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What drives tourists to adopt self-driving cars?

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ABSTRACT

Autonomous vehicles are expected to shape mobility and tourism. This paper introduces an extension to the TAM to better understand the adoption of self-driving cars for tourism purposes. The new model (TAMAT) confirms some under-explored impacts of tourism-related variables, such as Openness to Tourism Usage and Unusual Surroundings, and the Adherence to Conventional Use on the Intention to Use self-driving cars. The research is based on online data collection ($n = 646$) and applies Covariance-Based Structural Equation Modelling. Findings indicate that the opportunity of using self-driving cars for tourism and unusual environments has a positive impact, while adherence to conventional car use has a negative impact on the intention to use self-driving cars.

1. Introduction

The impact of automation on passenger transport has been growing steadily in recent years. Automation is expected to have a positive impact on road safety and urban sustainability (Alonso, Faus, Esteban, & Useche, 2021). In autonomous vehicles (AVs), driving tasks are being taken over by artificial intelligence (AI) (Bagloee, Tavana, Asadi, & Oliver, 2016; Rezaei & Caulfield, 2020; Maeng & Cho, 2022). As of 2022, vehicles in SAE2 (partial automation) and SAE3 (conditional automation) are available, according to the SAE (Society of Automotive Engineers) framework (SAE International, 2018).

Despite the study of technology acceptance of AVs is rapidly growing in social sciences, the analysis of tourists' intention to use is still marginal. Automation might have a great influence on passenger transport by 2030 (Miskolczi, Földes, Munkácsy, & Jászberényi, 2021), which also affects travelling habits and tourism. Radical alterations in tourism services (e.g., guided tours, sightseeing opportunities), and individual mobility are predicted (Tussyadiah, Zach, & Wang, 2017; Prideaux & Yin, 2019; Cohen & Hopkins, 2019; Cohen, Stienmetz, Hanna, Humbracht, & Hopkins, 2020; He & Csiszar, 2020).

The technology acceptance of AVs is primarily based on the extension of the traditional Technology Acceptance Model (TAM) (Davis, 1986) or the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003), with a particular focus on consumer characteristics (e.g., Leicht, Chtourou, & Youssef, 2018; Zhang et al., 2019; Syahrivar et al., 2021) and latent socio-psychological and socio-demographic factors (e.g., Acheampong & Cugurullo, 2019). However, the potential use and impacts of AVs in tourism have received little attention. Previous research has mainly focused on rural tourism (Ribeiro, Gursoy, & Chi,

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2021) or the willingness to rent self-driving cars for tourism purposes (Tan & Lin, 2020). It has not been examined how the creation of new tourism services based on self-driving vehicles (e.g., sightseeing, interior design) or some unusual, tourism-related environmental stimuli (e.g., side of the road tourists must drive on, unfamiliar road sections, eye-catching attractions) affect the intention to use AVs. Based on this research gap, our research question was how the above-mentioned tourism-related factors influence the intention to use AVs at the level of full automation (SAE5). Following the widely accepted terminology of transport sciences, the term autonomous vehicle (AV) regards to self-driving cars in this study.

To answer the research question, an online survey has been conducted in Hungary. The endogenous variables of the TAM model (Venkatesh & Davis, 2000) have been extended with three tourism-related exogenous variables (Openness to tourism usage – OTU, Unusual Surrounding – UNS, Adherence to Conventional Use – ACU), the validity of which was tested applying the covariance-based structural equation modelling (CB-SEM) method. It is expected that tourism factors that influence the acceptance of AVs may be revealed to identify service development opportunities.

The paper is structured as follows: In Section 2, a literature review on the technology acceptance of AVs is introduced. The methodology is described in Section 3 highlighting the stages of empirical research. The research design and the hypothetical model developed (TAMAT – Technology Acceptance Model of Autonomous Vehicles for Tourism Purposes) are presented in Section 4. The results of structural equation modelling are discussed in Section 5. Finally, conclusions are drawn.

2. Literature review

Technology acceptance is a theory that describes how a person relates to the adoption of new technologies (Davis, 1986). The emergence of the theory was enhanced by the rapid development of information and communication technology. Technology acceptance allows researchers to appraise adoption during the introduction, highlighting the potential gaps and identifying the wrong development directions (Venkatesh & Davis, 2000).

The first technology-acceptance model (TAM1) was developed by F. D. Davis in 1986 (Davis, 1986). The original model was improved (TAM2 – Venkatesh & Davis, 2000), and new models were created, such as the Unified Theory of Acceptance and Use of Technology (UTAUT1) (Venkatesh et al., 2003), which focuses on technology adoption in workplaces. The latest TAM3 (Venkatesh & Bala, 2008) and UTAUT2 (Venkatesh, Thong, & Xu, 2012) aim to analyze technology acceptance beyond the workplace environment. In transport sciences, CTAM (Car Technology Acceptance Model) and TPB (Theory of Planned Behaviour) are also frequently applied

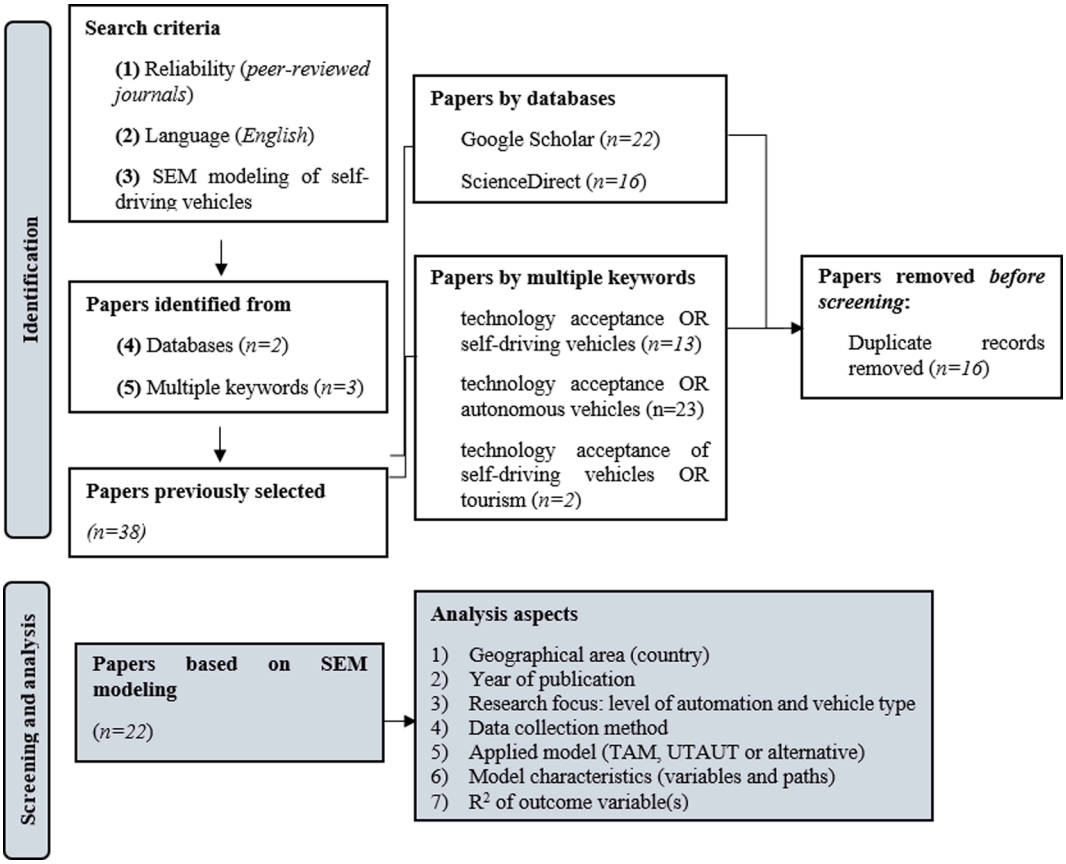

Fig. 1. Flow diagram of the literature review.

theories (Osswald, Wurhofer, Trösterer, Beck, & Tscheligi, 2012; Koul & Eydgahi, 2018).

A literature review has been conducted based on the PRISMA guidelines (Page, McKenzie, & Bossuyt, 2021) to explore which models are employed and created in AV adoption. Only studies based on structural equation modelling (SEM) have been considered.

Fig. 1 outlines the main steps of the review process. For detecting papers, online search engines and multiple keywords have been applied. Papers published in English and peer-reviewed journals were included. The search yielded 22 relevant records after the exclusion of 16 duplicated records (for details, see this online Table of records). The papers have been analyzed according to seven aspects.

Researchers mostly verify theories by addressing the endogenous variables of TAM (Perceived Ease of Use – PEOU, Perceived Usefulness – PU, Intention to use – ITU) or UTAUT (Behavioral Intention to Use – BIU, Usage Behavior – UB) (Fig. 2) or employ only some exogenous variables and create new (hybrid) ones (Adnan & Nordin, 2018). Based on the theory of TAM, exogenous variables affect PEOU and PU. PEOU has a positive effect on PU and PEOU and PU together have a positive effect on ITU. Moreover, ITU affects UB (Venkatesh & Davis, 2000). In the case of UTAUT, a simpler path of variables can be seen: Exogenous variables affect BIU and, thus, UB (Venkatesh et al., 2003).

Table 1 presents SEM models based on TAM-extension and the seven analysis aspects. Table 2 represents SEM models based on UTAUT or alternative hybrid theories and the seven characteristics analyzed (in this case, only the R^2 of the outcome variables are presented).

Most papers report findings from Asia, and the United States; nine papers have been found from Europe (UK, France, Germany, Hungary, Greece, Turkey, Ireland, Spain). All papers were published between 2018 and 2021, which also proves the novelty of the research field. Online and offline surveys among the adult population (aged 18–70) are the common data collection methods. In the case of some exceptions, respondents shared their opinions after having tested the vehicle. In some cases, a specific target group has been involved, such as college students (Du, Zhu, & Zheng, 2021), employees working at a truck accessory manufacturer (Koul & Eydgahi, 2018), or licensed drivers (Montoro et al., 2019; Useche, Peñaranda-Ortega, Gonzalez-Marin, & Llamazares, 2021). Some researchers (Acheampong, Cugurullo, Gueriau, & Dusparic, 2021) have also investigated the technology acceptance of AVs according to different modes of use (e.g., shared, private, public transport). Based on sample size, the typical number of elements is below 400, which is exceeded by five surveys (Montoro et al., 2019; Keszey, 2020; Syahrivar et al., 2021; Acheampong et al., 2021; Useche et al., 2021). Following Chin's threshold for R^2 values of latent variables (Chin, 1998), findings report strong explanatory power of intention to use AVs. The majority of papers reported a moderate variance of ITU ($0.33 \leq R^2 \leq 0.67$) explained by the independent variables, except for four models where R^2 of ITUs exceeds the substantial value (≥0,67).

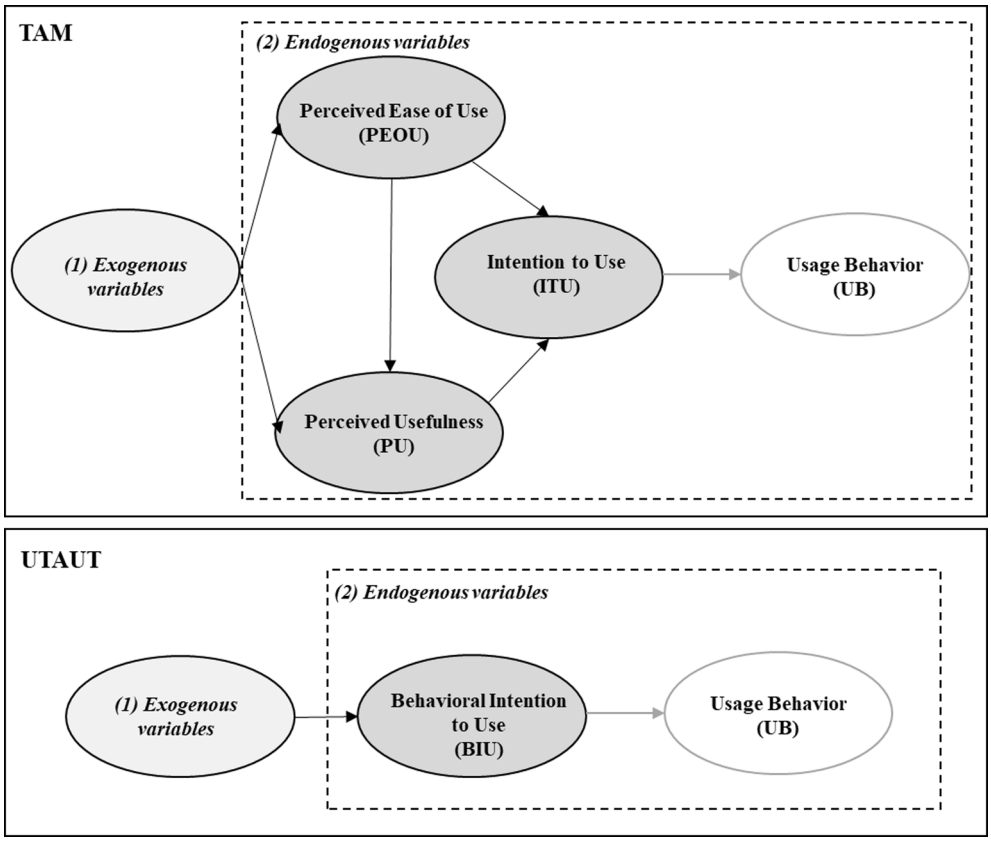

Fig. 2. Exogenous variables applied in TAM and UTAUT.

Table 1
Research on the acceptance of AVs – TAM-extension modelling.

Author and year of publication	Country	Focus	Data		Model	R^2		
			from	n		PU	PEOU	ITU
Panagiotopoulos and Dimitrakopoulos (2018)	Greece	SAE5	Online survey	N/D	PU, PEOU, *PT*, *SI* - > BIU (ITU)	0.213	N/D	0.437
Dirsehan and Can (2020)	Turkey	SAE5	Online survey	391	*T* - > PU, PEOU, *SC* - > BIU	0.744	0.590	0.570
Xu et al. (2018)	China	SAE3	Vehicle test and survey	N/D	*T*- > PU, PEOU, *PS* - > BIU, (WTRR)	0.38	0.29	0.55
Zhang et al. (2019)	China	SAE3	Survey with drivers	216	PEOU, PU, *PSR*, *PPR* - > *IT*- > ATT - > BIU	0.33	N/D	0.61
Chen (2019)	Taiwan	SAE4-5	Vehicle test and survey	N/D	PEOU, PU, *T*, PE - > A- > ITU	0.562	N/D	0.523
Lee et al. (2019)	Korea	SAE5	Online survey	313	*SE*, *RA*, *PO* - > *PR*, PEOU, PU- > ITU	0.591	0.559	0.520
Koul and Eydgahi (2018)	U.S.	SAE5	Survey	377	PEOU, PU, *YDE*- > ITU	N/D	N/D	0.622
Buckley et al. (2018)	Australia	SAE5	Vehicle test and survey	74	*ATB*, SN, *PBC* - > *T*, PEOU, PU	0.69	0.15	0.41
Yuen et al. (2021)	China	SAE5	Survey	274	*RA*, I, *C*, RD, *V*, *Tr* - > PEOU, PU - > BIU	0.86	0.77	0.75
Rahman et al. (2019)	U.S.	SAE5	Online survey	173	A, *T*, *C* - > *PS*, PU - > ACC *(ITU)*	N/D	N/D	0.77
Zhu et al. (2020)	China	SAE5	Survey	355	*MM*, *SM* - > SE, SN- > PU, *PR*- > ITU	N/D	N/D	0.54

Notes: Variable names are in alphabetical order. New variables (not included in the original TAM) are in italics and underlined. ATB = Attitude towards the Behavior, ATT = Attitude Towards Trust, BIU = Behavioral Intention to Use, C = Compatibility, I = Image, IT = Initial Trust, MM = Mass Media, PBC = Perceived Behavioral Control, PE = Perceived Enjoyment, PEOU = Perceived Ease of Use, PO = Psychological Ownership, PPR = Perceived Privacy Risk, PR = Perceived Risk, PS = Perceived Safety, PSR = Perceived Safety Risk, PT = Perceived Trust, PU = Perceived Usefulness, RA = Relative Advantage, RA = Relative Advantage, RD = Result Demonstrability, SC = Sustainability Concerns, SDC = Self-driving car, ASS = Autonomous Shuttle Service, SE = Self-efficacy, SI = Social Influence, SM = Social Media, T = Trust, Tr = Trialability, V = Visibility, WTRR = Willingness to Re-ride,
YDE = Years of Driving Experience.

Table 2
Previous research on the acceptance of AVs – not TAM-based (UTAUT or alternative) modellings.

Author and year of publication	Country	Focus	Data		Model	R^2
			from	n		BIU
Du et al. (2021)	China	SAE5	Survey	173	*MM*- > SN, SE - > *T* - > ITU *(BIU)*	0,58
Ribeiro et al. (2021)	U.S.	SAE5	Survey	N/D	SI, HM, *T* - > PPE, *PR* - > *E*- > ITU/(OTU)	0,76
Syahrivar et al. (2021)	Hungary /Indonesia	SAE1-5	Online survey	457	*DFC*, *DLC* (<-*PD*) - > A- > ITU *(BIU)*	0,703
Tan and Lin (2020)	Taiwan	SAE5	Survey	198	*TM*, *LC* - > *DEE*- > DCRI *(ITU)* (<-*TR*)	0,35
Karnouskos (2020)	Germany	SAE5	Online survey	62	*TEC*, *SES*, *U* - > SDCA *(BIU)*	N/D
Kaur and Rampersad (2018)	Australia	SAE4-5	Survey	101	PE, *R*, *SEC*, *PR* - > *T* - > A *(BIU)*	N/D
Leicht et al. (2018)	UK/ France	SAE5	Online survey	241	PE, EE, SI - > PI *(BIU)*	N/D
Keszey (2020)	Hungary	SAE4-5	Survey	992	HM, *UM*, *TA*, *DPC* (<-*PITI*) - > BIU - > *EOM, RM, ECB, ENB*	0,69
Acheampong et al. (2021)	Ireland	SAE5	Survey (online/ offline)	1223	*PBC, PEOU, FA, SN, ATA, DATF, PC, A, E - > AVAI (BIU)*	N/D
Useche et al. (2021)	Spain	SAE5	Online survey	856	*ICTs, GC, RDD, FECS, TE, IS - > ITU*	N/D
Montoro et al. (2019)	Spain	SAE3-5	Survey	1205	*TL, F, E, ICTs, DI, DE, DC, PS, VA - > ITU*	N/D

Notes: Variable names are in alphabetical order. New variables (not included in the original theories) are in italics and underlined. BIU = Behavioral Intention to Use or other outcome variable which represent technology-acceptance, HM = Hedonic Motivation, DCRI = Driverless Car Rental Intention, DEE = Destination Experience Expectation, DFC = Desire for Control, DLC = Driver Locus of Control, DPC = Data Privacy Concerns, E = Emotion, ECB = Economic Benefits, ENB = Environmental Benefits, EOM = Equal Opportunity for Mobility, LC = Leisure Constraint, MM = Mass Media, PD = Power Distance, PE = Performance Expectancy, PITI = Personal Information Technology Innovativeness (moderator variable), PPE = Perceived Performance Expectancy, PR = Perceived Risk, PR = Privacy, R = Reliability, RM = Residence Mobility, SDCA = Self-driving Car Acceptance, SE = Self-efficacy, SEC = Security, SN = Subjective Norm, SS = Self-Safety, T = Technology, T = Trust, TA = Technological Anxiety, TM = Travel Motivation, TR = Technology Readiness, U = Utilitarianism, UM = Utilitarian Motivation, PBC = Perceived Benefits Composite, FA = Fear and Anxiety, PEOU = Perceived Ease of Use, ATA = Attitude Towards Automation, DATF = Driver Assisted Technologies Familiarity, PC = Perceived Control, A = Age, E = Education, AVAI = Autonomous Vehicles Adoption Intention, ICT = Interaction with ICTs, GC = Greater connectivity, RDD = Reduction of Driving Demands, FECS = Fuel/Energy Consumption Saving, TE = Travel Efficiency, IS = Increased Safety, TL = Trip Length, F = Frequency, DI = Driving Intensity, DE = Driving Experience, DC = Driving Crashes, PS = Perceived Safety, VA = Value Attributed.

The SLR confirmed the research gap that the study on the technology acceptance of Avs considering tourism-related aspects is marginal. As a synthesis of the literature review, five main categories of new variables can be identified:

(1) Impacts of media usage and reference group opinion: The analysis of reference group opinion (e.g., Panagiotopoulos & Dimitrakopoulos, 2018), the impact of technology-related information on the user attitude (e.g., mass media and/or social media – Zhu, Chen, & Zheng, 2020; Du et al., 2021) or the technology image (Yuen, Cai, Qi, & Wang, 2021) belong to this category.
(2) Issues about the operation: Impacts of perceived risks of technology use. Trust or fear (technology-related anxiety) as a variable is often included in the models (e.g., Panagiotopoulos & Dimitrakopoulos, 2018, Chen, 2019, Dirsehan & Can, 2020, Karnouskos, 2020, Ribeiro et al., 2021; Acheampong et al., 2021), and it is closely related to perceived self-safety, data privacy (Xu et al., 2018), the visibility of operation (Yuen et al., 2021), and the perceived sustainability (Dirsehan & Can, 2020) or control (Acheampong et al., 2021). These variables have major negative influence on the ITU.
(3) Perceived benefits of use: User enjoyment (Chen, 2019), economic benefits of use (Keszey, 2020), efficacy and relative advantage (Lee, Lee, Park, Lee, & Ha, 2019), perceived benefits-composite (Acheampong et al., 2021) build up this category.
(4) Consumer traits: Years of driving experience (Koul & Eydgahi, 2018), the desire for the different levels of control (Buckley, Kaye, & Pradhan, 2018; Syahrivar et al., 2021), vehicle ownership (Lee et al., 2019), and general socio-demographic variables (e.g., age and education – Acheampong et al., 2021, Montoro et al., 2019, gender – Useche et al., 2021) are sorted here.
(5) Tourism perspectives: Only two papers included tourism-related extensions. Performance expectancy and hedonic motivation, namely the pleasure or enjoyment of using AV (Tan & Lin, 2020; Ribeiro et al., 2021). Tourists are open to using self-driving cars, but Tan and Lin (2020) focused only on nature and rural tourism destinations. Ribeiro et al. (2021) revealed that performance expectancy increases user satisfaction, and hedonic motivation has a positive impact on ITU.

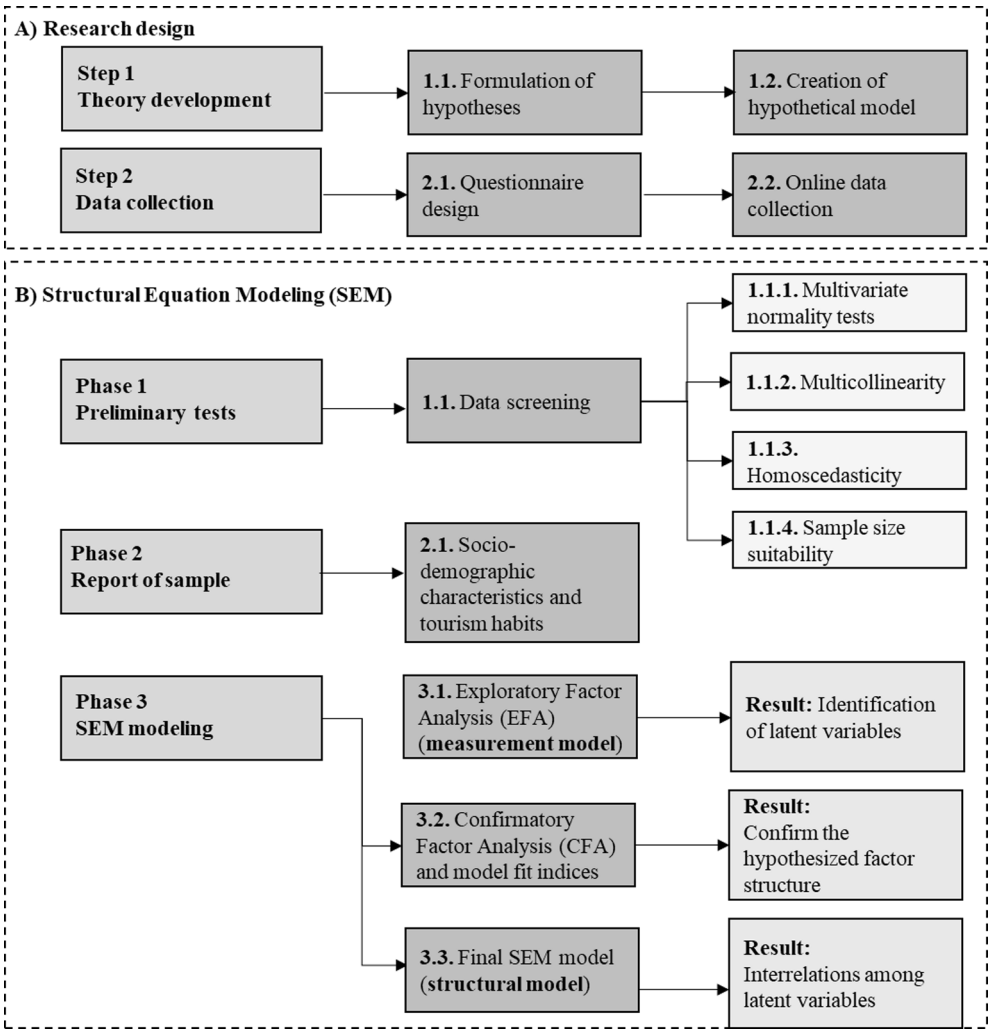

Fig. 3. Empirical research.

3. Methodology

The main stages of empirical research are presented in Fig. 3.
Two main stages are distinguished:

A) **Research design:**

Step 1: Hypotheses and a hypothetical model are formulated based on the literature review,
Step 2: Online data collection is conducted to test the attitude of respondents towards AV-based tourism services.

B) **Structural Equation Modelling (SEM):** The analysis is summarized by the three accepted phases in CB-SEM (Kline 2011 Hoyle 2011):

Phase 1: Preliminary tests are run to exclude outliers, and test normality and sample size suitability.
Phase 2: After data cleansing, sample characteristics are examined.
Phase 3: Exploratory factor analysis (EFA) is applied to identify latent variables. Confirmatory factor analysis (CFA) aims to confirm the factor structure. Finally, the goodness of model fit and the final structural model are analysed.

4. Research design

Step 1 – Theory development

Though less attention has been paid so far to the tourism-related impacts of AVs, some findings prove (Tan & Lin, 2020; Ribeiro et al., 2021) that tourism perspectives might have a significant impact on ITU. Previous research (e.g., Adnan & Nordin, 2018; Rahman, Deb, Strawderman, Burch, & Smith, 2019; Yuen et al., 2021) has demonstrated that TAM-based models have a high

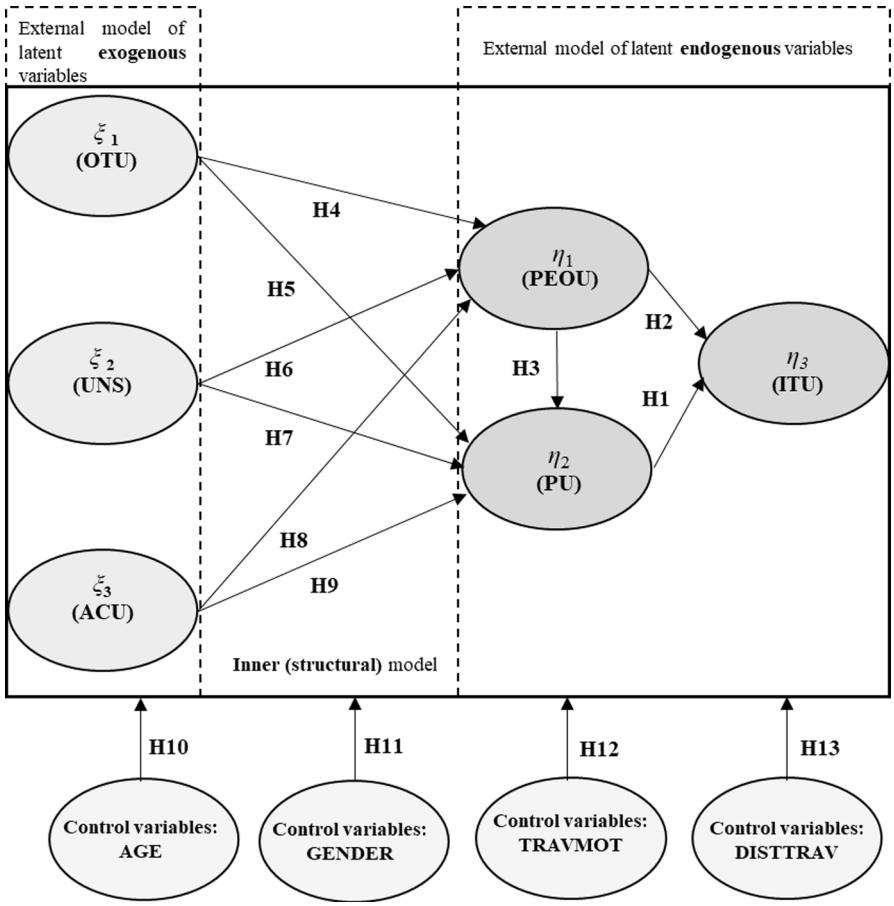

Fig. 4. The theoretical model of TAMAT.

explanatory power (based on the reported R^2 values of ITU – Table 1) for assessing the technology acceptance of AVs. Based on this, we applied the endogenous variables of TAM in our hypothetical model to explore the tourism aspects (Fig. 4).

The extended theoretical model has been created (Fig. 4) based on Hair, Ringle, and Sarstedt (2011). The hypothetical paths (H_n, $n = 1.0.13$) between exogenous (ξ_n, $n = 1.0.3$) and endogenous (η_n, $n = 1.0.3$) variables, and the hypothetical control variables, such as age, gender, travel motivation, distance travelled are noted. This model, TAMAT (Technology Acceptance Model of Autonomous vehicles for Tourism purposes) considers a several tourism-related aspects.

4.1. Endogenous variables

Following the relationships between endogenous variables of the original TAM model, three hypotheses have been formulated:

- **H_1:** *Perceived Usefulness (PU) has a positive impact on the Intention to Use (ITU).*
- **H_2:** *Perceived Ease of Use (PEOU) has a positive impact on the Intention to Use (ITU).*
- **H_3:** *Perceived Ease of Use (PEOU) has a positive impact on the Perceived Usefulness (PU).*

Since this research aims to reveal only the attitudes towards the usage of AVs, the variable Usage Behavior (UB) is out of scope.

4.2. Openness to tourism usage

The possible changes in tourism were sorted into groups based on Ivanov and Webster (2017), Kellerman (2018), Cohen and Hopkins (2019), and Cohen et al. (2020):

1) **Approaching the destination:** Using AVs would contribute to a smoother way of traveling (Cohen & Hopkins, 2019). Fewer resting stops would be enough altering tourists' preferences (e.g., decreasing the need to have accommodation).
2) **Traveling within the destination:** AVs may enhance the tourism experience by allowing all passengers to admire the environment (e.g., natural and built attractions) (Cohen & Hopkins, 2019; Cohen et al., 2020).
3) **Enhanced tourism services:** Sightseeing with AVs would be an innovative way of exploring the destination (e.g., AI-guided tours instead of traditional guided tours or hop-on and hop-off services). AVs could also function as mobile restaurants or hotel rooms, which would enhance the visiting experience (Cohen & Hopkins, 2019). The introduction of AVs is expected not to happen at once, even in highly innovative destinations. Therefore, the opportunity to test self-driving cars might become a primary tourist attraction (Kellerman, 2018).

Since previous research has not considered all the predicted tourism impacts summarized here, our research aim is to investigate how the attitude towards these tourism services affects the intention to use AVs:

- **H_4**: Openness to Tourism Usage (OTU) has a positive impact on the Perceived Ease of Use (PEOU).
- **H_5**: Openness to Tourism Usage (OTU) has a positive impact on the Perceived Usefulness (PU).

4.3. Unusual surrounding

The environment significantly affects mode choice (Levinson & Wynn, 1963; Cervero & Kockelman, 1997). Spatial diversity, namely the dissimilarity of the traveller's surroundings (e.g., narrow streets in old towns) is associated with lower intention to drive a car (Cervero & Kockelman, 1997; Boarnet & Sarmiento, 1998; Potoglou & Kanaroglou, 2008). Spatial design characteristics such as the density of the built environment, unusual street characteristics, or traffic rules also decrease car usage (McNally & Kulkarni, 1997; Hess, Vernez Moudon, Catherine Snyder, & Stanilov, 1999), mainly in the case of recreational travelling (Meurs & Haaijer, 2001).

During tourism trips, travellers might encounter several unusual environmental stimuli because of the spatial diversity and design, such as the side of the road they must drive on, unfamiliar road sections, and eye-catching attractions, which may influence the intention to use AVs.

This research aims to unveil how unusual surroundings (UNS) affect the intention to use AVs for tourism purposes:

- **H_6:** Unusual Surrounding (UNS) has a negative impact on the Perceived Ease of Use (PEOU).
- **H_7:** Unusual Surrounding (UNS) has a negative impact on Perceived Usefulness (PU).

4.4. Adherence to conventional use

The anxiety over the loss of conventional use has a significant impact on the intention to use AVs. Liljamo, Liimatainen, and Pöllänen (2018) argued that only 5% of their sample was willing to give up driving activities completely, and<20% agreed that AVs would increase travel comfort and experience. A stronger desire for control, especially among those using their cars, decreases the positive attitude toward self-driving cars (Bergman, Schwanen, & Sovacool, 2017; Lee et al., 2019, Syahrivar et al., 2021).

Accordingly, the impact of ownership preferences and attachment to manual control are considered:

- **H_8**: Adherence to Conventional Use (ACU) has a negative impact on Perceived Ease of Use (PEOU).
- **H_9**: Adherence to Conventional Use (ACU) has a negative impact on Perceived Usefulness (PEOU).

4.5. Control variables

Dixon, Hart, Clarke, O'Donnell, and Hmielowski (2020) highlighted that men are less concerned with risks related to the use of self-driving vehicles. Rödel, Stadler, Meschtscherjakov, and Tscheligi (2014) and Hulse, Xie, and Galea (2018) also found similar results when examining the role of gender in the adoption of AVs. Rahman et al. (2019) emphasized that older adults (aged 60 or over) are positively related to the use of AVs. Useche et al. (2021) stress that men's intentions are strongly influenced by increased travel efficiency, while women are more open to technology because of increased comfort and safety.

Two categories of control variables are considered in the analysis based on socio-demographic characteristics, such as gender and age:

- **H_{10}:** There is a difference based on AGE in ITU.
- **H_{11}:** There is a difference based on GENDER in ITU.

The differences based on the preferred tourism product (TRAVMOT) –such as urban tourism, recreational holidays, etc.–, as well as the distance travelled by car (DISTTRAV) are considered to understand the tourism habits of travellers who are open to using AVs:

- **H_{12}:** There is a difference based on TRAVMOT in ITU.
- **H_{13}:** There is a difference based on DISTTRAV in ITU.

Step 2 – Data collection

The data collection was carried out by an online survey in the Qualtrics Online Survey Software in autumn 2020. The online survey resulted in 671 responses. Respondents were asked to associate the period before the COVID-19 pandemic. On average, the survey took about 15 min to complete.

The proportion of participants by gender and age group was determined in relation to the Hungarian population. However, the final sample slightly differs from these criteria, as the analysis methods applied required data cleansing (e.g., multivariate normality analysis to detect outliers). The sample is therefore not representative, but it provides valuable data due to the number and diversity of the sample elements. Moreover, given the early stage of technology diffusion, respondents have little or no experience with AVs, thus their perceptions may be distorted by lack of experience and information. The online survey consisted of multiple-choice and scale-type (1–7) questions. The data was analyzed based on Covariance-Based Structural Equation Modelling, which enables the modification and validation of theoretical models (Dragan & Topolšek, 2014). The IBM SPSS Statistics 25 and IBM SPSS AMOS 26 software were applied for the analysis.

5. Results

Phase 1 – Preliminary tests

Preliminary tests suggested by the literature (Jarrell, 1992; Osborne Osborne & Overbay, 2008)) have been conducted to ensure the suitability of the dataset for multivariate analysis (CB-SEM).

1.1.1. Multivariate normality analysis: It was run to detect multivariate outliers based on Mahalanobis distance (MD). With the measurement of MDs, cases can be deleted from the dataset which is higher than the Critical Value (CR of MD) (Cabana, Lillo, & Laniado, 2019). The elements of the dataset with an MD above CR (41.34, $df = 28$; $p < 0.05$) were excluded ($n = 25$) from further analysis (remaining number of responses is 646).

1.1.2. Multicollinearity: It was measured by Variance Inflation Factors (VIF) and tolerance. In two cases of all observed variables selected for analysis ($n = 27$), the values exceeded the thresholds (VIF > 4.0, tolerance ≤ 0.2) (Hair, Celsi, Ortinau, & Bush, 2010), therefore, these observed variables were excluded from the analysis. For further analysis, 25 observed variables were considered.

1.1.3. Homoscedasticity: It has been tested using scatter plots suggested by Gaskin and Happell (2014). Results supported the homoscedasticity of the distribution since residuals are evenly scattered along the straight line (Hair et al., 2010).

1.1.4. Sample size calculation: Prior to the CB-SEM analysis, the suitability of the sample size has been examined based on methods suggested by Westland (2010) and Soper (2021). Sample size calculation proposed a minimum size of 170 for model structure and detected the effect of variables based on the research objectives (number of variables: observed = 25; latent = 6, anticipated size effect = 0.3, desired statistical power level = 0.8; $p < 0.05$). The sample size proposed is highly exceeded by the database selected ($n = 646$); therefore, the hypothetical model can be tested.

Phase 2 – Report of sample

Table 3 represents socio-demographic characteristics of the sample ($n = 646$) applied for structural equation modelling. Although the sample is not fully representative, it is heterogeneous in terms of socio-demographic characteristics. Female respondents are over-represented. The age of respondents ranged from 19 to 81. By education, the sample covers all categories, with the highest proportion

of people with a secondary-high school certificate (i.e., mostly undergraduate students). By place of residence, the number of respondents from the capital city Budapest is higher than in the total population as app. 18% of the population live in Budapest.

Table 4 summarises the tourism characteristics that are assumed to be the control variables of the model: respondents were asked which tourism products they are most interested in. Based on the outcomes, recreational holidays (25.32%) are dominant, followed by urban tourism (sightseeing, heritage tourism) (16.56%), wellness tourism (spas as primary motivation) (14.25%), and VFR (visiting family and friends) tourism (12.58%). Rural and wine tourism also play an important role (10.88%), but the demand for other tourism products such as MICE (meeting, incentives, conferences, exhibitions) tourism, active tourism, medical tourism, festival tourism, or other niche tourism is below 10%.

The most significant proportion of respondents who travel by car for tourism purposes chooses this transport mode for 300 to 500 km (23.83%) and 500 to 1,000 km (25.94%). 18.63% are willing to travel 100 to 300 km, while 25.52% are willing to travel>1000 km by car. The data show that only 6.08% of car users use their vehicles for short journeys (up to 100 km).

Phase 3 – SEM modelling

All remaining variables observed after data screening ($n = 25$) were included in Exploratory Factor Analysis (EFA). EFA aims to identify relationships between observed variables and find latent variables for the next step of SEM modelling (Confirmatory Factor Analysis – CFA) (Brown, 2015; Harrington, 2009). In the case of factor analysis, Internal Consistency (1), Convergent Validity (2), and Discriminant Validity (3) should be analyzed (Hair et al., 2010; Gaskin & Happell, 2014).

Phase 3.1. Exploratory factor analysis (EFA) (measurement model)

For *Internal Consistency*, the Keiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy (MSA) test was run to prove the suitability of the dataset for carrying out EFA. Calculation proved (KMO = 0.906) that the partial sum of correlations is not large relative to the sum of correlations; therefore, factor analysis could result in reliable factors (Hoyle, 2011; Kline, 2011. While performing EFA, Principal Component Analysis (PCA) with Promax rotation was applied to detect and remove values of communality below 0.2, as suggested by Child (2006) and Gaskin and Happell (2014). In this case, all values met the criteria (exceeded the threshold 0.2). Based on K1 (Kaiser criterion), Initial Eigenvalues of components must exceed 0.1. All factors have an Eigenvalue above 1, which explains more variance than a single observed variable. Therefore, six factors as latent variables are created, see in Table 5.

Proving the construct reliability suggested by Hair et al. (2010) and Gaskin and Happell (2014), Cronbach's alpha coefficients have been calculated. According to the values, individual constructs are reliable (exceed the cut-off value of 0.7).

For *Convergent Validity*, Composite Reliability (CR) and Average Variance Extracted (AVE) values have been tested. All constructs met the criteria of Convergent Validity (CR $\geq$ 0.7; AVE $\geq$ 0.5) (Hair et al., 2010).

For *Discriminant Validity*, the square root of AVE must exceed the correlation between the factors (Hair et al., 2010). As Table 6 shows, all constructs met this criterion.

Factor loadings should exceed the threshold of 0.8 (Preacher & MacCallum, 2003; Gaskin & Happell, 2014). As Table 7 shows, all constructs met the discriminant validity criteria and indicated high reliability. Based on all validity tests, the reliability of the measurement tools was sufficient for this study.

Phase 3.2. Confirmatory Factor Analysis (CFA) and model fit indices

CFA has been conducted to test the reliability (fit) of measures (Brown, 2015; Harrington, 2009). The fit of the structural model

Table 3
Sociodemographic characteristics.

Characteristics	Category	Percentage
Gender	Female	56.87%
	Male	43.13%
Age group	18–29	24.06%
	30–39	19.28%
	40–49	14.09%
	50–59	17.18%
	60–	25.39%
Educational level	Primary studies	1.94%
	Secondary-high school	35.48%
	Vocational school qualification	6.39%
	BA, BSc	27.6%
	MA, MSc	18.26%
	Ph.D., DLA	2.46%
	N/A	0.78%
Place of residence	Capital city	40.16%
	Urban region	46.76%
	Rural region	12.69%

Table 4
Tourism habits.

Characteristics	Category	Percentage
Travel motivation (TRAVMOT)	VFR (visiting friends and relatives) tourism	12.58%
	MICE (meeting, incentives, conferences, exhibitions) tourism	2.92%
	Recreational holiday	25.32%
	Rural and wine tourism	10.88%
	Sightseeing, heritage tourism	16.56%
	Active tourism (skiing, biking, mountain climbing, etc.)	8.03%
	Medical tourism (medical, dental treatments)	2.01%
	Festival tourism	6.59%
	Wellness tourism	14.25%
	Niche tourism (disaster tourism, volunteer tourism)	0.87%
	VFR (visiting friends and relatives) tourism	12.58%
Distance travelled (DISTTRAV)	≤100 km	6.08%
	≤300 km	18.63%
	≤500 km	23.83%
	≤1000 km	25.94%
	>1000 km	25.52%

Table 5
List of remaining observed variables (items) and related latent variables (factors) after data screening and CFA.

Observed variables			Latent variables (constructs)
Code	Items	Mean	Name
PU_1	I find it useful in self-driving cars that I can hand over the driving tasks to the machine.	4.87	Perceived Usefulness (PU)
PU_2	I find it useful in self-driving cars that I no longer have to monitor my surroundings.	5.38	
PU_3	I find it useful in self-driving cars that I am only a passenger while travelling.	5.35	
PU_4	I find it useful in self-driving cars that I can carry out other activities (e.g., work, entertainment) while travelling.	4.66	
PEOU_1	I think it is easy to learn how to use self-driving cars.	4.51	Perceived Ease of Use (PEOU)
PEOU_2	I think using self-driving cars is less physically demanding.	5.27	
PEOU_3	I think using self-driving cars is less mentally demanding.	5.32	
ITU_1	I would like to use a car that does not need to be manually controlled.	5.24	Intention to Use (ITU)
ITU_2	I would like to use a self-driving car that is controlled by a machine (artificial intelligence).	4.98	
ITU_3	I would like to use a car that can be used at the highest level of automation.	4.52	
UNS_1	In less familiar or unfamiliar surroundings (a destination I have never been to before), I would prefer to hand over the driving tasks to a self-driving car.	4.71	Unusual Surrounding (UNS)
UNS_2	In traffic conditions that are unusual for me (e.g., left-hand traffic), I would prefer to hand over the driving tasks a self-driving car.	4.45	
UNS_3	In an unfamiliar surrounding (e.g., when travelling abroad for tourism purposes), I would prefer to hand over the driving tasks to a self-driving car.	4.53	
UNS_4	In an unfamiliar surrounding (a destination I have never been to before), I would prefer to hand over the driving tasks to a self-driving car to get to know the environment.	4.52	
UNS_5	In an unfamiliar surrounding (a destination I have never been to before), I would prefer to hand over the driving tasks to a self-driving car to do other activities.	4.49	
OTU_1	I would use self-driving cars for guided city tours (AI as a tour guide) during a tourism trip.	4.77	Openness to Tourism Usage (OTU)
OTU_2	I would use self-driving cars in a destination visited to get to the places of my interest (e.g., tourism services, attractions).	4.51	
OTU_3	I would use self-driving cars with an interior space for rest and sleep (e.g., like a mobile hotel) during a tourism trip.	4.54	
OTU_4	I would use self-driving cars with an interior space for other tourism-related services (e.g., mobile meeting room, hospitality).	4.57	
OTU_5	I would use self-driving cars for experience "driving" during a tourism trip.	4.70	
ACU_1	It is important for me to keep the manual controls (e.g., steering wheel, pedals) in a self-driving car.	4.80	Adherence to Conventional Use (ACU)
ACU_2	It is important for me to decide when the self-driving car can take control.	5.23	
ACU_3	When travelling, I prefer to drive the car myself (and not another person or the machine).	5.34	
ACU_4	I prefer to use my own car when travelling.	5.55	
ACU_5	I consider buying a car is a life goal to be achieved.	5.66	

should be analyzed based on some of the most important fit measures suggested by Falk and Miller (1992), Schermelleh-Engel, Moosburger, and Müller (2003), and Hair et al. (2010). Table 8 summarizes all the fit indices suggested by the literature. Absolute fit indices prove how well the constructed model fits the database (Hoyle 2012); incremental (or comparative) fit indices study the fit improvement of the hypothetical model concerning the fit of the model (Kline, 2015; Hoyle 2012). In sum, all fit indices provide a good fit, since metrics are within the accepted thresholds.

The nomological validity, namely the degree to which a construct behaves as expected within a system of related constructs, can be evaluated with squared multiple correlation coefficients (R^2). R^2 values of endogenous variables must be higher than 0.1 to be

Table 6
Correlation matrix and the square root of the AVEs.

Construct	PU	PEOU	ITU	OTU	UNS	ACU
PU	**0.725**					
PEOU	0.554**	**0.755**				
ITU	0.628**	0.641**	**0.759**			
OTU	0.621**	0.487**	0.517**	**0.976**		
UNS	0.650**	0.608**	0.622**	0.645**	**0.816**	
ACU	−0.650*	−0.160**	−0.150**	0.036*	−0.123**	**0.722**

Note:
*Correlation is significant at the 0,05 level (2-tailed).
**Correlation is significant at the 0,01 level (2-tailed).

Table 7
Summary of factor analysis – Measurement model – Cronbach's Alpha, CR and AVE of constructs.

Construct	N of items	Cronbach's Alpha (α)	CR	Factor Loadings (√CR)	AVE
Name	**Observed variables**	**α > 0.7**	**CR > 0.7**	**√CR 0.8–0.9**	**AVE > 0.5**
PU	4	0.913	0.760	0.942	0.526
PEOU	3	0.924	0.726	0.994	0.570
ITU	4	0.833	0.789	0.897	0.576
OTU	5	0.848	0.988	0.852	0.953
UNS	5	0.945	0.887	0.872	0.667
ACU	5	0.801	0.804	0.888	0.522

Table 8
Fit indices.

Fit index	Threshold/ Cut-off value	Value	Note
Absolute fit indices			
Chi-Square (χ^2)	Low χ2 relative to degrees of freedom ($p > 0.05$)	9.565**	Good fit
Normed (relative) Chi-Square (χ2/d)	$\chi^2/d < 3$ (good) $\chi^2/d < 5$ (permissible)	3.18	Permissible
RMSEA (Root Mean Square Error of Approximation)	RMSEA < 0.08 (good) RMSEA > 0.10 (unacceptable)	0.054	Good fit
GFI (Goodness of Fit)	GFI ≥ 0.95 (good) GFI ≥ 0.90 (acceptable)	0.991	Good fit
AGFI (Normed-Fit Index)	AGFI ≥ 0.90 (good)	0.934	Good fit
Incremental fit indices			
NFI	NFI ≥ 0.95 (good)	0.987	Good fit
NNFI (Non-normed Fit Index *or* TLI (Tucker Lewis Index)	NNFI ≥ 0.95 (good)	0.968	Good fit
CFI (Comparative Fit Index)	CFI ≥ 0.90 (good)	0.994	Good fit

Note: ** Correlation is significant at the 0.01 level (2-tailed).

considered adequate (Falk & Miller, 1992). R^2 values of the structural model met this criterion ($R^2_{PEOU} = 0.489$; $R^2_{PU} = 0.647$; $R^2_{ITU} = 0.650$). Fig. 5 represents the standardized regression coefficients (β weights) which prove the strength of the relationship between two variables while adjusting for the impact of all other variables of the model (Hoyle 2012).

Phase 3.3. SEM model (structural model – TAMAT)

Fig. 5 and Table 9 summarize the relationships between variables on the significance level of $p < 0.01$. In Table 9, hypothesises are also noted whether the results prove or disprove them. PU and PEOU explained 65% of the variance in ITU (moderate level achieved – Chin, 1998). OUT, UNS and ACU collectively explain 64% of the variance of PEOU (moderate level). OTU, UNS and ACU collectively explain 48% of the variance of PU (moderate level).

Based on the analysis, the TAMAT model proves the following relationships and paths between variables:

- The relationship between the endogenous variables of the original TAM is validated, i.e., PEOU has a positive effect on PU ($\beta = 0.21$), and PEOU ($\beta = 0.5$) and PU ($\beta = 0.55$) together have a positive effect on ITU.
- OTU also has a positive impact on both endogenous variables (PEOU – $\beta = 0.18$; PU – $\beta = 0.3$) of TAM. OTU represents the attitude towards the expected changes in conventional tourism services with the spread of self-driving cars.

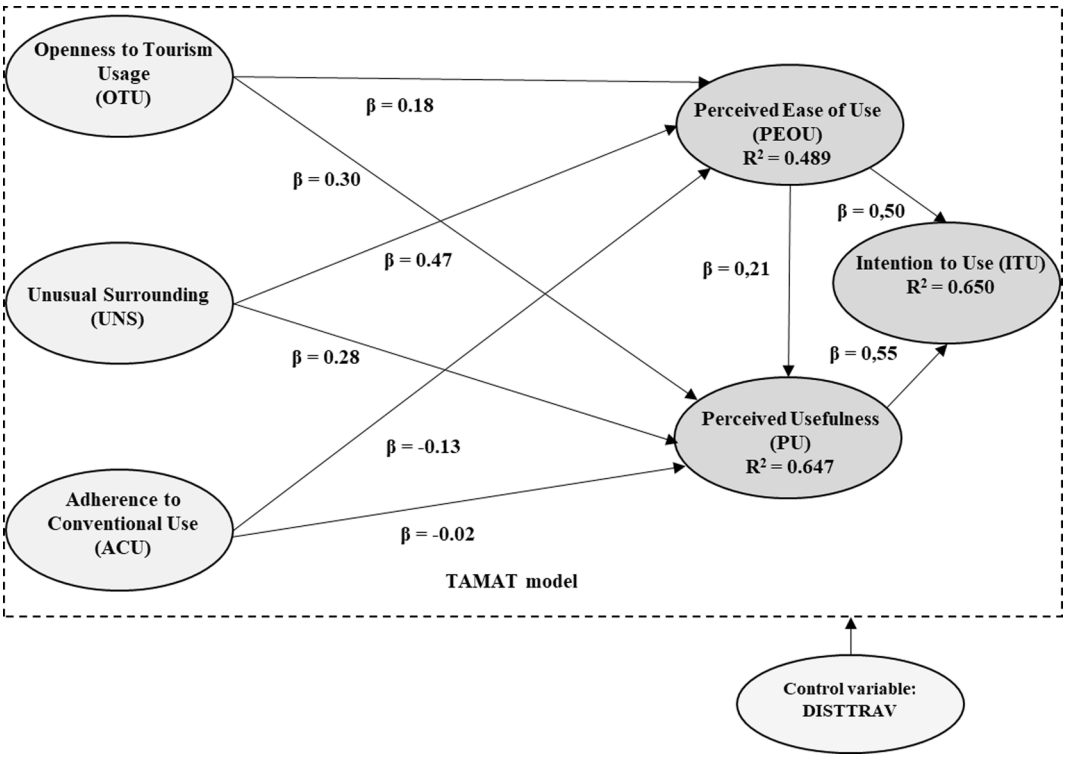

Fig. 5. Relationships between variables in the TAMAT model.

Table 9
Direct effects of paths.

Paths	Estimate *(β)*	*p*	Hypothesis	Hypothesis testing results
ITU ← PU	**0.548**	**	H1	Supported
ITU ← PEOU	**0.502**	**	H2	Supported
PU ← PEOU	**0.213**	**	H3	Supported
PEOU ← OTU	**0.178**	**	H4	Supported
PU ← OTU	**0.3**	**	H5	Supported
PEOU ← UNS	**0.473**	**	H6	Not supported
PU ← UNS	**0.278**	**	H7	Not supported
PEOU ← ACU	**−0.134**	**	H8	Supported
PU ← ACU	**−0.025**	**	H9	Supported

Note: ** Correlation is significant at the 0.01 level (2-tailed).

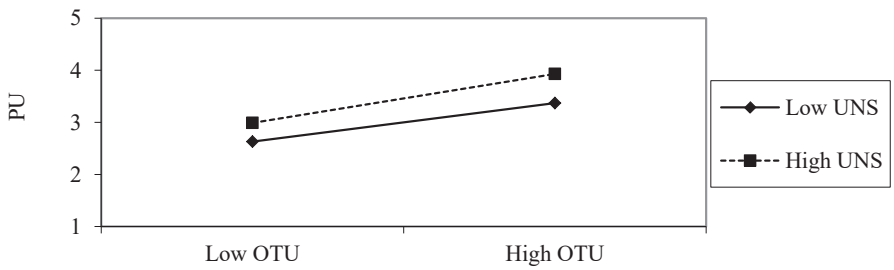

Fig. 6. Moderation effect of UNS on the relationship between OTU and PU.

- UNS represents a so far under-researched aspect in the technology acceptance of AVs. Findings proved that the environmental motives positively affect PEOU ($\beta = 0{,}47$) and PU ($\beta = 0{,}28$). An important finding is that spatial diversity reduces the demand for car use in the case of recreational travelling revealed by Meurs and Haaijer (2001) cannot be supported by our analysis in the case of self-driving cars.
- ACU, which represents the importance of vehicle ownership and the desire for manual control negatively, affects PEU ($\beta = -0{,}13$) and PU ($\beta = -0{,}02$) of AVs. A new finding related to this phenomenon is that the two preferences can negatively influence ITU.

Considering the moderation of variables, two statistically significant effects have been detected. The interaction between OTU and UNS proved that UNS strengthens the positive relationship between OTU and PU (Fig. 6.).

The interaction between ACU and UNS proved that ACU dampens the positive relationship between UNS and PEOU (Fig. 7.). The analysis of moderating effects proved that the role of ACU is strong enough to weaken the positive influence of the tourism-related variables (UNS and OTU) on ITU.

For multigroup analysis, a Chi-square difference test with the unconstrained vs. constrained models was run and found no significant difference based on AGE, GENDER, and TRAVMOT variables. Therefore, H_{10}, H_{11}, and H_{12} are not supported by the multivariate analysis. H_{13} is supported since multigroup analysis proved the significant impact ($p < 0.006$) of the control variable DISTTRAV on the model. Results proved that the longer the distance is, the greater the negative impact of ACU on PEOU and PU is. This suggests that the intention to use self-driving cars is stronger for shorter distance tourist trips (<500 km).

6. Conclusion

It is expected that AVs will play a significant role in tourism, but no previous empirical, SEM-based evidence has been found to understand the tourism-related impacts of AVs. The main contribution of this paper is the newly developed Technology Acceptance Model of Autonomous Vehicles for Tourism Purposes (TAMAT).

The systematic literature review revealed four main categories of variables that researchers use to assess the general technology acceptance of AVs. A particular focus is on the impacts of media usage and reference group opinion (e.g., Zhu et al., 2020; Yuen et al., 2021), the issues about the operation (e.g., Dirsehan & Can, 2020; Acheampong et al., 2021), the perceived benefits of use (e.g., Chen, 2019; Acheampong et al., 2021), and the consumer traits (e.g., Acheampong et al., 2021, Montoro et al., 2019).

The TAMAT model employs endogenous variables (Perceived Ease of Use – PEOU, Perceived Usefulness – PU, Intention to Use – ITU) of TAM (Davis, 1986), which is one of the most frequently used and widely accepted theory among the reviewed papers. TAMAT explains tourists' attitudes towards tourism-related AV services (OTU) and the environmental aspects of the usage (UNS). Moreover, the model considers the negative impacts of the adherence to conventional use (ACU), and thus leads to conclusions about future passenger transport and tourism.

For the empirical research, we applied covariance-based structural equation modelling (CB-SEM), a popular method for determining technology acceptance of different phenomena. Considering the model characteristics and the direct effects of our hypothetical model (H_1-H_9), moderating and multigroup effects (H_{10}-H_{13}) have been analyzed. Since all the fit indicators and R^2 values are met the criteria, and the intention to use (ITU) of AVs is moderately represented ($R^2 = 0{,}65$) by the variables of the model (Chin, 1998), the validity of our structural model is satisfactory.

The results show that tourism-related aspects also influence the acceptance of AVs besides the variables revealed by other researchers. Tourists would be open to using AVs for travelling from home to the destination and for sightseeing. Tourists would welcome the car interior extension for tourism purposes (e.g., mobile hotel room, meeting room). In unfamiliar environments, the attitude is more positive toward self-driving cars, which further strengthens the potential of technology in the tourism sector. However, resolving the perceived risks associated with AVs (e.g., Keszey, 2020; Useche et al., 2021) is critical to the diffusion of the technology.

Overall, the usability of AVs for tourism could significantly increase the adoption of self-driving cars. Especially self-driving cars affect urban tourism and its sub-segments (e.g., heritage tourism, conference tourism) since the application of AVs will first be possible mainly in urban passenger transport.

In addition to the theoretical implications, results are also worth considering for practitioners. For the automotive industry, results can be useful in better understanding user attitudes related to in-vehicle activities (Keseru & Macharis, 2018) or driving and its road

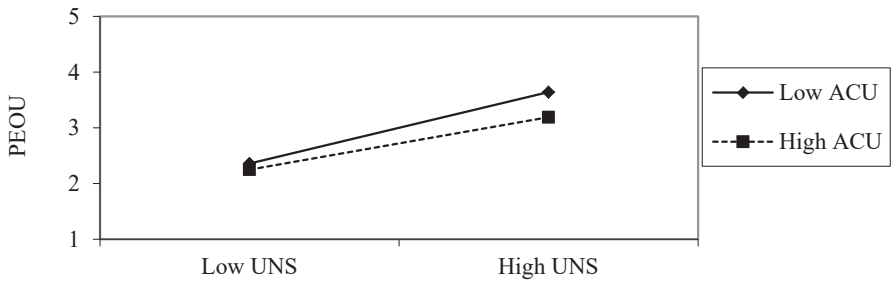

Fig. 7. Moderation effect of ACU on the relationship between UNS and PEOU.

safety aspects (Pauer, 2017, Pauer, Sipos, & Török, 2019) and, thus, rethinking improvements to the vehicle interior and user interfaces. For the tourism sector, the results suggest that AVs could become an important means of transport for tourism travel in the near future and indicate that the industry needs to consider the externalities (e.g., changing consumer preferences - demand for accommodation, travel leisure, etc.) and benefits (e.g., new tourism services based on AVs) resulting from this future trend. Based on the consumer attitudes revealed, there will be soon a demand for AV use for tourism purposes, and the sector must prepare for the expected penetration of the technology. For tourism development strategies should be developed considering the impacts of automation for which the main conclusions of our research can serve as a basis.

For further research, the potential distorting effects of COVID-19 on technology acceptance should also be addressed. The results proved that a deeper understanding of consumer perceptions of tourism products and travellers' behaviour, which are changing with technology, will be essential in social sciences. Most importantly, the cooperation between tour companies (e.g., Hop-on Hop-off) and automotive companies to develop AV-based tourism services needs to be analyzed in the near future. It is necessary to conduct an attitude analysis based on real experiences (e.g.: participation in living lab surveys) to verify the validity of the exogenous variables of the TAMAT. Another interesting path of further research could be the development of technology acceptance models focusing on specific sub-fields of the tourism sector or consumer segments.

CRediT authorship contribution statement

Melinda Jászberényi: Conceptualization, Supervision, Funding acquisition, Writing – review & editing. **Márk Miskolczi:** Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **András Munkácsy:** Writing – review & editing, Validation, Conceptualization. **Dávid Földes:** Writing – review & editing, Validation, Conceptualization.

Declaration of Competing Interest

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

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