992. Reconceptualizing the determinants of risk behavior. Acad. Manag. Rev. 17 (1), 9–38. https://doi.org/10.2307/258646.
Society of Automotive Engineers (SAE), 2018. Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems. J3016_201806 (Report).
Syahrivar, J., Gyulavári, T., Jászberényi, M., Ásványi, K., Kökény, L., Chairy, C., 2021. Surrendering personal control to automation: appalling or appealing? Transp. Res. Part F Traffic Psychol. Behav. 80, 90–103. https://doi.org/10.1016/j.trf.2021.03.018.

Taylor, L.A., Hall, P.D., Cosier, R.A., Goodwin, V.L., 1996. Outcome feedback effects on risk propensity in an MCPLP task. J. Manag. 22 (2), 299–322. https://doi.org/10.1177/014920639602200205.

Tomczak, M., Tomczak, E., 2014. The need to report effect size estimates revisited. An overview of some recommended measures of effect size. TRENDS Sport Sci. Vol. 1, 19–25 (o).

Van Acker, V., Witlox, F., 2010. Commuting trips within tours: how is commuting related to land use? Transportation 38 (3), 465–486. https://doi.org/10.1007/s11116-010-9309-6.

Vance, C.M., McNulty, Y., Paik, Y., D'Mello, J., 2016. The expat-preneur: conceptualizing a growing international career phenomenon. J. Glob. Mobil. 4 (2), 202–224. https://doi.org/10.1108/JGM-11-2015-0055.

Venkatesh, V., Davis, F.D., 2000. A theoretical extension of the technology acceptance model: four longitudinal field studies. Manag. Sci. 46 (2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926.

Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: toward a unified view. MIS Q. 27 (3), 425–478. https://doi.org/10.2307/30036540.

Wang, W., Zhao, J., Zhang, W., & Wang, Y., 2015. Conceptual framework for risk propensity, risk perception, and risk behaviour of construction project managers. In: Proceedings of 31st Annual ARCOM Conference', Association of Researchers in Construction Management, Lincoln, UK (pp. 165-174). ⟨https://core.ac.uk/download/pdf/188255518.pdf#page=179⟩.

Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., Liu, P., 2018. What drives people to accept automated vehicles? Findings from a field experiment. Transp. Res. Part C Emerg. Technol. 95, 320–334. https://doi.org/10.1016/j.trc.2018.07.024.

Yang, S., Liu, W., Sun, D., Li, C., 2013. A new extended multiple car-following model considering the BackwardLooking effect on traffic flow. J. Comput. Nonlinear Dyn. 8 (1), 11016. https://doi.org/10.1115/1.4007310.

Yang, J., Coughlin, J.F., 2014. In-vehicle technology for self-driving cars: advantages and challenges for aging drivers. Int. J. Automot. Technol. 15 (2), 333–340. https://doi.org/10.1007/s12239-014-0034-6.

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. Transp. Res. Part A Policy Pract. 94, 1–16. https://doi.org/10.1016/j.tra.2016.09.003.

ZalaZONE, 2023. Where Innovation Leads. ⟨https://zalazone.hu/⟩.

Zhang, T., Tao, D., Qu, X., Zhang, X., Lin, R., Zhang, W., 2019. The roles of initial trust and perceived risk in public's acceptance of automated vehicles. Transp. Res. Part C Emerg. Technol. 98, 207–220. https://doi.org/10.1016/j.trc.2018.11.018.

Zhu, A., Yang, S., Chen, Y., Xing, C., 2022. A moral decision-making study of autonomous vehicles: expertise predicts a preference for algorithms in dilemmas. Personal. Individ. Differ. 186, 111356 https://doi.org/10.1016/j.paid.2021.111356.

Zmud, J., Sener, I.N., Wagner, J., 2016. Self-driving vehicles: determinants of adoption and conditions of usage. Transp. Res. Rec. J. Transp. Res. Board 2565 (1), 57–64. https://doi.org/10.3141/2565-07.