Márk Miskolczi

Impacts of highly automated vehicles on urban passenger transport and tourism

Corvinus University of Budapest

Department of Tourism

Supervisors:

Dr. Melinda Jászberényi, *habil. associate professor*

Dr. András Munkácsy, *senior researcher*

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Impacts of highly automated vehicles on urban passenger transport and tourism

Doctoral dissertation

Márk Miskolczi

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KEY TO ABBREVIATIONS

ACU	Adherence to Conventional Use
ADAS	Advanced Driver Assistance System
AGFI	Adjusted Goodness of Fit Index
AGI	Artificial General Intelligence
AI	Artificial Intelligence
ANI	Artificial Narrow Intelligence
ASI	Artificial Super Intelligence
AU	Actual Use
AV(s)	Autonomous Vehicle(s)
AVE	Average Variance Extracted
BIU	Behavioral Intention to Use
CB-SEM	Covariance-Based Structural Equation Modeling
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
COVID19	Coronavirus Disease-19
CR	Convergent Validity
CR	Critical Value
DISTTRAV	Distance Travelled
EFA	Exploratory Factor Analysis
EVs	Electric Vehicle(s)
GFI	Goodness of Fit
GHG	Greenhouse Gas
GIS	Geographic Information System
GM	General Motors
GPS	Global Positioning System
ICT	Information and Communications Technology
IPAS	Intelligent Parking Assist System
ITU	Intention to Use
KMO	Keiser–Meyer–Olkin
LIDAR	Light Detection and Ranging
MD	Mahalanobis Distance
MICE	Meetings, Incentives, Conferences, Exhibitions
NFI	Normed Fit Index
NHTSA	National Highway Traffic Safety Administration
NNFI	Non-normed Fit Index
OECD	Organisation for Economic Co-operation and Development
PCA	Principal Component Analysis
PEOU	Perceived Ease of Use
PLS-SEM	Partial Least Square Equation Modeling
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
PU	Perceived Usefulness
RADAR	Radio Detection and Ranging
RMSEA	Root Mean Square Error of Approximation
SAE	Society of Automotive Engineers
SARS-COV-2	Severe Acute Respiratory Syndrome Coronavirus 2
SLR	Systematic Literature Review
TAM1-2-3	Technology Acceptance Model 1-2-3
TAMAT	Tourism-based Technology Acceptance Model of Autonomous Vehicles
TLI	Tucker Lewis Index
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TRAVMOT	Travel Motivation
UNS	Unusual Surroundings
UTAUT1-2	Unified Theory of Acceptance and Use of Technology 1-2
VFR	Visiting Friends and Relatives
WTO	World Tourism Organization

I INTRODUCTION – THEORETICAL CONTEXT AND METHODS

I.1 The relevance of the topic

Our socioeconomic environment has been undergoing a major transformation, fostered by the current industrial revolution (Industry 4.0). Among Industry 4.0 solutions, the most impactful phenomenon is automation, which describes a broad spectrum of technologies that minimize human intervention in different work-related processes (Fagnant and Kockelman 2015). With the development of automation, the use of machines to replace human labour is on the rise and could also fundamentally shape urban passenger transport in the near future.

The development of autonomous vehicles (AVs) and related infrastructures raises highly multidisciplinary problems, as still many technical, legal, and even social and economic aspects are unanswered or uncertain (Bagloee et al. 2016; Bergman et al. 2017). AV technology is an incremental innovation that can be interpreted based on the international framework created by the Society of Automotive Engineers (SAE) (SAE International 2021). Currently, AVs on Level 2 and 3 are available (e.g., Tesla, Honda models, or some forms of shared mobility services – UBER, Waymo). With the continuously emerging artificial intelligence (AI) solutions, AVs can move and reach their destination under decreasing human control, since these vehicles are aware of their surroundings by means of various sensors (e.g., optical sensors, laser radar, image analysis) (Tromaras et al. 2018).

The prime reason for developing the technology is to increase road safety, i.e., to minimise and then eliminate the number of road accidents caused by human error (Shoettle and Sivak 2014). Furthermore, the diffusion of the technology can contribute greatly to reducing traffic externalities (e.g., congestion, reducing greenhouse gas emissions from passenger transport) (McEvoy 2015; Clements and Kockelman 2017).

However, in addition to the expected positive effects of AVs, non-technological aspects (socio-economic, moral, legal) may hinder its diffusion since many unresolved issues can be still identified around the technology. Empirical research (Zawieska and Pieriegud 2018; Freudendal-Pedersen et al. 2019, Melander et al. 2019) emphasise that the key to widespread adoption of AVs is to address the shortcomings of the technology, while at the same time to increase consumer acceptance by identifying the factors that influence the intention to use.

While the scope of research on the social impact of automated vehicles is growing, detailed sectorial analyses are still limited. Cohen and Hopkins (2019) underline that tourism is one of the tertiary sectors most exposed to technology, as tourism travel is greatly influenced by innovations in the passenger transport system. Nevertheless, tourism-specific empirical research is currently still very limited.

In the light of these, my research question (RQ) is the following: *How does the spread of highly automated (SAE 4-5) vehicles affect the tourism sector, especially the mobility for tourism purposes, and conventional tourism services?*

To answer the research question, the phenomenon itself (AV technology) needs to be analyzed from different aspects. For the summary of my research findings, an article-based dissertation has been made, which consists of four peer-reviewed papers.

The dissertation is structured as follows: before presenting the journal articles, the theoretical background is introduced in Chapter I.2, including the basic concepts of automation, and the interpretation of the tourism system in the light of the expected changes brought about by AVs. Since my intention is to reveal tourists' attitudes towards AVs and AV-based tourism services, the theory of technology acceptance models, and thus the conceptual framework of my research is also presented. In Chapter I.3, the data collection, the qualitative and quantitative methods applied are summarized. As the journal articles presented below are co-authored, Chapter II clarifies the authors' contributions based on the framework suggested by Brand et al. (2015). The four journal articles (P1-P4) are then presented in Chapters III-VI. In chapter VII, the theoretical and practical contributions of my research are outlined together with the limitations and future research directions.

I.2 Theoretical background

In this section, the basic concepts of automation, tourism, mobility, and the theories of technology acceptance are discussed, and then the conceptual framework of my research are presented.

I.2.1 Industry 4.0. – definition of automation, autonomous vehicles (AVs) and artificial intelligence (AI)

Autonomous vehicles (AVs) (*also known as self-driving, driverless, or robotic*) can detect their surroundings with specific sensors and operates with decreasing human intervention (Clements and Kockelman 2017). AVs are based on automation technology, an invention of the industry 4.0.

The term industry 4.0 has been used in the literature since the mid-2010s (Lasi et al. 2014; Davis et al. 2015) and has since related to several radical technological innovations across disciplines and sectors. The previous industrial revolutions also reshaped both our transport opportunities and habits. In the 19th century, the internal combustion engine (ICE), the application of conveyor belts, and the oil industry started to force horse-drawn vehicles out of the sector (Hatamleh and Tilesch 2020). Today, passenger transport is facing a very similar transition, as Industry 3.0 (convergence of intelligent software and web-based services) and Industry 4.0 solutions (AI-based services, spread of shared mobility) are starting to replace conventional vehicles, and thus completely transform infrastructural (e.g., capacity utilisation of urban spaces, parking, and road use) and travel mechanisms (e.g., commuting preferences and opportunities) (Coppola and Silvestri 2019).

Pfohl et al. (2015) define Industry 4.0 as a disruptive innovation aiming to minimise the need for human resources. According to Yoon (2017), Industry 4.0 will be a coexistence of physical and virtual space, with AI-based solutions leading to a high degree of integration between devices and people, and a new level of human existence. Prisecaru (2017) distinguishes two areas of Industry 4.0, biological (genetic engineering) and physical (robotics) innovation. In robotics, AI is an outstanding innovation that focuses on the development of computer programs capable of performing tasks that previously required human resources (Winter et al. 2016). AI uses algorithms to learn and understand complex situations. Its applications have become more widespread in recent years (a common example is the AI-based Google search interface) (Coppola and Silvestri 2019).

Based on Hatamleh and Tilesch (2020), 3 levels of AIs can be distinguished, of which 2) and 3) are still theoretical:

1) **Artificial Narrow Intelligence (ANI):** It has a limited scope and only one functional area. ANI is capable of performing better than humans in that specific area. They have a narrow set of capabilities, such as suggesting products to an e-commerce user or forecasting the weather, or controlling smart home devices (for example Siri, Alexa, Cortana, Google Assistant).
2) **Artificial General Intelligence (AGI):** AGI will be able to understand its environment and think in a similar way to humans, alongside other human cognitive abilities. Currently, this type of AI is only theoretical.
3) **Artificial Super Intelligence (ASI):** If technological progress reaches this level in the future, ASI will be able to surpass human intelligence in every field.

Coppola and Silvestri (2019) also divide AI into two additional categories, namely Strong (has wider application and human-level intelligence) and Weak (capable of only specific tasks) Artificial Intelligence. Following the typologies presented, AVs belong to the ANI and the Weak AI categories, since these vehicles are operated by artificial intelligence, although they are only capable of managing specific tasks (taking over the driving of a vehicle in certain situations).

Based on Hirz and Walzel (2018), Zhao et al. (2018), and Shreyas et al. (2020), the background technology of AVs can be classified into four parts:

1) **Car navigation system:** it includes Geographic Information System (GIS) and Global Positioning System (GPS) which receive longitude and latitude positioning information from satellites. This data serves as the input to the intelligent route planning algorithms.
2) **Route planning:** it is closely related to the previous function since route (path) planning is used to identify the optimal driving route between the starting point and the endpoint.
3) **Environment perception:** it consists of sensors that aim to analyze the immediate surrounding to manage the vehicle.

For environment perception, three major types of sensors can be distinguished in AVs: cameras (1), lidars (2), and radars (3).

3.1. *Camera sensors*: AVs are equipped with video cameras to sense and understand objects on the road. With cameras, vehicles can manage a 360° view of their external surroundings, giving them a broader picture of the traffic conditions. 3D cameras are also available and used to display realistic images of every object in the surrounding (e.g., cars, pedestrians, cyclists, traffic signs and signals, pavement markings, bridges).

3.2. *Lidar (Light Detection and Ranging):* These sensors operate in a similar way to radar systems, except that they use lasers instead of radio waves. Lidar can rotate 360° to get a better view of the surrounding environment. It can detect thousands of laser pulses per second thus helping to control breaks in case of an emergency and helping to accelerate when there are no objects in front of the vehicle. With data from the lidar sensor, vehicles can create 3D models of their direct surroundings.

3.3. *Radar (Radio Detection and Ranging):* sensors emit radio waves that detect objects and measure their distance and speed relative to the vehicle. Two types of radars based on their range are applied: long-range (77 GHz – for automatic distance control and brake assistance, and short-range (24 GHz – aims to monitor blind spots and manage lane-keeping assistance and parking). Radar sensors also perform well under unfavourable circumstances (e.g., in bad weather).

3.4. There are some *complementary sensors* that aim to enhance the accuracy of operation (e.g., microphones to record audio of the surroundings – emergency sirens).

4. **Vehicle control***:* Vehicle control means managing the speed and direction of the vehicle. There is a *central computer* built into the vehicle to make all the driving decisions and thus control the vehicle along with specific algorithms. Vehicle control also detects the vehicle status to enhance safe operation.

Since AV technology is incremental innovation, the progression of that is defined at different levels. Table 1 presents the differences between SAE levels based on how the responsibilities of the machine (AI) and the human driver vary for each driving task (SAE International 2021).

SAE levels			Control tasks[1]	Monitoring the environment	Fallback when machine fails[2]
	0	*No automation*	human driver	human driver	human driver
Driver assistance system	1	*Driver assistance*	human driver/machine	human driver	human driver
	2	*Partial automation*	machine	human driver	human driver
	3	*Conditional automation*	machine	machine	human driver
Highly automated system	4	High automation	machine	machine	machine
	5	Full automation	machine	machine	machine

Table 1. Levels of automation based on SAE International (2021), own editing

Currently, vehicles on SAE Level 2 and 3 are commercially available. These vehicles are equipped with advanced driver assistance systems (ADAS) and can manage certain road sections (highways) without human intervention, but the presence of a human driver is still mandatory (Freudendal-Pedersen et al. 2019). Vehicles on Level 4-5 can manage the entire journey without human assistance (SAE International 2021). Key differences in SAE automation levels are discussed by Paper 1 (Section: III) and Paper 3 (Section: V) in detail.

Yet, the diffusion of AVs is still uncertain, according to researchers' predictions. Market forecasts, however, indicate a positive trend in terms of AV diffusion. Statista.com (2021) – a global business data platform specialising in market and consumer behaviour research – predicts that AV sales are expected to grow in the period 2019-2030 (Figure 1). By 2030, global sales of these vehicles are projected to hit 58 million units globally. Future scenarios related to the possible impact and spread of AVs are discussed in Paper 2 (Section: IV).

[1] for example: steering, acceleration, deceleration, etc.
[2] traffic situation that cannot be handled by AI

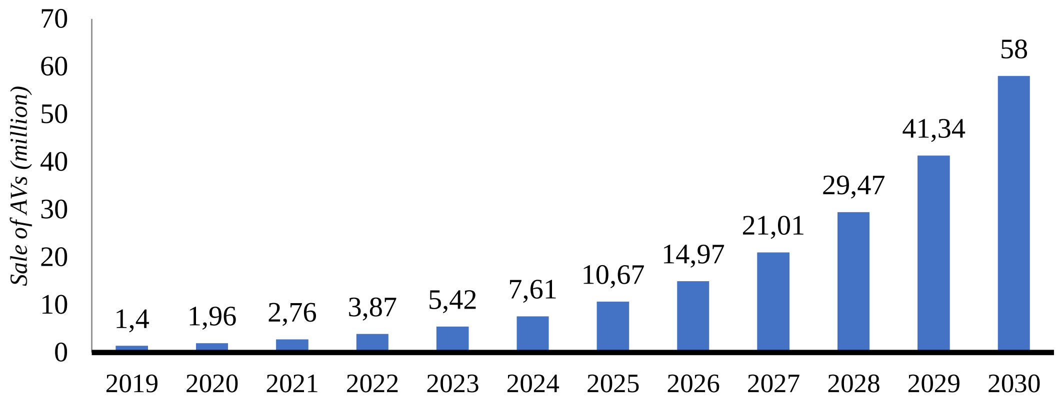


Figure 1. Projected sale of AVs worldwide from 2019 to 2030 (in million units) based on Statista.com (2021), own editing

Based on Statista.com (2021), it is predicted that 63% of vehicles sold globally in 2025 will be on SAE Level 2 or higher (Figure 2). In 2030, about the same proportion of new vehicles sold globally will be on Level 2 or higher. However, it is predicted that vehicles with more advanced autonomous driving features (SAE Level 4-5) will begin to enter the market in 2030.

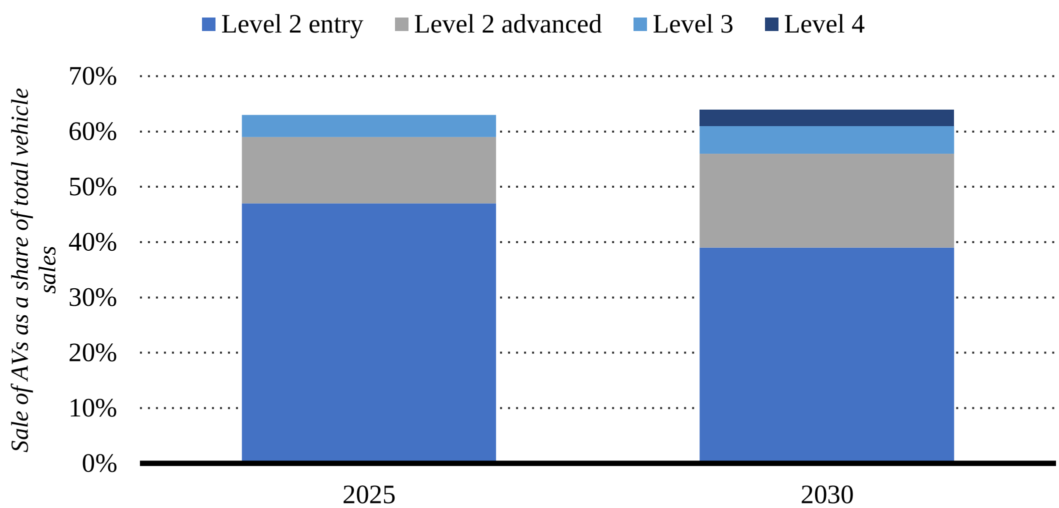


Figure 2. Projected sale of AVs worldwide from 2019 to 2030 (in million units) based on Statista.com (2021), own editing

Several automotive companies have started to develop self-driving cars/advanced driver assistance systems, pioneered by Tesla and Waymo, a former subsidiary of Google, which is testing its highly automated vehicles on public roads (Diamandis and Kotler 2020). AVs of Waymo company have travelled 16 million kilometres since 2009 and estimates that by 2022, at least 1.5 million kilometres will be added to that number every day

(Diamandis and Kotler 2020). General Motors (GM)[3] also invested $1.1 billion in 2016 in its self-driving vehicle development division. Bloomberg (2021)[4] reports that self-driving vehicles are currently being tested on public roads in 138 cities. Uber's self-driving cars travel an average of 15 million km per day (Diamandis and Kotler 2020). In the next ten years, based on predictions (Becker et al. 2020) we can expect a consolidation of the car industry, which could be greatly boosted by the spread of AVs.

Recognising the relevance of the technology, significant steps have been taken to support automotive development in Hungary, both on-road and closed-track testing. In 2016, a decision was taken to build an automotive proving ground in Zalaegerszeg, which will also be suitable for testing highly automated vehicles[5]. In 2015, a Budapest-based company, AImotive[6] (formerly AdasWorks), a self-driving vehicle technology company, was also established to develop Level 5 self-driving vehicles. As further support for domestic vehicle development, a decree issued by the Ministry of National Development (2017) allowed for the testing of autonomous vehicles on the roads[7].

At present, AVs on Level 4-5 are not yet widely available, so their expansion does not affect passenger transport and indirectly other sectors and industries. However, as can be seen from the description, the technology has developed rapidly in recent years and is predicted to continue to do so in the coming years. This means that we are still in time, in the early stages of the technology's diffusion, to identify the dilemmas and opportunities associated with the spread of AVs and to prepare for their expected sectorial impacts. Scholars (McEvoy 2015; Cohen et al. 2020) stress the importance of tourism-specific studies to avoid damaging externalities, too, which also confirms the relevance of my research question. The expected impacts on tourism are described in the following section.

[3] https://fortune.com/2016/03/11/gm-buying-self-driving-tech-startup-for-more-than-1-billion/
[4] https://avsincities.bloomberg.org/
[5] https://zalazone.hu/hu/bemutatkozas/
[6] https://aimotive.com/solutions
[7] NFM Decree 11/2017 (IV. 12.) on the testing of vehicles for development purposes. (*A fejlesztési célú járművek tesztelésével kapcsolatos 11/2017. (IV. 12.) NFM rendelet*) URL: https://net.jogtar.hu/jogszabaly?docid=A1700011.NFM&timeshift=20170427&txtreferer=00000001.txt

I.2.2 Tourism and mobility – definitions and expected impacts driven by AVs

Tourism is a remarkable social phenomenon for centuries. Yet, modern tourism developed in the late 18th century, with the industrial revolution laying the foundations for the sector (Towner and Wall 1991). At that time, increased mobility opportunities and shifting social patterns have created new leisure opportunities for a wider range of people, and thus establishing the basis for mass tourism (Lengyel 1992, Michalkó 2004; Irimiás et al. 2019). Today, tourism has become a leading global industry, contributing on average 10% of total GDP (Bayramov and Agárdi 2018).

Industry 4.0 could also reshape tourism, the consequences of which are already beginning to be noticed. In light of this, in presenting the basic concepts of tourism, the expected impacts and open issues related to AVs are highlighted. The need to analyze the impacts of AVs is supported by the core definition of tourism defined by the Hague Declaration (1989). The definition clearly demonstrates the vital role of transport in tourism, stating that *tourism includes* all free *movement of people* outside their place of residence and work, and the services created to meet their needs (WTO 1989).

The links between the sectors are also underlined by the structure of tourism defined by Lengyel (2005) (Figure 3), which provides an understanding of the main market mechanisms (supply and demand) of the sector. Following the traditional elements of the model, Figure 4 highlights the presumed changes brought about by industry 4.0. and other – currently leading – trends.

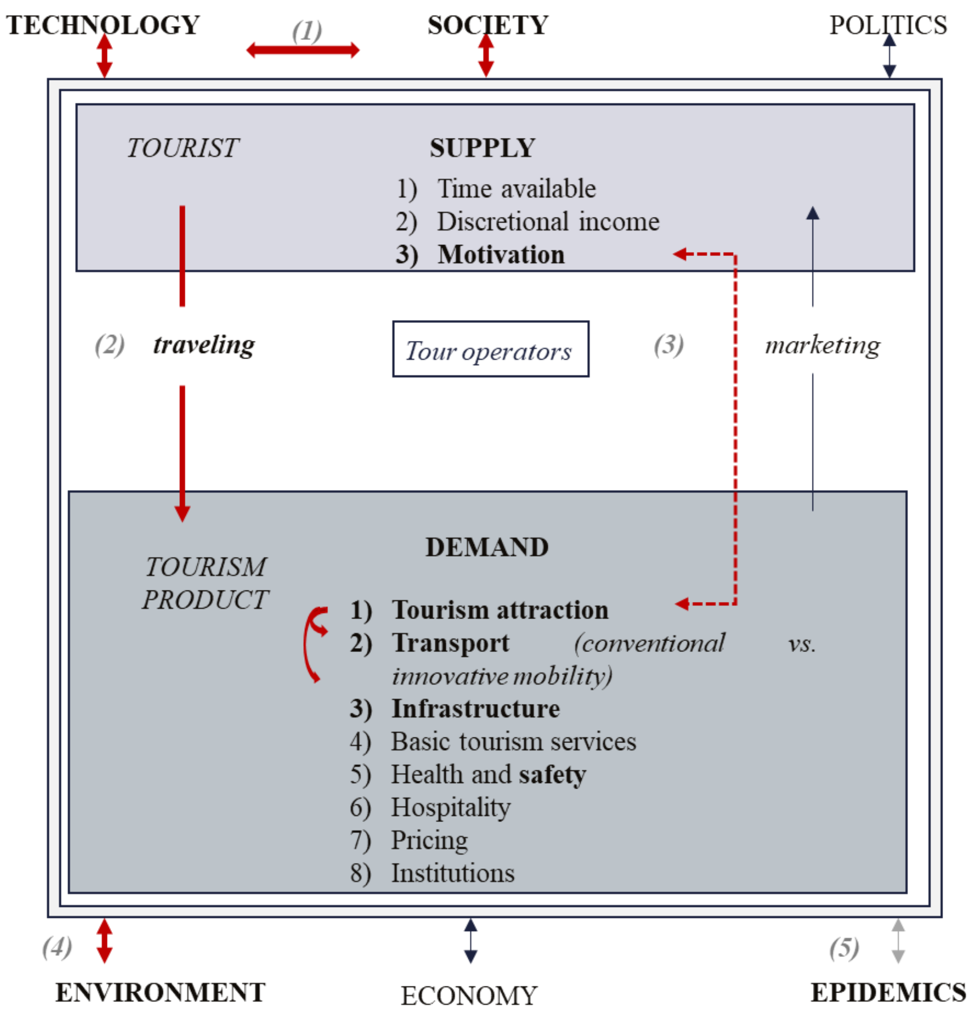


Figure 3. The tourism system based on Lengyel (2005) and Munkácsy (2018) with modifications, own editing

The model describes tourism as an open system, influenced by a wide range of external factors (environmental, social, political, technological, economic and others), which are in strong interaction with each other (Lengyel 2005; Michalkó 2016). Based on the research theme, five main alterations can be emphasized in tourism, considering the current leading trends and the expected spread of AVs.

(1) In terms of external elements, the impact of automation as a leading technological phenomenon needs to be highlighted, which interacts very closely with the social milieu, as the rapid development of Industry 4.0 technologies (e.g., the emergence of AI-based services and partially automated vehicles) might alter our everyday lives (e.g., consumption habits, human-machine interaction) (Bonnefon et al. 2016). Consequently, automation also could reshape the system of tourism. Stakeholders of the sector experienced how the spread of the internet has influenced the role of

traditional travel agencies, or the rise of sharing economy reshaped accommodation services (e.g., Airbnb). Findings (Wicaksono and Maharani 2020; Jung et al. 2021) proved that changes in social openness have played a key role in these transformations. Scholars (Zhang et al. 2019; Du et al. 2021) also highlight the links between the spread of automation and changing social attitudes.

(2) Based on this, major changes in the internal system (supply and demand factors) of tourism might be observed in the upcoming years. Owing to the spread of AVs, the connection between tourists and tourism products, i.e., the way of approaching a tourism attraction, might be transformed in several ways (e.g., travel distanced by car, preferred means of transport, consumption during the journey – Cohen and Hopkins 2019). The importance of this issue is further underscored by the long dominant role of car use in tourism (Ward 1987). A significant proportion of car usage comes from tourism-related travel, which generates heavy traffic on the road network both seasonally (e.g., at the beginning and end of summer holidays) and spatially (e.g., around coastal resorts) (Munkácsy 2018). Hence, an innovation that affects individual passenger transport can have also an indirect impact on tourism-related travel.

(3) With the spread of AVs, the motivation of individuals to participate in tourism trips may also change. At this point, it is important to clarify that mobility may not only be a means of realising tourism consumption, but that mobility itself, or the use of a particular means of transport (e.g., nostalgia trains, cruise ships), may also appear as a tourism attraction for travelers (Jászberényi and Pálfalvi 2006; Munkácsy 2018). Based on this, the innovative forms of car use enhanced by automation (e.g., sightseeing with AVs) might appear as a tourist attraction in the future (Cohen and Hopkins 2019). Another trip-generating factor could be the ability to see the local (smart) urban infrastructure that will be improved by the spread of AVs (Csiszár and Földes 2017; Csiszár et al. 2019). In addition, high or full automation (SAE Level 4-5) will lead to a driverless operation which might expand the range of on-board services and thus the passenger experience. Bearing this in mind, my intention is to identify changes in supply and demand mechanisms within the tourism system, including both changes in demand (consumer attitudes) and tourism services resulting from the spread of AV.

(4) Climate change and the increasing frequency of natural disasters all around the world affect tourism both indirectly and in the form of the emerging responsible travel

behaviour (Rosselló et al. 2020). Since AVs – based on current forecasts and industry plans (Bagloee et al. 2016) – will be mainly electric or other alternative propulsion vehicles, they could also be a catalyst for more environmentally friendly passenger transport. On the other hand, by increasing the mobility alternatives of individuals (e.g., cars can be used without a driving license at the level of full automation), the risk of excessive car use could be increased, which may contribute to the worsening of currently serious traffic problems (e.g., congestion, capacity utilisation of urban spaces and roads) (Bagloee et al. 2016; Bergman et al. 2017; Coppola and Silvestri 2019). Therefore, it is of paramount importance to explore the social openness to a sustainable application of AVs (e.g., the openness to use shared and self-driving vehicles).

(5) In the light of the current crisis, I also indicated the epidemic as an external phenomenon of the tourism system, which is currently of particular importance, as the COVID19 outbreak caused by the SARS-COV-2 virus has led to a worldwide recession in tourism (Škare et al. 2021). Based on current predictions (Jia and Yang 2020; Alamo et al. 2021), the frequency of outbreaks of epidemics (e.g., endemics) might increase in the coming decades, which will require the impact of epidemic risk to be considered as a permanent external element of the tourism system.

As mentioned above, the spread of AVs raises several questions for the sector – the possible applications of self-driving cars for tourism purposes, how these will affect traditional tourism services, and how tourists will relate to the expected changes by the spread of AVs –, therefore, it is reasonable to examine consumer attitudes from a tourism perspective.

I.2.3 Theories of technology acceptance

To explore consumer attitudes towards AVs (e.g., factors affecting the intention to use), I applied the theory of technology acceptance models. Since the concept of technology acceptance is closely related to the innovation theories, the most employed definition of innovation by the OECD in its Frascati Manual (2002) is presented here.

Innovation is defined as the transformation of an idea into either a new or improved product launched on the market, a novel or improved operation applied in industry, or a new or improved approach to social service (OECD 2002).

The Oslo Manual further distinguishes four types of innovation (OECD 2002):

- **Product innovation**: a new or considerably improved product or service. Product innovation might cover substantial improvements in technical specifications, materials, or other functional characteristics.
- **Process innovation**: A new or greatly improved method of production or delivery. This includes major changes in techniques, facilities and/or software.
- **Marketing innovation**: A new marketing technique that involves major changes in product design or packaging, or in other marketing components (commercial, pricing, etc.).
- **Organisational innovation**: A new way of organising business practice or relationships with stakeholders.

The technology of AVs can be considered primarily as *product innovation*, although considering the impacts of its diffusion on tourism, it covers all the innovation sub-cases, as the usage of self-driving cars may change the way of approaching the destination (*process innovation*), the traditional value creation of tourism service providers (*organisational innovation*), and the consumer behavior, i.e., the intention to purchase tourism-related services can also be redefined (*marketing innovation*). The spread of technology is therefore disruptive for the tourism sector, thus prompting a deeper, sector-specific analysis of the phenomenon.

Scholars emphasize (Davis 1986; Venkatesh 2000) that innovation depends to a large extent on the factors that influence consumers' willingness to adopt changes. For a better understanding of consumer attitudes, technology acceptance models have been developed which describes the adaptability of consumers along with different influencing factors.

The theory is based on the Theory of Reasoned Action (TRA) developed by Martin Fishbein and Icek Ajzen (1967) which also aims to understand the connection between attitudes and behaviours in human action.

The first technology-acceptance model (TAM1) was developed in 1986 by Davis, which suggests that there are two main factors that influence consumers' acceptance of technology (Figure 4): the perceived ease of use (PEOU) of the technology and the perceived usefulness (PU). Perceived ease of use has a positive effect on perceived usefulness, which influences the consumers' attitude towards technology. Attitude affects the level of the intention to use the technology which may lead to actual use in the future (Davis 1986).

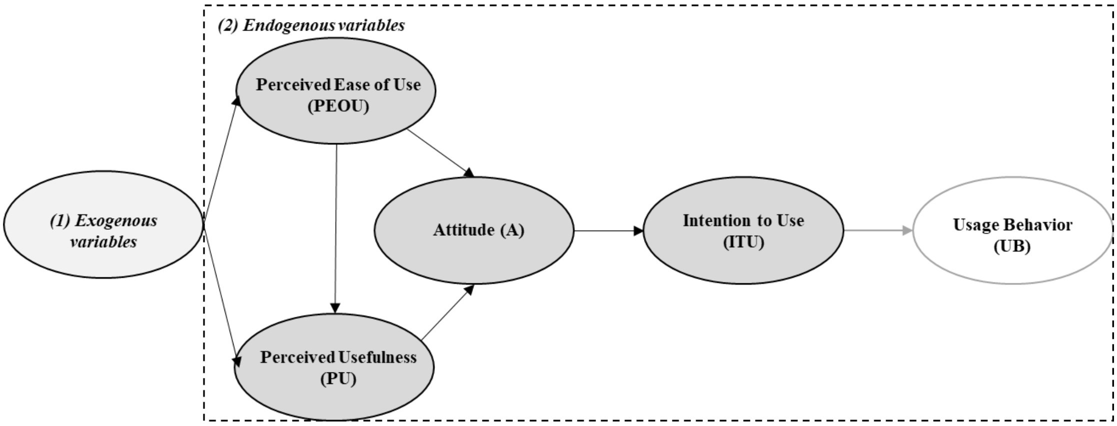


Figure 4. TAM1 (Technology Acceptance Model – version 1) based on Davis (1986), own editing

The elements of the TAM1 model:

- **Perceived usefulness (PU):** represents the subject's perception of how their performance is affected (improved or declined) using technology.
- **Perceived ease of use (PEOU):** includes consumer perception of the effort (physical and mental) required to use the technology.
- **Attitude (A):** the previous two variables (PU and PEOU) determine the general opinion/approach of consumers towards technology.
- **Intention to Use (ITU):** defines the consumer's attitude that characterizes the strength of consumer's adaptability.
- **Actual Use (AU):** indicates the extent to which the intention to use leads to actual use (Davis 1986).

Based on the theory, external variables may be consumer or technology-specific, do not directly affect consumer attitudes, but directly affect PEOU and PU (Davis 1986). Davis (1986) tested the model on IT systems (e.g., mail system) by introducing the technology to the subjects and then asking questions related to the variables in the form of a questionnaire. The main advantage of the *TAM1* model is the flexibility of the independent variables which makes it easily adaptable to test the acceptance of various technologies.

Over the past decades, researchers have developed several technology-acceptance models. To improve the forecasting ability of TAM1, additional variables, and so the *TAM2* model has been created by Venkatesh and Davis (2000). Attitude (A) variable has been removed from TAM2 and two new categories of external variables have been added (Figure 5):

- **Independent variables of social influence processes***: Subjective Norm* (the relevance of the opinion of the subject's reference group about the technology), *Voluntariness* (the degree of usage voluntarily) and *Image* (represents the general perception of the technology).
- **Cognitive instrumental processes elements**: *Job Relevance* (represents how the technology serves (helps) the subject's working process), *Output Quality* (refers to the quality of the results achieved through the usage of the technology), and *Result Demonstrability* (includes the level of process transparency) (Venkatesh and Davis 2000).

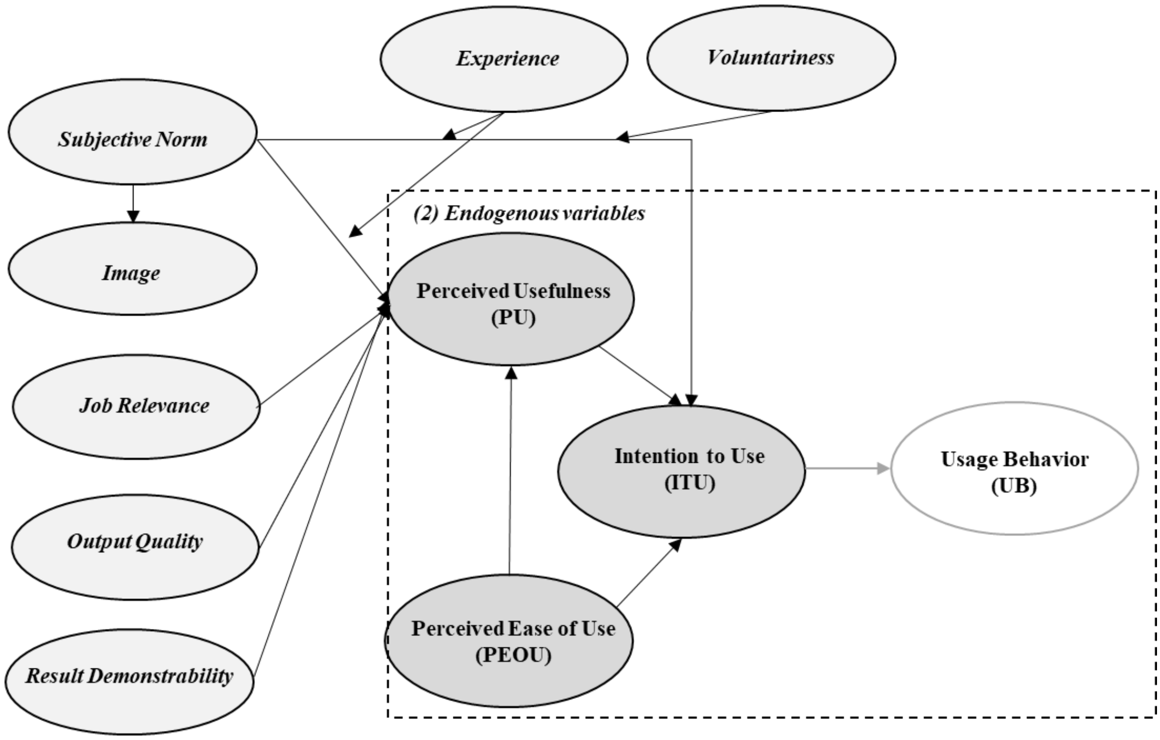


Figure 5. TAM2 (Technology Acceptance Model – version 2) based on Venkatesh – Davis (2000), own editing

The theory introduces two moderating variables (*Experience, Voluntariness*). The experience moderates the impact of subjective norm on perceived usefulness and on the intention to use in a negative direction. That is, if subjects have little experience, subjective norms are more likely to influence the perceived usefulness and the intention to use (Venkatesh and Davis 2000). The model emphasizes, that cognitive instrumental processes have a positive influence on PU and ITU.

As a further development of the model, *TAM3* has been developed by Venkatesh and Bala (2008). TAM3 includes new external (exogenous) variables to increase the complexity of using the technology (Venkatesh and Bala 2008).

- **Computer Self-Efficacy:** the degree of subject's abilities required to manage the system),
- **Perception of External Control:** how the subject perceives the availability of the facilitating technical background while using the technology),
- **Computer Anxiety:** the degree of the subject's anxiety caused using the technology),
- **Computer Playfulness:** the degree of cognitive spontaneity),

- **Perceived Enjoyment:** it represents how enjoyable the usage of the technology is based on the subject's experience,
- **Objective Usability:** it evaluates the system according to the actual level of effort required to perform a task.

As the further progression of the theory, Venkatesh (2003) has created a unified model of technology-acceptance (UTAUT – Unified Theory of Acceptance and Use of Technology). *UTAUT1* includes eight theories (Theory of Reasoned Action - TRA, Technology Acceptance Model – TAM, Motivation Model, Theory of Planned Behavior – TPB model, Combination of TAM and TPB, Personal Computer Usage Model, Rogers Diffusion Theory, and social cognitive theory) (Venkatesh et al. 2003). Its purpose is to estimate the probability of success of the new technology.

UTAUT1 identifies four new variables that affect intention to use and actual use:

- **Performance Expectancy:** it expresses how much the system helps to improve the user's performance,
- **Effort Expectancy:** it represents how much effort the user perceives to be required for the usage of the system,
- **Social Influence:** it shows the importance of the reference group's opinion about the technology,
- **Facilitating Conditions:** it indicates the availability of facilitating tools for use.

The four variables affect Behavioral Intention to Use (BIU). The relationship between dependent and independent variables is influenced by the moderated variables of Experience and Voluntariness as in the TAM2 and TAM3 models. Besides, two new moderating variables (*Gender* and *Age*) have been introduced to represent the impact of demographic characteristics on consumer behavior (Venkatesh et al. 2003).

In 2012, a further development, *UTAUT2* (Unified Theory of Acceptance and Use of Technology 2) was created (Venkatesh et al. 2012). Unlike previous models, this model not only analyses the influencing factors in a workplace context but also measures the acceptance of technologies applied in everyday life. *Voluntariness* has been removed as a moderating variable, as it is not considered to be relevant in everyday technologies.

The model has three new variables:

- **Hedonic Motivation:** it shows the degree of fun while using the technology,
- **Price Value:** according to the theory, the user feels comfortable when the perceived usefulness is greater than its cost,
- **Habit:** it represents the role of previous habits and experiences of subjects regarding similar technologies (Venkatesh et al. 2012).

The TAM model has been criticised by scholars over the years. Researchers (Legris et al. 2003; Lee et al. 2003) highlighted that there can be redundancy between exogenous variables of models presented above, which makes it difficult to identify the phenomena that really influence technology acceptance. Researchers (Zhang et al. 2019; Zhu et al. 2020) underline that improved models (see TAM2, TAM3, UTAUT2) are less suitable for modelling the acceptance of disruptive technologies without changes due to their complexity and specific variables (e.g., computer use, internet-related variables – see TAM3).

However, several studies (Xu et al. 2018; Buckley et al. 2018; Chen 2019; Yuen et al. 2020; Zhu et al. 2020) have demonstrated the validity of the TAM dependent variables (PEOU, PU, ITU) for exploring attitudes towards new technologies. This is confirmed by the fact that many researchers have successfully modelled the technology acceptance of self-driving vehicles primarily by utilising the variables of the TAM or UTAUT (e.g., Dirsehan and Can 2020; Zhang et al. 2019; Rahman et al. 2019). Since the efficiency of the endogenous variables of TAM2 has been proven by previous studies, I also adopted these variables (PEOU, PU, ITU) in modelling the technology acceptance of self-driving cars. Researchers (Al-Emran 2018; Sagnier et al. 2020) have suggested that technology acceptance models should be employed only in a specific context. Following this, I focused on the technology-acceptance of AVs and their applicability in the context of tourism-related traveling.

I.2.4 Conceptual framework

Following the basic concepts and open issues related to the technology and industrial implications presented above, it can be concluded that Industry 4.0 and the spread of AVs might result in several changes in society and economy, and thus in the field of passenger transport and tourism. In light of this, four research objectives have been set (Table 2).

No.	Research objective statement	Related Qs
1	Identification of the leading socio-economic impacts and dilemmas associated with the diffusion of self-driving vehicles.	Q1
2	Identification of the key innovations affecting passenger transport and their interconnections in the near future (by 2030).	Q2
3	Exploration of the changes expected in the tourism sector associated with the spread of AVs and consumer attitudes towards them.	Q3
4	Exploration of the factors influencing tourists' intention to use AVs, thereby creating a tourism-specific model specialised in the technology acceptance of self-driving vehicles.	Q4

Table 2. Research objectives, own editing

Following the research objectives, a research question (RQ) (*How does the spread of highly automated (SAE 4-5) vehicles affect the tourism sector, especially the mobility for tourism purposes, and conventional tourism services*?) and four sub-questions are formulated. The conceptual framework (research process) along with the RQ, sub-questions (Q1, Q2, Q3, Q4), and key outputs of the research are illustrated in Figure 6.

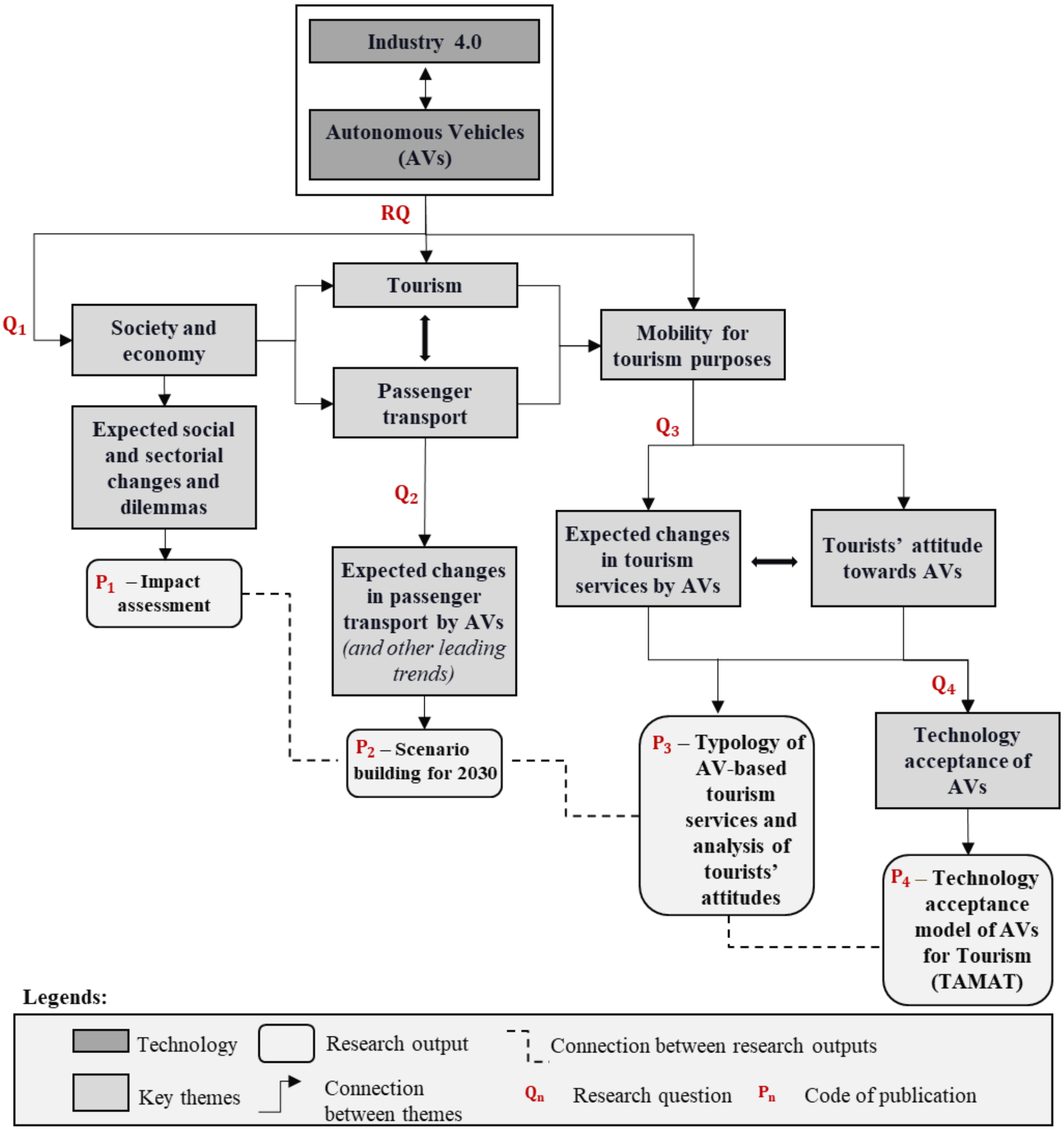


Figure 6. Conceptual framework of key themes and research outputs, own editing

- **Q1:** *With the spread of self-driving vehicles, what socio-economic changes can be expected?*

While exploring the impact of AVs on passenger transport and tourism, it is particularly important to understand the general socio-economic and sectorial impacts arising from Industry 4.0 and the spread of AVs. In this context, before focusing on the tourism-specific analysis, other aspects of the technology (social, moral, industrial) should be discussed, which can both determine the relevance of the RQ and help to formulate a critique of diffusion from a social and economic perspective. Therefore, the general – not only tourism-specific – impact assessment of the technology is considered in this thesis which is presented in Paper 1 (P1 – Section III).

- **Q$_2$:** *What major trends shape urban mobility in the tangible future, i.e., until the 2030s and what role will self-driving vehicles have in this alteration?*

The strong interconnection between transport and tourism is evident. Therefore, expected changes in passenger transport need to be analyzed thoroughly also for a comprehensive, tourism-related analysis. In relation to the spread of AVs and their role in passenger transport, several forecasts have been made, which make it uncertain how strong the penetration of the technology will be. Some researchers (Brenden et al. 2017; Zmud et al. 2013; Marletto 2014, 2019; Shergold et al. 2015, Zmud et al., 2014, Banister, 2013, Fulton, 2017) predict a slow spread of automation, while others (Marletto 2019; Milakis et al. 2017; Brenden et al. 2017; Rohr 2016) foresee its radical advance and emphasize its remarkable socioeconomic impacts. Considering this, it is desirable to analyse research forecasts to get a more accurate picture of the effects of AVs and its role in passenger transport. Findings (scenario building for 2030) related to this sub-question are presented in Paper 2 (P2 – Section IV).

- **Q$_3$:** *How might tourism services change with the spread of self-driving vehicles and how do tourists relate to these potential changes?*

After the general impacts and the possible directions of changes are identified, my research concentrates on the expected impacts of AVs in the tourism sector. The identification of tourism impacts is currently very limited, also in the international literature. Following this, there is a need to systematise the already identified expected changes in tourism services by scholars (e.g., Cohen and Hopkins 2018; Cohen et al. 2020; Tan and Lin 2020; Ribeiro et al. 2021), and to identify tourists' attitudes towards AVs conducting empirical research. Typology of AV-based tourism services, alterations, and interpretation of tourists' attitudes are presented in Paper 3 (P3 – Section V).

- **Q$_4$:** *What drives tourists to adopt self-driving cars for tourism purposes?*

Following the exploration of tourists' attitudes towards tourism changes induced by AVs, my objective is to identify the factors influencing the intention to use AVs and the interaction between these factors. There is a growing interest among researchers to investigate the technology acceptance of self-driving vehicles (e.g., Rahman et al. 2019; Zhu et al. 2020), though research including tourism aspects is very limited (e.g., Tan and Lin 2020; Ribeiro 2021). In this context, the final phase of the research is the development of a new technology acceptance model which is suitable to determine the tourism-related aspects of the intention to use AVs. A technology acceptance model specialised in tourism is presented in Paper 4 (P4 – Section VI).

I.3 Research methods applied

This chapter describes both qualitative and quantitative methods applied. *Qualitative research* is an exploratory method that does not provide quantitative outputs. It is usually based on a small sample and aims to understand the research problem. In contrast, *quantitative research* is based on numerical data, concentrates on specific hypotheses, and involves statistical analysis (Malhotra – Simon 2009; Babbie 2020).

The publications (P1-P4) presented below adopted a sequential approach, as qualitative research was followed by quantitative analysis (Figure 7).

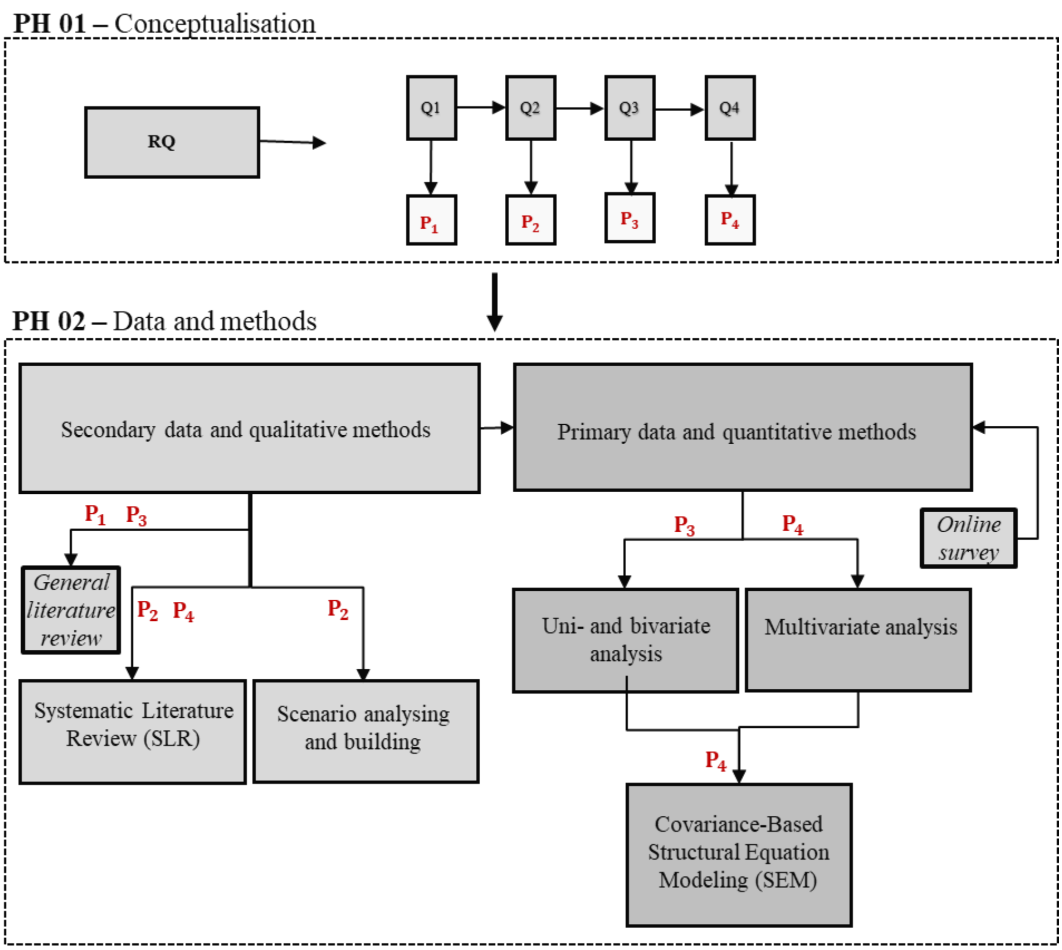


Figure 7. Framework of data collection and research methods applied, own editing

I.3.1 Data collection

For the analysis, secondary and primary data collection has been conducted. A systematic literature review was carried out on several topics in the context of secondary data collection, the methodology of which is briefly described in this chapter, and the details of the analysis are presented in journal articles P2 and P4.

The quantitative data analysis required measurable data, for which an online questionnaire was conducted. Based on the typology of online sampling techniques, the data collection applied is based on random systematic sampling (Malhotra – Simon 2009). Questionnaire data collection is the most widely used method in social sciences. Online sampling is becoming more common, as it is more cost-effective and nowadays it can reach a wide range of the population (Alessi and Martin 2010). Questionnaires, with their structured nature, provide a well-defined, accurate database that can be used for statistical analysis (Babbie 2020). However, it has the disadvantage that in the case of attitude surveys, latent needs and opinions are difficult to uncover and the results of the questionnaire may be distorted by incorrect questioning (Malhotra 2009).

During the primary data collection, subjects with tourism experience were asked to participate in the research. Furthermore, the proportion of participants by gender (male – 43%; female – 57%) and age group (18-29 – 20%; 30-39 – 21%; 40-49 – 18%; 50-59 – 19%; 60-75 – 22%) was determined in relation to the Hungarian population (KSH.hu 2020). However, the final sample slightly differs from the criteria presented above, and the analysis methods applied (CB-SEM) required data cleansing (e.g., multivariate normality analysis to detect outliers), so the sample cannot be considered fully representative.

The questionnaire consisted of closed, structured questions for CB-SEM modelling. This required respondents to rate their level of agreement with a given statement on a scale of 1-7. The questionnaire also consisted of multiple-choice questions, mainly to explore subjects' transport (e.g., preferred means of transport) and tourism habits (e.g., preferred tourism product, frequency of traveling, etc.).

I.3.2 Systematic literature review

As the first step of the research, the findings of previously published papers related to the RQ have been systematized. For this, a qualitative research methodology, the systematic literature review (SLR) has been applied.

SLR aims to summarise the body of knowledge in a specific area, which can be used to set future research paths and answer questions that would not otherwise be answered by previous findings (Denney and Tewksbury 2013). During an SLR, authors must follow a transparent and rigorous methodology to prove the reliability of the findings. The Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) is a guideline that focuses primarily on the reporting of reviews and thus enhances the validity of systematic reviews and meta-analyses (Page et al. 2021). The PRISMA guideline provides a template, which can be applied and partly adjusted depending on the intention of the SLR or the topic (Figure 8).

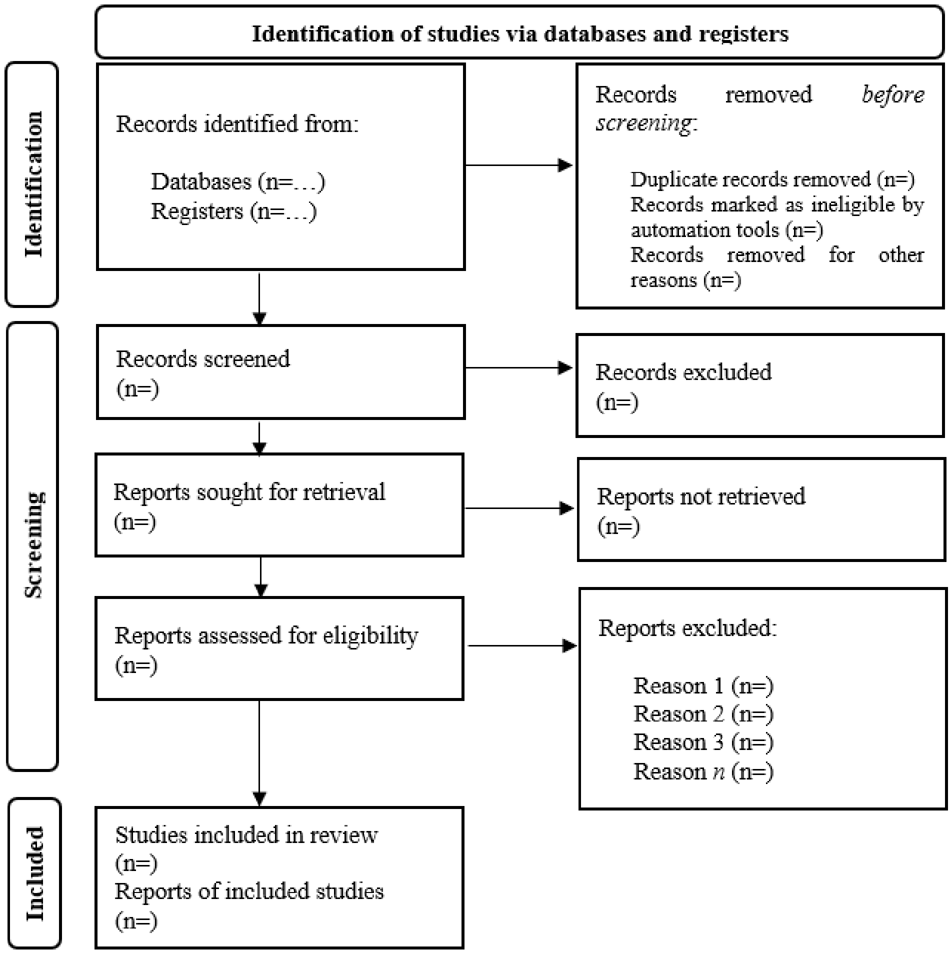


Figure 8. PRISMA flow diagram (template) based on Page et al. (2021), own editing

PRISMA guideline suggest three main phases of SLR, details of which are presented in Paper 2 and 4.

1) *Identification*: this includes criteria for paper selection (e.g., databases, keywords that researchers use). At this stage, duplications can be filtered out.
2) *Screening*: the second phase is the systematization of the remaining papers. First, the categorization according to each search criterion created during the identification, and then the exclusion criteria for the papers are clarified.
3) *Included papers*: in the third phase, the remaining papers are systematically analyzed and further categorized according to the researcher's criteria (Page et al. 2021).

I.3.3 Scenario analysing and building

As part of the SLR, the expected role of automation in urban passenger transport has been explored. For this, we collected and analysed 62 journal articles concerning the future of passenger transport. Based on this, scenarios of urban passenger transport have been created.

Scenarios involve imagined, expected, in most cases positive, or in some way contradictory visions of the future (Melander 2018). Their purpose is to anticipate expected changes and to identify trends and risks of the upcoming period (Melander 2018; Bishop et al. 2007). For financial studies, quantitative scenario analysis methods are commonly employed for risk analysis. As the trends in passenger transport are not always defined based on quantitative data, qualitative analysis techniques are also widely accepted. For our analysis, a novel scenario analysis and building method has been created.

The method consists of the following three main phases which is described in detail (with all sub-steps) in Paper 2:

- **S0 – Synthetisation**: In the first step, the metadata (year of publication, methodology used, geographical scope) of the papers selected for the analysis are categorised, and a similarity analysis is performed to identify co-citation to filter out over-matchings.
- **S1 – Thematic scenario analysis**: In the second step of the qualitative analysis, the themes (e.g., leading social, environmental, trends of the upcoming change)

of the scenarios are extracted, and their expected changes are assessed on a 3-point scale (no change, moderate change, significant change) to ensure the comparability of scenarios analyzed.

- **S2 – Scenario building**: In the last phase, key themes are identified (which in most cases determined the future vision), and the scenarios are then grouped into homogeneous groups based on the 3-point evaluation of the themes.

I.3.4 Uni-and bivariate analysis

Descriptive statistics have been used to analyse attitudes towards tourism services based on self-driving vehicles in Paper 3 and Paper 4. For this, the most important univariate indicators were applied based on (Sajtos – Mitev 2007, Fliszár et al. 2016).

During the analysis of database from the online survey, the *mean* of the elements has been considered which is most appropriate for interval and ratio scales (Fliszár et al. 2016). The disadvantage of this indicator is that all values have the same effect, i.e., outliers can have a significant effect on the mean. This problem does not exist for the median and mode, therefore, these indicators have also been calculated. The *median*, i.e., the mean value at which half of the items are greater and half are less when the cases are ranked (Sajtos – Mitev 2007). The median is most appropriate for ordinal scales. The *mode*, which represents the most frequently occurring element (for a discrete criterion) or the maximum position of the frequency curve (for a continuous criterion) can be used for nominal, interval, and ratio scales (Sajtos – Mitev 2007). Among the dispersion indicators (range, standard deviation, variance), the standard deviation is the most employed. *Standard deviation* indicates how much the items diverge from the mean on average (Fliszár et al. 2016). The indicator can be applied to a metric scale and was applied for tourists' attitude analysis in Paper3.

The univariate analyses were followed by bivariate analyses to examine attitudes towards the use of different AV-based tourism services. In Paper 3, the Kruskal-Wallis (H)-test has been applied for this purpose.

The Kruskal-Wallis test or H-test is a non-parametric statistical technique to test whether individual samples can be derived from the same distribution (Spurrier 2003).

It is calculated based on the following equation:

$$H = \left[\frac{12}{n(n+1)}\sum_{j=1}^{c}\frac{T_j^2}{n_j}\right] - 3(n+1)$$

Where:

- n = total number of values
- c = number of samples
- T= sum of ranks in the j^{th} sample
- n_j = size of the j^{th} sample (Spurrier 2003)

It is used to compare more than two independent samples along with a single variable, which may have the same but different number of elements. A significant Kruskal-Wallis test indicates that at least one sample has stochastic dominance over another sample. Since the Kruskal-Wallis test is nonparametric, it does not require a normal distribution of samples (Spurrier 2003).

The Eta-squared (η^2) is used as an effect size indicator. η^2 represents the explained variance (Tomczak and Tomczak 2014). Eta-squared only provides information about the effect size of the sample (not the population), thus any added variable will increase its value, overestimating the effect size.

η^2 can be calculated based on the following equation:

$\eta^2 = \text{Between-Groups Sum of Squares} / \text{Total Sum of Squares}$.

η^2 ranges between 0 and 1. Cut off value based on Tomczak and Tomczak (2014):

- ≥0.01: small
- ≥0.06: medium
- ≥0.14: large

I.3.5 Structural equation modeling

As part of the research, a technology acceptance model has been created, which describes consumer attitudes towards self-driving vehicles in a tourism context. The process of model creation is presented in Paper 4. For testing my hypothetical model, we applied a method known as Structural Equation Modelling (SEM).

Structural Equation Modelling (SEM) is an advanced statistical technique that aims to confirm hypotheses and validate the correlation between the variables of the model (Hair et al. 2010; Gaskin and Happell 2014). SEM modelling is based on path analysis, which uses regression equations to analyse the relationship between variables (Hair et al. 2010).

SEM is a well-known technique internationally but has only started to be widely used in Hungary in the last decade. It is often used to support hypotheses and to model theories (e.g., technology acceptance models) in the social and economic sciences (especially in the field of marketing).

Structural equation modelling aims to identify latent variables of the model. Latent variables are concepts that cannot be measured directly, and can only be measured using directly measurable, so-called manifest (observed) variables (Brown 2015). The main advantage of SEM is that factor and regression analysis can be performed simultaneously (Harrington 2009; Brown 2015). SEM thus achieves both the creation of latent variables from indicators (observed variables) and the examination of the correlation between latent variables (Hoyle 2011).

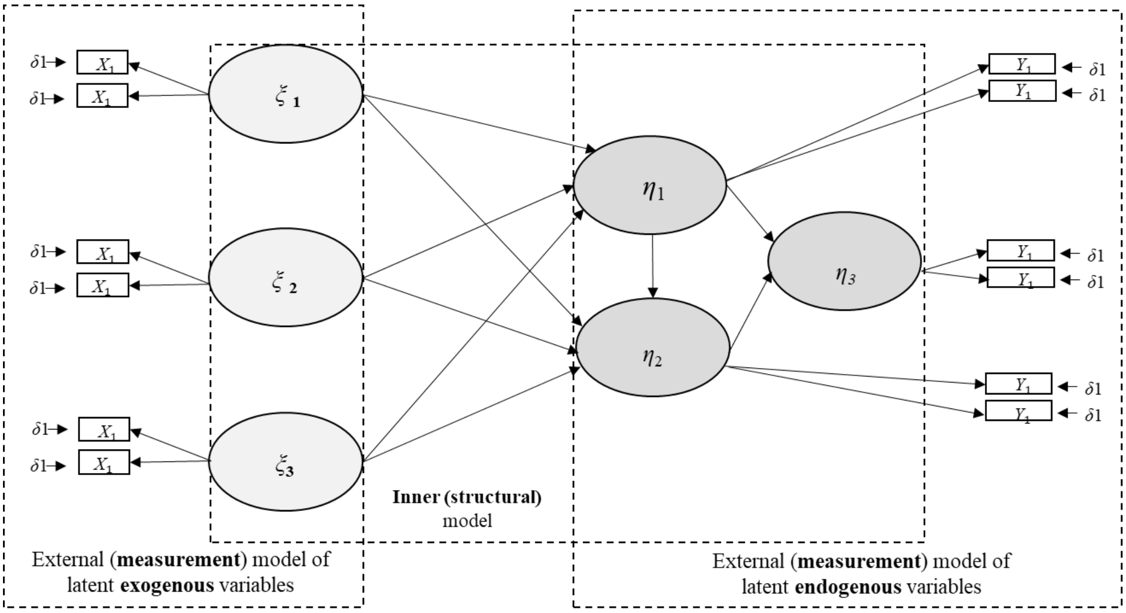


Figure 9. Conceptual framework of SEM modeling based on Kazár (2014), own editing

SEM models can be divided into two parts (Figure 8): the external and the internal (structural) model. The external model describes the relationships, i.e., the regression equations between the manifest (exogenous) (X and Y, respectively) and the latent (endogenous) variables (ξ and η, respectively), while the internal model measures the relationships between the latent variables and presents the regression equations and paths between them (Hoyle 2011). Exogenous (not influenced by other variables) and endogenous variables (influenced by at least one variable) can be visualized in a path diagram (Hoyle 2011) as seen in Figure 9.

SEM modelling can be used for either confirmatory or exploratory purposes, therefore, two types of SEM can be distinguished: covariance-based structural equation modeling (CB-SEM) and partial least square equation modeling (PLS-SEM). In my analysis, we have applied CB-SEM modeling, which has some advantages over PLS-SEM modeling (Table 3).

Aspects of application	CB-SEM	PLS-SEM
Criteria	Normal distribution	Normal distribution is not required.
Number of elements	n ≥ 100-200	Also applicable for smaller samples (n ≤ 100)
Focus	Testing theories	Exploratory research, parameter estimation
Fit tests	Numerous	No specific fit indicator

Table 3. Comparison of CB- and PLS-SEM approaches based on Kazár (2014), own editing

CB-SEM is well suited for testing theories, relationships, hypotheses, as opposed to PLS-SEM, which is more useful for exploratory analysis. CB-SEM can be applied to larger samples, whereas PLS-SEM has the advantage of being more flexible in terms of the number of sample elements. The most important advantage of CB-SEM is that several goodness-of-fit indices can be applied, allowing the validity of the results to be better determined (Kazár 2014).

Due to the wide range of goodness-of-fit indicators that can be used in CB-SEM, I chose this method to prove a stronger validity of the hypothetical model. The interpretation and use of goodness-of-fit tests are extensively discussed in the literature.

In examining the fit of the structural model, we primarily followed the guidelines of Hair et al. (2010), Byrne (2010), and Gaskin and Happell (2014), and examined the fit indices presented in Table 4.

Fit index	Threshold/Cut-off value
Absolute fit indices	
Chi-Square ($\chi 2$)	Low $\chi 2$ relative to degrees of freedom ($p > 0.05$)
Normed (relative) Chi-Square ($\chi 2/d$)	$\chi 2/d<3$ (good) $\chi 2/d<5$ (permissible)
RMSEA (Root Mean Square Error of Approximation)	RMSEA<0.08 (good) RMSEA>0.10 (unacceptable)

GFI (Goodness of Fit)	GFI≥0.95 (good) GFI≥0.90 (acceptable)
AGFI (Adjusted Goodness of Fit Index)	AGFI ≥0.90 (good)
Incremental fit indices	
NFI	NFI≥0.95 (good)
NNFI (Non-normed Fit Index *or* TLI (Tucker Lewis Index)	NNFI ≥ 0.95 (good)
CFI (Comparative Fit Index)	CFI≥0.90 (good)

Table 4. Fit indices based on Hair et al. (2010), own editing

- The Chi-squared test indicates the difference between the observed and assumed covariance matrices (Hair et al. 2010). Values close to zero suggest a better fit, as there is less difference between the expected and observed covariance matrices. The chi-square test is very sensitive to the number of elements in the sample, the complexity of the model and the distribution of variables, which justifies the testing of additional fit indicators.
- The normed or relative chi-square is the ratio of the chi-square to the degree of freedom (Hair et al. 2010). The value of the relative chi-square is considered good if it is below 3, with a value of 5 being the cut-off point.
- The RMSEA compares the hypothetical model with optimal parameters and the population covariance matrix, regardless of the number of elements. The lower the RMSEA value, the better the model fit. Values of 0.08 or less indicate an acceptable model fit, values above 0.1 are unacceptable (Gaskin and Happell 2014).
- The GFI indicator measures the fit between the hypothetical model and the observed covariance matrix. Since this calculation depends on the number of variables associated with the latent variables, the AGFI indicator is also employed. The two indicators have a value between 0 and 1, with a value of 0.95 indicating a good fit and a value above 0.90 indicating an acceptable fit (Byrne 2010).
- Incremental fit indicators compare the chi-square value of a hypothetical model with a null model. In this category, the NFI – which is highly sensitive to the number of elements – and the NNFI index, or the Tucker-Lewis Index (TLI) can

be measured. They consider the complexity of the model and are independent of the number of elements in the sample, but sometimes incorrectly indicate a value less than zero or greater than one. Both indicators fall between 0 and 1 and values above 0.95 are considered acceptable (Hair et al. 2010).

- The CFI indicator measures the difference between the data and the hypothetical model and indicates the fit between the null model and a perfectly fitted model. The value of the indicator can be between 0 and 1. In general, a value of 0.9 or greater indicates a good model fit (Gaskin and Happell 2014).

According to the guidelines (Hair et al. 2010; Byrne 2010; Gaskin and Happell 2014), the minimum indicators to be considered are Chi-square, RMSEA, and CFI to assess the validity of the model. In my research, we considered all the fit indicators presented above, the results of which are summarized in Paper 4.

II STATEMENT OF CONJOINT WORK

The thesis presents the following journal articles:

Paper 1 (P1): Miskolczi, M., Ásványi, K., Jászberényi, M., Kökény, L. (2021). Hogyan döntsön a mesterséges intelligencia? – Az önvezető autók morális dilemmái. *Magyar Tudomány*, 182.

Paper 2 (P2): Miskolczi, M., Földes, D., Munkácsy, A., Jászberényi, M. (2021). Urban mobility scenarios until the 2030s. *Sustainable Cities and Society*, 103029.

Paper 3 (P3): Miskolczi, M., Kökény, L., Ásványi, K., Jászberényi, M., Gyulavári, T., Syahrivar, J. (2021). Impacts and potential of autonomous vehicles in tourism. *Deturope*, 13(2): 34-51.

Paper 4 (P4): Miskolczi, M., Munkácsy, A., Földes, D., Jászberényi, M., Syahrivar, J. (2022). Autonomous vehicles in tourism – technology acceptance from the tourists' perspective. *Turizmus Bulletin* (*accepted*)

Since the publications are co-authored, the contribution of each author should be presented. To provide a detailed description, the framework created by Brand et al. (2015) has been employed which is a standard method of author statements in international journals.

Table 1 presents the contributions of each author and summarises the details of the publications (e.g., publisher, journal, category, language).

General data		P1	P2	P3	P4
Status		Published	Published	Published	Accepted
Digital Object Identifier (DOI)		DOI	DOI	-	-
Language		English	Hungarian	English	Hungarian
Journal data	**Publisher**	Elsevier BV	Akadémiai Kiadó Zrt.	University of South Bohemia, Hungarian University of Agriculture and Life Sciences, Regional Science Association of Subotica	Hungarian Tourism Agency Ltd.
	Journal	Sustainable Cities and Society	Magyar Tudomány	Deturope	Turizmus Bulletin
	Scopus/MTA-list	Q1 (D1)	MTA B	Q2	MTA C
	Impact factor (IF)	7.587 (*2021*)	-	0.71 (*2021*)	-
	Scimago Journal Rank (SJR)	1.645 (*2021*)	-	0.246 (*2021*)	-
Authors' contribution	**First author**	Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization	Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization	Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization	Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization
	Second author	Methodology, Formal analysis, Writing - Review & Editing	Writing - Review & Editing, Validation	Methodology, Formal analysis, Visualization	Conceptualization, Writing - Review & Editing, Supervision
	Third author	Conceptualization, Formal analysis, Writing - Review & Editing, Supervision	Writing - Review & Editing, Validation	Formal analysis, Writing - Review & Editing	Writing - Review & Editing, Validation
	Fourth author	Conceptualization Supervision Funding acquisition	Conceptualization Supervision Funding acquisition	Conceptualization Supervision Funding acquisition	Conceptualization Supervision Funding acquisition
	Fifth author	-	-	Validation	Validation
	Sixth author	-	-	Validation	-

Table 1. Authors' contribution based on the framework suggested by Brand et al. (2015), own editing

III HOW SHOULD ARTIFICIAL INTELLIGENCE DECIDE? – MORAL DILEMMAS OF AUTONOMOUS VEHICLES (AVS)

Reference: Miskolczi, M., Ásványi, K., Jászberényi, M., Kökény, L. (2021). Hogyan döntsön a mesterséges intelligencia? – Az önvezető autók morális dilemmái. *Magyar Tudomány*, 182.[8]

Abstract: The use of autonomous vehicles (AVs) could be a promising transport innovation of the next decade, but there are still many unanswered questions surrounding the technology. In this study, we lay out the basic concepts of automation and the stages of development of AVs. The aim of the analysis is to explore the socioeconomic impacts and moral dilemmas regarding the development of technology. The literature suggests that decision-making algorithms of AVs should be developed based on the principles of utilitarianism. In our analysis, we also emphasize the most important aspects challenging utilitarianism and highlight the open questions for the industries most involved in the spread of AVs. Identifying the moral, industrial, and social dilemmas linked to autonomous vehicles can help to bring forward the still open issues alongside the socio-economic impacts of future vehicle developments.

III.1 Introduction

The future of passenger transport is highly undefined. The dynamics of the social structure (e.g., changing needs for mobility) fundamentally define the parameters of the transport system (e.g., the volume of movements, spatio-temporal distribution). The stability of supply-demand relations can be improved by different forms of transport innovation (e.g., product – vehicle development, process – way of transport). The most promising technological improvement of the second decade of the 21st century is automation, which relates to most of Schumpeter's innovation cases (e.g., production of new quality goods – cars with upgraded interiors, new market setup – new actors and target groups). At the same time, experts developing the technology and studying the socio-economic impacts must face several new challenges. The timeliness of impact analysis of automation is clearly shown by the fact that while AVs are currently tested on the streets of 138 cities worldwide (URL_1), at the same time, the usage of these vehicles, the opportunities and risks of the technology are still under-researched, especially in

[8] This article was published in Hungarian. The translation presented here is identical to the original paper, no changes have been made to the content.

Central and Eastern European countries. The spread of AVs is held back just the same by the vagueness of social and moral dilemmas, as by technological challenges, so in this study, we unveil the moral questions of *AI-based decision making (1) and the moral dilemmas based on socio-economic consequences of autonomous vehicles (2).*

III.2 Automation – basic definitions

Automation is an innovation of the fourth industrial revolution (Industry 4.0), which is rooted in the acceleration of information and communication technologies (ICT) in the second half of the 20th century. The questions around AVs are numerous and variable, therefore the knowledge of industrial and consumer behavior is limited, even controversial in some cases. While analyzing the automated solutions, we must separate the definition of automatic and autonomous. The first definition means that the systems are pre-programmed and algorithm-based, while the latter covers self-learning technologies that can make individual decisions (Csonka-Csiszár, 2017).

An example of an automated system is the M4 metro line between Budapest Kelenföld Railway Station and Keleti Railway Station, which operates without a driver and is only under central control (URL_2). In our case, opposite to this example, AVs are components of autonomous technology. It is important to emphasize that regarding AVs we discuss the incremental technology that not only free of human intermission but is able to transport by itself. The current technology described as self-driven is still depends on the decisions of the human driver, but the real self-driving experience is getting closer with the help of intense development. Based on international standards we can distinguish five levels of automation as suggested by the Society of Automotive Engineers (SAE) (URL_3):

- **Level 0: No Automation:** The only controller of the vehicle is the human driver; the phase is described with the complete lack of automation.
- **Level 1: Driver Assistance:** The only controller of the vehicle is still the human driver, but there are supporting functions. For example, the change in the direction or speed, occasional automated steering of wheel (parking).
- **Level 2: Partial Automation:** The only controller of the vehicle is still the human driver, but the supporting functions can be applied simultaneously. The most modern cars currently available for purchase fall in this category (e.g., Tesla Model 3).

- **Level 3: Conditional Automation:** The role of the human controller is necessary, but the continuous observation of the surroundings is not required, the car is able to handle the driving operations. Despite this fact, when the car notifies the driver, they must take control over the driving, and because of this aspect, this phase of automation can be the most dangerous.
- **Level 4: High Automation:** The car can control every task under the entire time of the journey. The presence of the human driver is only optional in this phase, the system does not require them to take control over the driving. Based on the predictions of top companies of automotive industry (Tesla, BMW, Google Waymo) cars with high level of automation can be expected in the middle of the 2020s.
- **Level 5: Full Automation:** All the aspects of driving can be owned and sustained by the car for the entirety of the travel. It is an open question whether steering wheels and pedals will be needed for manual control at this stage of development, and how future road users will react to the complete removal of the driving experience.

AVs are built on the growing impact of Artificial Intelligence (AI). Artificial intelligence is part of robotics which aims the development of computer programs that are able to achieve tasks needing human resources (Winter et al. 2016, Baranyai et al., 2019). AI can learn and understand complicated situations. The scope of application is ever wider (e.g., AI-based Google Search engine). The most relevant difference between automated and AI-based systems is that the former is only used for repetitive tasks (e.g.: fixed rail transportation), so it is not required for the system to „think". AI-based systems are rooted in deep learning, in models trying to imitate the mechanism of human brain function (e.g., can differentiate between the shapes of objects laying in front of and can categorize according to the identified characteristics) (Schmidt et. al., 2015).

III.3 AI-based decision-making and the moral dilemmas arising from the socio-economic consequences of its use

The ethics of artificial intelligence is the part of the discipline that studies moral issues related to technology and it specializes in AI-based robotics (Winter et al 2016). The field can be divided into roboethics, which describes the human behavior related to AI systems (machine-human interactions, acceptance, and role of machines in society) and machine ethics, dealing with decisions made by AI and the moral fundamentals (Holstein, 2017; Karnouskos, 2018; Trappl, 2016). The development of AVs emphasizes the necessity of both fields, and the complexity of the topic requires the cooperation between representatives of different fields of science (e.g., engineers, psychologists, economists, and legal experts). In recent years – with the higher number of roadside testings – autonomous vehicles were involved in several, fatal accidents (UBER – hit and run of cyclist (URL_4)). It is important to stress that, given the current shortcomings of the technology, the presence of human drivers is essential, and their main task is to avoid such accidents. This requires a constant standby state and vigilance, which means an extraordinary mental load on the test driver. Accidents of the recent past put forward the legal dilemmas (*Who is responsible?)* and drew attention to the significance of studies made in the topic of moral dilemmas of decision making of AI (*What decision should the machine make?).*

III.4 Moral dilemmas of MI technology

The ethical system of algorithms (and the vagueness of it) behind the decision-making of AI is being analyzed by several researchers (e.g., Borenstein et al., 2019; Nyholm, 2018). The biggest challenge of the technology is to define AI decisions, which were either previously made by humans (driver, people participating in transport) or happened randomly (unexpected traffic situations).

In transport research, the analysis of moral dilemmas is a mature topic. In the 1960s Philippa Foot, a British philosopher came up with the trolley dilemma, which explored the possible outcomes of personal decision-making in the context of human-machine interactions (Gawronski-Beer, 2017). Given an unstoppable trolley, and on the rails 5 people. There is a second railway siding with one person. The operator of the shift lever is the subject of the theory, and must decide: who should be saved – the five people on the main rail or the one on the siding?

The main point of the theory is to explore the reasons behind the decision-making in situations that can only have negative outcomes. In the case of recent empiric research, 90% of the involved subjects choose the trolley to go on the siding (Bonnefon et al. 2016), so the participants make decisions along with utilitarianism. Utilitarianism was born as part of the Anglo-Saxon ethics of the 19th century and originates in the ideas of maximizing happiness and minimizing negative consequences.

The question arises if this utilitarian decision-making can be implemented on artificial intelligence in AVs. Research regarding this question (Bonnefon et al. 2016; Awad et al., 2018) are extremely limited to the shortages in consumer knowledge and experiences. Awad et al. (2018) use 13 traffic situations to analyze ethical patterns in the answers of participants for the future development of AI-based vehicles.

While evaluating traffic situations, Moral Machine respondents must weigh in different aspects: gender of passengers, age, medical conditions, social status, obeying traffic rules, protection of others. Based on the research of Awad et al. (2018) the following can be established:

- Utilitarianism applies to the respondents until the traffic situation does not include themselves or their loved ones.
- In the responses, the segmentation by age is important, the younger lives worth more than the older.
- Social status and medical condition are also important indicators: respondents tend to save the healthier and wealthier people (e.g., physicians, managers, athletes, etc.) against homeless or overweight people.
- Saving animals is secondary to saving people.

The research of Moral Machine points out that AVs should decide based on utilitarianism and evaluation of living creatures. At the same time, the question arises if this approach really helps the decision-makers (AI developers) building a morally acceptable decision-making algorithm (*does that even possible*?). This leads to three main dilemmas:

Rational decision-making = evaluation of human lives?

The basic question of moral philosophy is whether decisions related to human lives can be transferred to artificial intelligence. In this case, machines face a situation where not even human participants can make rational judgments; accidents happen mostly coincidentally. The question arises that it might be a better way to decide not solely on an evaluation of living creatures but based on traffic regulations with the intention of minimizing losses without considering the participants' individual characteristics.

Falsifiable utilitarianism

The results of Moral Machine emphasize that the involved parties only consider utilitarianism as an acceptable mechanism for decision-making as outsiders (Awad et al., 2018). As soon as they become participants in a traffic situation the emotional factors (protection of loved ones) and self-defense (egoism) come to the forefront, which means utilitarianism is not widely accepted. Utilitarianism-driven decision-making also indicates economic concerns. The biggest argument for AVs is the increase of transport safety. Will the consumer be willing to buy a durable product (in this case car) if it will sacrifice the life of the owner if an accident occurs and the vehicle will decide that the other party's life is more valuable, so it must be saved? In this case, the acceptance of AVs is likely to face obstacles.

Instead of (alongside) developing machines, improving traffic culture?

This topic is not highly researched, but with developing AI decision-making principles, preparing the society to changed circumstances of mobility is equally important. Improving traffic culture is significant in improving traffic safety, and in the acceptance of AVs. While developing automation the human errors in the control of the vehicle can be minimized, but other participants of traffic (pedestrians, motorcyclists, cyclists) are still risks to traffic safety. Reducing this risk is possible with strict enforcement of traffic rules and implementing more strict traffic control. Beyond technology solution can be the remodeling of mobility opportunities (e.g., zone restrictions for traditional vehicles), which can help achieve safer operations for autonomous vehicles. Indirectly the shaping of mobility needs (e.g., the opportunity of distance learning, flexible work conditions – occasional remote working, flexible working hours) can cause a more balanced traffic flow and can minimize the number of situations causing accidents.

III.5 Moral dilemmas arising from socio-economic changes

The socio-economic effects of automation, which create further dilemmas, are increasingly being researched. In this study, the moral dilemmas of the most involved industries are presented. The economic valuation is based on the journals of the past few years (Clemens et al., 2017; Fagnant – Kockelman, 2015; McEvoy, 2015; Hussain – Zeadally, 2018), which show different prognoses for the near future. The generic point of view for the researchers is that higher level of automation results in positive economic consequences through increase in efficiency (e.g., automation of production), but we can also count on losses or significant reorganization (e.g., of human resources, workflow) in numerous fields.

Based on the socio-economic impact assessment we have made; the most involved industrial dilemmas can be identified in four main areas.

Table 1. Socio-economic changes and moral backgrounds

Industrial Dilemma	Example
Changes in need for human resources	The changes in the labour market, lower importance of certain positions
Changes in industrial revenue from traditional vehicle-usage	Healthcare, Insurance market, Oil industry
Changes in social phenomena generated by AVs	Growing digital dependence, Organ donation options
(Potential) damage of social and environmental sustainability	Growth of car usage, environment protection, overtourism

Source: Authors' own editing

Logically, the most intense changes will happen in *the automotive industry*. If society accepts the usage of AVs, and not fully automated cars will not become luxury products on the market, the mobility options for societies with limited opportunities (people with reduced mobility, people without license) will also improve. The demand can further strengthen if travelers will still look for individual car ownership.

Automation can have significant benefits in the *ICT sector*, which provides the know-how for AI-based developments. As a result of the human driver's decreasing role, the demand for digital appliances that can be used through the time of travel might grow. Therefore, the *moral responsibility of* the even growing significance of the *ICT sector* is emphasized. Overuse of digital appliances can cause *addiction to virtual life* and to online platforms.

AVs offer important solutions to *cargo transport*. The sector fights the shortage of drivers globally, and on the long-term technology can fully overtake the role of the human driver. On the other hand, this solution is a threat as it *risks the livelihood of drivers*. The question arises of how the changed market circumstances will be handled by decision makers and if they offer answers to the questions of secondary social consequences.

The same problem exists in other industries as well: higher traffic safety is obviously important, but consequently, *the need for vehicle repairs, traffic-specified insurances and* *lawyers can drop in the near future*. It is necessary to emphasize that the role of lawyers in the transitional period of automation can amplify because of the vagueness of the legal background. Significant restructuring can occur in health departments and policing. Decrease and total lack of human driving offenses (traffic infringement – driving under influence) can *reduce the need of traffic police* and result in revenue loss.

With the rise of AVs, the number of people requiring emergency care can significantly drop, so the revenues of the health care system might also decrease. Based on estimates by NHTSA the sector has around 20 billion dollars revenue alone on motorcycle accidents (Hussain – Zeadally, 2018). A positive effect can be the improving efficiency of emergency care units with the reorganizations of professionals. The *topic of organ donors* poses a moral dilemma. The main reason for brain death is traffic accidents, so the opportunities for donation can be rearranged. The weighing of this phenomenon can be the most critical moral dilemma of the near future, but with the development of medicine (artificial organs), it can be solved.

The oil industry is also a unique field, whose transport role may disappear in the (distant) future with the rise of alternative vehicle propulsion systems, which can be further strengthened by the spread of autonomous vehicles. It is still an open question what AVs powered by in the future, and if the fuel will cause *climate change concerns*.

Perceivable effects in the tertiary sector can be shown in tourism. AVs that offer comfortable, independent mobility could significantly increase the demand for tourism-related mobility, while at the same time increasing road traffic problems (*congestion*). Autonomous vehicles are not only means of transport but can also pose as a service package with tourism elements for passengers. These cars on SAE Level 4-5 can be moving meeting rooms (MICE tourism), restaurants, or even accommodations, and the AI-based technological background can serve as a virtual companion and information resource. In this case, the *role and need of tour guides, taxi drivers, hop-on-hop-off bus rides is being questioned*. Without responsible vehicle use, the phenomenon of *overtourism* and its environmental impacts can increase. The main challenge of the sector in the future is finding the balance between economic interest and socio-economic, environmental sustainability.

III.6 Summary

This analysis was made with dual purpose: it draws attention to the moral dilemmas of decisions made by AI controlled vehicles and to the background of socio-economic, sectorial consequences of AVs. We can conclude that the undefined technologies and vagueness of the moral background can significantly influence the spread of AVs. The progression of the technology can unquestionably have several positive effects, but the same time the question exists: do these advantages outweigh the damaging externalities of the usage? The highly intertwined moral topics such as the valuation of human lives, the roles of utilitarianism and traffic culture in AI-based decision-making mechanisms the dilemmas of socio-economic impacts (disappearance of industries and jobs, revenue losses, reorganization of social phenomena and questions of sustainability) can all result in sociopsychological, economical and legal consequences, therefore interdisciplinary research will be necessary in the future. Analyzing society's relation to intelligent appliances (roboethics) and in-depth exploration of aspects influencing acceptance of self-driving technologies (developing AV-specialized technology acceptance models) can help governments and other decision-making organizations (e.g., ICT sector and car industry companies, city maintenance, traffic planning) creating morally and economically acceptable paths to the improvement of AVs (e.g., creation of responsible use, machines operating based on widely acceptable ethical mechanism; opportunities for retraining and redesigning of sectors).

IV URBAN MOBILITY SCENARIOS UNTIL THE 2030S

Reference: Miskolczi, M., Földes, D., Munkácsy, A., Jászberényi, M. (2021). Urban mobility scenarios until the 2030s. *Sustainable Cities and Society,* 103029.

Abstract: Urban mobility is particularly affected by technology development. This research focuses on the mobility system of cities in the foreseeable future – that is, until the 2030s. A systematic literature review (SLR) of 62 scientific documents and 52 scenarios predicted and developed by researchers are presented here, providing a comprehensive picture of current urban transport research perspectives. Based on a complex method built for this review, four scenarios ('Grumpy old transport', 'At an easy pace', 'Mine is yours', and 'Tech-eager mobility') have been created, each forecasting a different path towards future urban mobility. The scenarios so formed describe the expected role and potential of emerging mobility solutions (namely autonomous vehicles, shared mobility, and electrification) and include socio-economic and environmental perspectives. By 2030, most likely pathways are the 'At an easy pace' or the 'Mine is yours' scenarios, which means that only an incremental advance, such as a slow shift towards self-driving, electric and shared vehicle use is predicted.

Keywords: automation, autonomous vehicles; shared mobility; electrification; scenario analysis; scenario building; systematic literature review (SLR); future of urban mobility

IV.1 Introduction

While the future of urban mobility seems uncertain, several concepts are generated by new or improved technologies including autonomous vehicles (AVs), electric vehicles (EVs) and the integration of shared mobility services (Schuckmann et al. 2012; Nijkamp and Kourtit 2013; Dia 2019; Burns 2013). The evolution is constrained by increasing global challenges, such as rapidly changing and diverse consumer demands and urbanization (Brenden et al. 2017; Zmud et al. 2013). As a result, there is a growing demand for mobility services, including passenger and freight transport, which leads to severe problems in larger cities, such as congestion and air pollution (Tromaras et al. 2018; Menezes et al. 2017; Becker et al. 2020). A key challenge facing future urban mobility is to find an effective balance between economic sustainability, environmental regulations, and travellers' satisfaction (Nikitas et al. 2017; Canitez, 2019).

Currently, shared mobility is identified as one of the most promising solutions in urban mobility (Shaheen and Chan 2016; Nikitas et al. 2017; Standing et al. 2019) in order to reduce negative externalities and to raise user satisfaction. Other ways of reducing negative impacts of urban mobility could be a shift towards low and zero-emission modes, enhancing the role of EVs (Yamagata and Seya, 2013; Lee and Erickson 2017; Ferrero et al. 2018; Csonka and Csiszár 2017), and moderating travel demand (Lah et al. 2019; Bohnes et al. 2017). Reducing the burden on the environment may be achieved by minimizing travel needs (e.g., enabling telecommuting and distance learning, as well as improving and extending online services) and reorganizing the capacities of on-demand services (Liyanage et al. 2019). This could work within the framework of the Mobility-as-a-Service (MaaS) concept (Kane and Whitehead 2017; Smith et al. 2018; Kamargianni et al. 2016), which offers mobility services as packages rather than offering access to individual means of transport.

Another promising way to develop urban mobility systems is the spread of AVs (Schuckmann et al. 2012; Burns 2013; Tromaras et al. 2018). The purpose of automation is to ensure that various processes are carried out with minimum human intervention and in compliance with required cost-effectiveness criteria (Fagnant and Kockelman 2015). The expected impacts generated by AVs are the increased performance of the transport system, for instance, efficient route distribution (Pauer and Török 2019), safer transport, individual travel options for people without a driving license, increased energy efficiency and improved land use (Fagnant and Kockelman 2015; Török et al. 2018). The general approach is to think in terms of the highest automation level for vehicles, as defined by SAE (2018), which is usually foreseen for 2040 or rather 2050 (Bagloee et al., 2016).

Previous research into new technologies (Tromaras et al. 2018; Lyons 2018; Nikitas et al. 2017; Kane and Whitehead 2017) suggest that the implementation of shared solutions and the development of EVs and AVs are the possible drivers of future mobility systems; however, the role of these innovations in future urban mobility is not yet clear. Therefore, it is necessary to synthesize previous research on future mobility and narrow down the potential outcomes.

Accordingly, this paper provides a comprehensive insight into current expectations of researchers concerning future urban mobility. The objective of this research is to better understand what major trends shape urban mobility in the tangible future, i.e., until the 2030s. This has been translated into three (sub-)questions:

- What are the *technological innovations* that might shape the future of urban mobility?
- What are the *current issues of urban passenger* transport that thematize researchers' forecasts?
- Based on researchers' forecasts (scenarios), what are the *most likely directions for the alteration* in urban passenger transport?

A systematic literature review has been carried out to achieve the objective, paying particular attention to recent scientific literature (published between 2012 and early 2021). Potential transition pathways towards urban mobility and scenarios were identified.

The remainder of the paper is structured as follows. In Section 2, the methodology – the process of SLR, as well as scenario analysing and building – is introduced. Forecasts and scenarios built are presented and discussed in Section 3. Finally, conclusions and limitations are drawn.

IV.2 Methodology

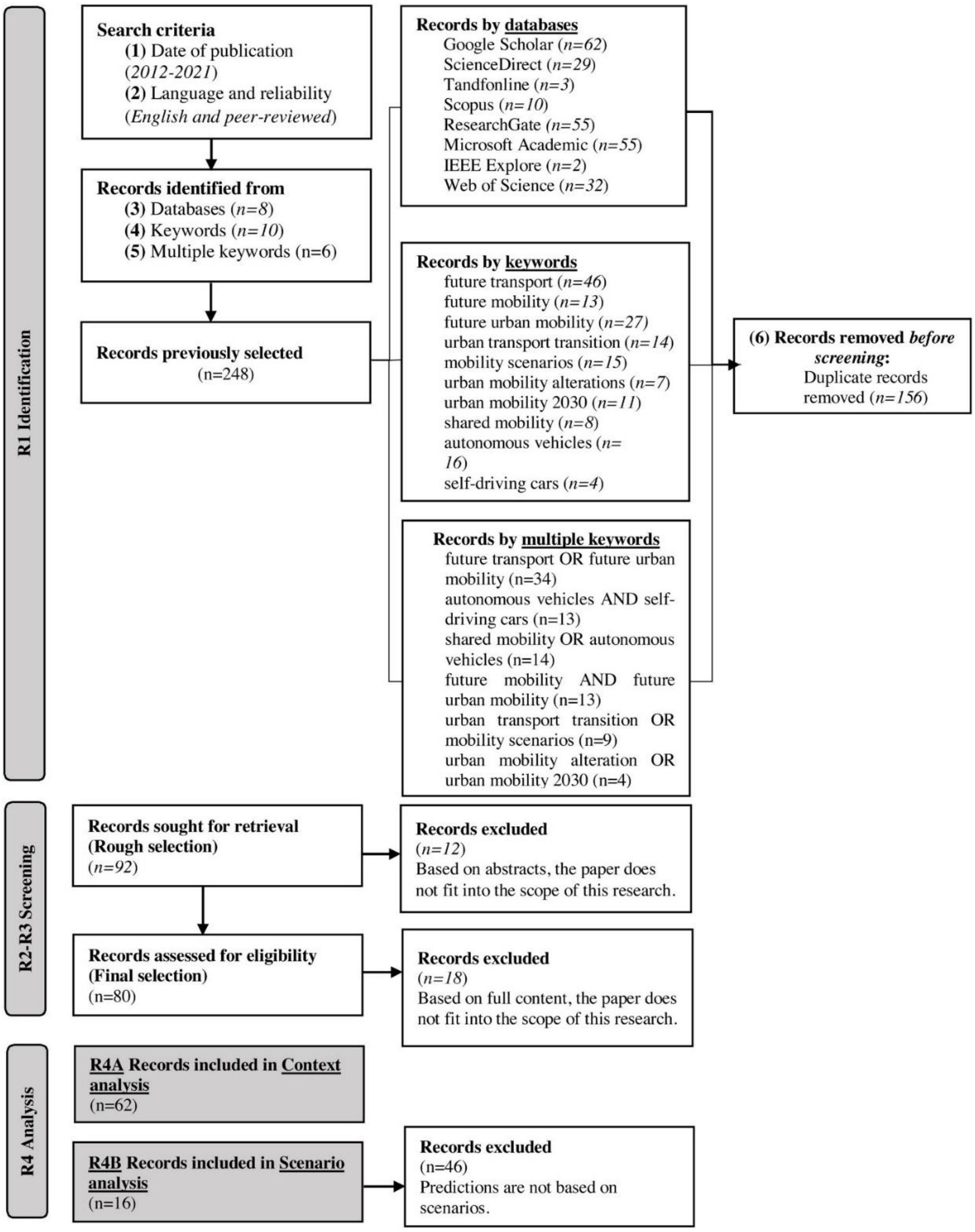
To explore the future of the transport sector is challenging, as in addition to technological changes, other aspects, such as user behaviour, policy perspectives and economic constraints also have significant influence. Most researchers have elaborated scenarios using the Delphi method (Jittrapirom et al. 2017; Spickermann et al. 2014) or conducting a literature review (Kamargianni et al. 2016; Standing et al. 2019; Sochor et al. 2015).

In this paper, a systematic literature review (SLR) is applied, an exploratory research method to synthesize and critically appraise research into a specific topic according to a pre-defined perspective (Denney and Tewksbury, 2013). SLRs aim to recognize areas that require more consideration from researchers and unify existing concepts. Herein, the SLR is used to analyse trends and *scenarios* of future urban mobility. Scenarios provide insights into the technological and socio-economic details of alterations as a conceptual proposal and particularly support decision-making in uncertain circumstances, especially for long-term planning (Melander 2018; Bishop et al. 2007, Wee 2016). The SLR has been carried out following the PRISMA guidelines, an evidence-based set of items for systematic reviews and meta-analyses (Page et al. 2021).

IV.2.1 Systematic literature review (SLR) method

Based on the PRISMA framework, a four-step literature analysis method has been elaborated and applied (Fig 1.): identification (R1), screening in 2 phases (R2 and R3), and analysis (R4).

Figure 1. SLR flow diagram



R1 Identification: defining the research criteria and conducting a systematic keyword-based search to find papers.

(1) *Date of publication:* defining the time interval. Papers published between 2012 and early 2021 were considered to identify research trends of recent years.

(2) *Language and reliability:* determining the languages and types of paper. Primarily, papers published in international peer-reviewed scientific journals in English were considered.

(3) *Database selection:* selecting the search engines. Comprehensive, reliable, and easily accessible databases were selected: Google Scholar, ScienceDirect, Tandfonline, Scopus, ResearchGate, Microsoft Academic, IEEE Explore, Web of Science.

(4) *Keyword selection:* determining the keywords according to the research objectives: searching papers including urban mobility scenarios or forecasts, and papers relating to urban passenger transport including different system features (especially technological, socio-economic and/or environmental). The following 10 keywords were applied: “future transport”, “future mobility”, “future urban mobility”, “urban transport transition”, “mobility scenarios”, “urban mobility alteration”, “urban mobility 2030”, “shared mobility”, “autonomous vehicles”, “self-driving cars”.

(5) *Multiple keywords:* determination of keyword-pairs to improve the searching process. Boolean operators were applied: OR searches including similar search terms were conducted to broaden the number of records on future mobility regardless of which term is used in the document, as well as AND searches were run to narrow the search and to capture documents in which both concepts appear.

(6) *Duplicate records:* removing duplicate records found in several databases. A total of 248 seemingly relevant results were detected in the first step. After organizing the records, duplications (n=156) were removed, thus 92 papers were included in the first screening (R2).

R2 Screening based on abstracts (Rough selection): screening of the identified 92 papers by title and abstract whether they fit in the scope of the research (to answer RQs). It resulted in the exclusion of 12 papers.

R3 Screening based on the full content (Final selection): screening of 80 papers by full text review resulted in the exclusion of 18 papers.

R4 Qualitative analysis: two-step analysis of topics and scenarios.

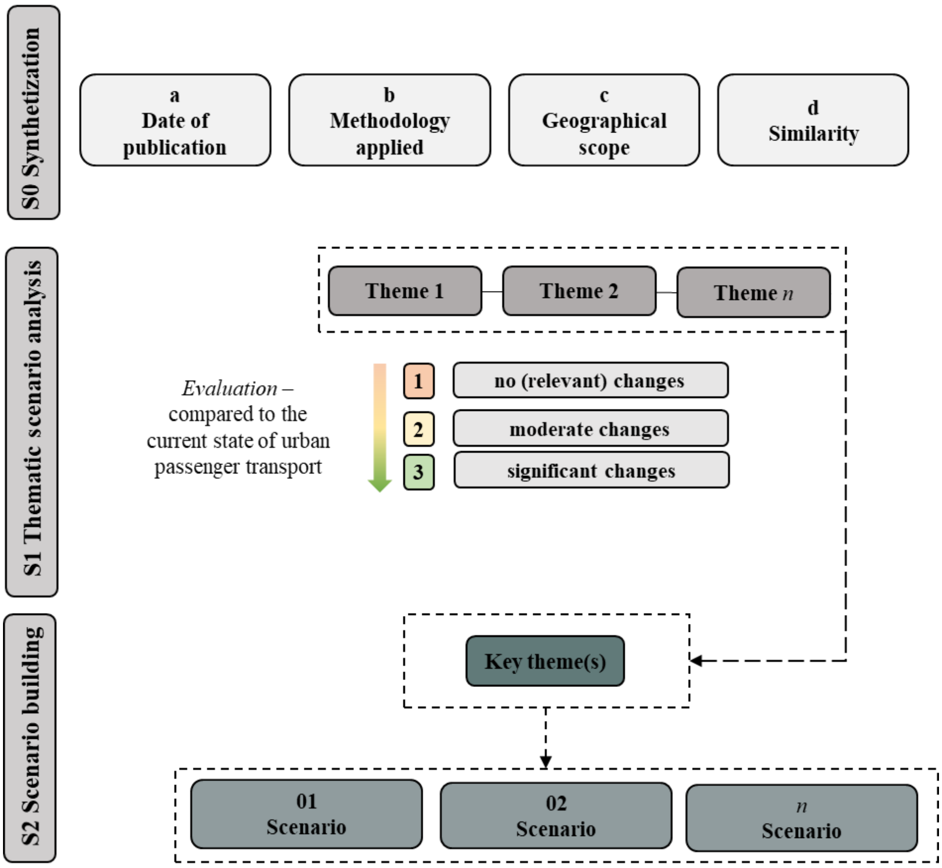
R4A Context analysis*:* an overview of the findings about the future transport in selected papers (n=62) to explore themes along which scenario analysis (S1 – Thematic scenario analysis – Fig. 2.) can be done.

R4B Scenario analysing and building: identifying future mobility scenarios. In total, 16 papers included explicit scenarios. These papers have been selected for analysis to formulate complex scenarios.

IV.2.2 Scenario analysing and building

In R4, papers including scenarios were further analysed to reveal their basic features (e.g., the similarity of papers, date of publication, methodology applied, geographical scope) (S0). A multi-criteria scenario building method was elaborated (S1-S2) to reveal alternative directions of the future (Fig 2.).

Figure 2. Scenario analysing and building method



S0 Synthetization: analysing the selected papers containing scenarios with the following attributes:

a. *Date of publication:* presenting differences in the interpretation of future mobility trends over time.

b. *Methodology applied:* explaining the reliability and standardization of the results.

c. *Geographical scope:* identifying the regions the results relate to, as well as to clarify the regional issues of each scenario.

d. *Similarity:* determining the similarity of scientific documents. Bibliographic coupling and co-citation analysis are applied to calculate the coupling strength among papers analyzed (Gipp and Beel, 2009). Papers are bibliographically coupled if they cite one or more documents in common (Zhang 2009). In contrast, two papers are co-cited if at least one paper cites both (Zhang 2009; Gipp and Beel 2009). During step S0, papers with scenarios are examined whether they refer to each other to point correlations between researchers' perceptions.

S1 Thematic scenario analysis: analysing scenarios in terms of themes selected based on the *context analysis* (R4A). A parameter was introduced for *evaluation* (Table 1) to assess the impacts of each theme in each scenario: 1 represents the current stage without relevant changes, 2 promises some (moderate) changes, and 3 indicates an expected future stage with a significant change(s).

Table 1. Evaluation parameter

x_i^j	**Meaning**	**Description**
1	current stage without relevant changes	It is stated that the theme does not make a significant change (*e.g., the mass public uptake of the technology has not happened),* or its effect is not mentioned.
2	moderate changes	The theme is mentioned, and its effects are clearly described (*e.g., the spread of the technology is increasing*), but it does not result in radical changes (*e.g., conventional means of transport remain essential*).
3	significant changes	The significance of the theme is highlighted (*e.g., innovation takes over the role of conventional solutions*).

Based on this, the evaluation value is x_i^j; where j is the evaluation of key themes (A-F) and i is the number of scenarios. To determine the aggregated evaluation value of scenarios, the x_i^j evaluation values are summarized (eq. 1). Accordingly, aggregated evaluation values (total score) can range from 6 to 18.

$$X^j = \sum_i x_i^j \tag{1}$$

S2 Scenario building: in the *Thematic scenario analysis* (S1), *key themes* are defined to categorize existing scenarios and create new homogenous groups, i.e., comprehensive scenarios based on existing scenarios from the literature. Key themes were selected from the themes that have the strongest influence on urban transport transition. The number of new scenarios depends on the heterogeneity of the existing visions (that is, how many groups can be classified as uniform according to the six themes examined).

IV.3 Results

IV.3.1 Context analysis

As a result of the literature review, 16 papers contain scenarios, and 46 further papers contain forecast trends or particular features of future mobility. In line with the introduction of the present paper providing general overview of current issues and emerging trends, a brief review of these 62 papers is carried out. Mobility-related problems and challenges identified by the papers are as follows:

- Researchers argue that, due to poor performances and the obsolescence of mobility services and vehicles, travel times are increasing (McCormick et al. 2013; Schuckmann et al. 2012; Dia 2019; Wegener, 2013), whilst consumer satisfaction is decreasing and environmental impacts, particularly *GHG emissions* are worsening (Dong et al. 2018; Waisman et al. 2013; Schipper et al., 2020; Moradi – Vagnoni, 2018, Lyons 2018).
- Social issues, especially *social attitudes*, such as individual beliefs and mobility culture (Bagloee et al 2016; Clements and Kockelman 2017; Bergman et al. 2017; Madigan et al. 2017), as well as consumers' mobility-related decisions influenced by economic measures (Manski 2000; Shaheen and Chan 2016; Standing et al. 2019; Nijkamp and Kourtit 2013) were pointed out as significant challenges.

- In the above-mentioned papers, one of the core topics is how to influence users' decision-making to relieve *congestion* and, thus, how to reduce the overload in the urban transport system.

Besides problems and challenges, solutions are also foreseen:

- Several studies (e.g., Currie 2018; Nikitas et al. 2017; Standing et al. 2019) found that *shared mobility* might be one to face major problems. Intermodal services, MaaS and basic forms of sharing mobility may encourage travellers to dispose their private cars (Spickermann et al. 2014; Madigan et al. 2017; Liyanage and Dia 2019). However, some of the papers reviewed (Kamargianni et al. 2016; Jittrapirom et al. 2017; Tokody and Mezei 2017) underline that the widespread use of shared mobility might have significant social constraints. Furthermore, sharing mobility does not address many of the comfort factors (e.g., driving without any zone restrictions) (Bergman et al. 2017). The integration of AV use into a shared mobility system or linking it to MaaS is also discussed as a potential solution to mobility problems (Aparicio 2017; Nikitas et al. 2017; Standing et al. 2019; Clements and Kockelman 2017; Zawieska and Pieriegud 2018, Narayan 2017).
- In general terms, *automation* is considered a tool for creating smart cities and smart mobility (Seuwou et al., 2020; Dey et al. 2018, Pauer and Török 2019; Canitez 2019, Coppola and Silvestri 2019) and faces several challenges. As regards economic impacts, the increasing adoption of automated technology affects almost every industry (Zawieska and Pieriegud 2018; Freudendal-Pedersen et al. 2019, Melander 2019, Shoettle and Sivak 2014). Many questions related to technology acceptance, barriers and risks (e.g., moral and legal dilemmas) of driverless cars seem to still be unanswered. The evolution will result in losses in some industries, for instance in employment in the legal profession, in the insurance sector and of professional drivers (Madigan et al. 2017). Moreover, several moral issues, such as re-training redundant workforce or managing human-machine interactions influence the extent of this technology (Fagnant and Kockelman 2015; Bergman et al. 2017; Török et al. 2018). However, during the transition period and due to the mixed technological scene and the uncertain legal environment, the role of some business areas resolving

uncertainty (e.g., the legal profession) will increase for a short period (Clements and Kockelman 2017).

- The future urban mobility predicted is not only shared and autonomous but *electric* (Becker et al., 2020; Csonka and Csiszár 2017). In that way, sustainability can be delivered (Lah et al 2019; Bohnes et al. 2017; Olsson et al. 2015; Burns 2013). However, others (Fagnant and Kockelman 2015; Freudendal-Pedersen et al. 2019; Dong et al. 2018) call into question the global sustainability of EVs (the environmental impacts of battery production, vehicle life cycle, etc.). Market positioning (Zawieska and Pieriegud 2018) and service standards (Lopez – Carreiro et al., 2020) of EVs also come into question. Some researchers (Jittrapirom et al 2017; Sochor et al 2015) emphasize that as part of mobility packages, low and zero emission mobility (e.g., human-powered micro-mobility: cycling, scootering, and walking) should dominate.

Based on context analysis, the *themes* selected for the analysis of scenarios (S1-S2) are *automation* (theme A), *shared mobility (B)*, *electrification* (C), as well as urban mobility problems to solve: *road congestion (D), social attitude (E)* and *GHG emissions (F)*.

IV.3.2 Scenario analysing and building

S0 Synthetisation:

Researchers predicted two to four different urban mobility scenarios, allowing us to identify a total of 52 scenarios. Names of authors and basic features (**a.** *Date of publication,* **b.** *Methodology applied* and **c.** *Geographical scope*) of the papers, as well as the list of scenarios and their timespan are shown in Table 2.

Table 2. S0 – Date of publication, methodology applied and geographical scope of scenario-based papers

Code	Author(s)	No. of scenarios	Scenario	Year	Date of publication	Methodology applied	Geographical scope
P1	Ecola et al.	1	The great reset	2030	2016	expert interviews, cluster analysis	Asia (China)
		2	Slowing but growing				
		3	Wild card - Low probability				
P2		4	Sub-optimal scenario A				Australia

	Kane and Whitehead	5	Sub-optimal scenario B	2030	2017	literature review	
		6	Sub-optimal scenario C				
		7	Sub-optimal scenario D				
P3	Kaufmann and Ravalet	8	Ultramobility	2050	2016	literature review, survey	Europe (France)
		9	Altermobility				
		10	Proxymobility				
P4	Keseru et al.	11	Slow is beautiful	2030	2019	stakeholder interviews	Europe
		12	Data world				
		13	Digital nomads				
		14	Minimum Carbon				
P5	Marletto	15	Auto-city	2030	2014	literature review	Europe (Netherlands)
		16	Eco-city				
		17	Electri-city				
P6	Marletto	18	Individual transition pathway	2040	2019	literature review	Europe (Netherlands)
		19	Shared Transition pathway				
		20	Smart transition pathway				
P7	Milakis et al.	21	AV in demand	2030	2017	stakeholder interviews/work shops	Europe (Netherlands)
		22	AV in doubt				
		23	AV in standby				
		24	AV in bloom				
P8	Brenden et al.	25	Same same but different	2030	2017	literature review	Europe (Sweden)
		26	Follow the path				
		27	Sharing is the new black				
		28	What you need is what you get				

P9	Schippl et al. 2016	29	Waterberg	2025	2016	stakeholder interviews/work shops	Europe
		30	Viga				
		31	Valanov				
P10	Shergold et al.	32	Home ties	2030	2015	expert interviews/work shops	Europe (UK)
		33	Communal Call-out				
		34	Gimme Shelter				
		35	Home alone and Wired				
P11	Zmud et al.	36	Scenario 1	2030	2013	expert interviews, cluster analysis	Europe
		37	Scenario 2				
P12	Zmud et al.	38	No Free Lunch	2030	2014	five-step scenario development based on both quantitative and qualitative (expert opinions) data	United States
		39	Fuelled and Freewheeling				
P13	Banister and Hickman	40	BAU	2030	2013	exploratory research – secondary data analysis	Asia (India - Delhi)
		41	Scenario 1—Lower Carbon Emissions Motor Vehicles 2030				
		42	Scenario 2—Increased Active Travel 2030				
		43	Scenario 3—Towards Sustainable Transport 2030				
P14	Fulton et al.	44	BAU - Limited intervention	2050	2017	exploratory research – secondary data analysis	United States, Europe, Asia (China and Japan)
		45	The 2R Scenario: Electrification and Automation				
		46	The 3R Scenario:				

			Adding Shared Mobility				
P15	Rohr et al.	47	Driving Ahead	2035	2016	Desktop research, expert interviews	Europe (UK)
		48	Live Local				
		49	Digital Divide				
P16	Julsrud and Uteng	50	Controlled mobility	2050	2015	Delphi-method	Europe (Norway)
		51	Technopolis				
		52	Shared mobility				

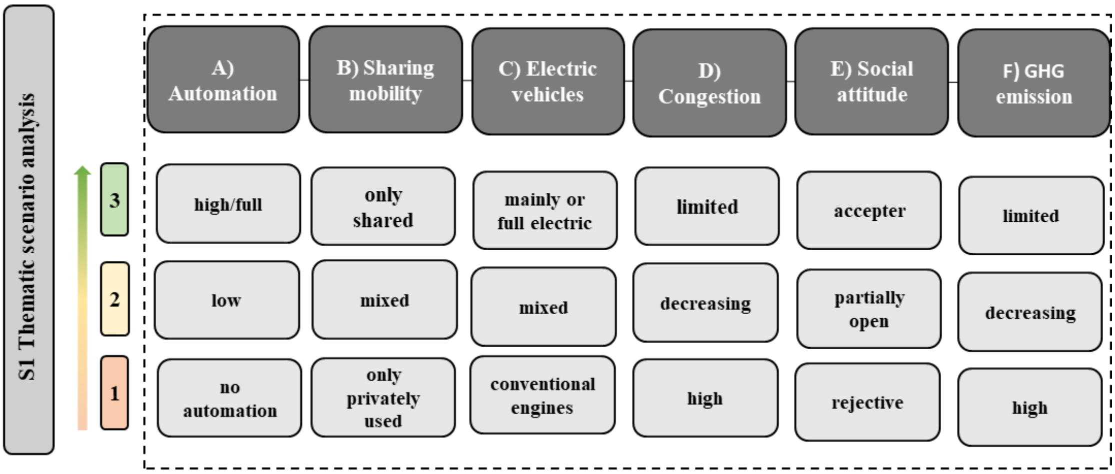
d. *Similarity:* only low correlation is detected between some of the scenario-based papers (Table 3). P6 and P16 are bibliographically coupled since they cite P5 in common. P5 and P7 are co-cited since they are cited by P6. P5 and P10 are co-cited since they are cited by P16. In the absence of significant overlaps, a reason for exclusion cannot be identified, therefore, 52 scenarios are analyzed in the next phase (S1).

Table 3. S0 – Reference-reference matrix of scenario-based papers

	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**	**P15**	**P16**
P1		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P2	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0
P3	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0
P4	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0
P5	0	0	0	0		**1**	0	0	0	0	0	0	0	0	0	**1**
P6	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0
P7	0	0	0	0	0	**1**		0	0	0	0	0	0	0	0	0
P8	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0
P9	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0
P10	0	0	0	0	0	0	0	0	0		0	0	0	0	0	**1**
P11	**1**	0	0	0	0	0	0	0	0	**1**		0	0	0	0	0
P12	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0
P13	0	0	0	0	0	0	0	0	0	0	0	**1**		0	0	0
P14	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0
P15	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0
P16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

S1 Thematic scenario analysis: interpretation of evaluation values related to *themes* identified in *Context analysis* (R4A) can be seen in Fig 3.

Figure 3. Scenario analysing and building method – Phase S1



In line with this, the evaluation of each theme in each scenario was carried out. Table 4 presents the results. The number of squares represents the values of x_i^j evaluation parameters.

Table 4. Evaluation of scenarios by themes

i	Scenario	x_i^j						Xi
		A	**B**	**C**	**D**	**E**	**F**	**Σ**
18	Individual transition pathway	1	1	1	1	1	1	**6**
36	Scenario 1	1	1	1	1	1	1	**6**
15	Auto-city	1	1	1	1	1	1	**6**
31	Valanov	1	1	1	1	1	1	**6**
39	Fuelled and Freewheeling	1	1	1	1	1	1	**6**
44	BAU - Limited intervention	1	1	1	1	1	1	**6**
25	Same same but different	1	1	2	1	1	1	**7**
21	AV in demand	1	1	2	1	1	1	**7**
40	BAU	1	2	1	1	1	1	**7**
50	Controlled mobility	1	1	2	1	1	1	**7**
22	AV in doubt	2	1	2	1	1	1	**8**

23	AV in standby	2	1	1	1	1	2	**8**
32	Home ties	2	1	1	1	2	1	**8**
4	Sub-optimal scenario A	2	1	1	1	2	2	**9**
8	Ultramobility	2	1	1	1	2	2	**9**
45	The 2R Scenario: Electrification and Automation	2	1	2	2	1	1	**9**
51	Technopolis	2	1	1	1	2	2	**9**
1	The great reset	2	1	2	2	1	2	**10**
34	Gimme Shelter	2	1	1	2	2	2	**10**
38	No Free Lunch	2	1	2	1	2	2	**10**
48	Live Local	2	1	1	2	2	2	**10**
26	Follow the path	2	1	2	2	2	2	**11**
29	Waterberg	2	1	2	2	2	2	**11**
33	Communal Call-out	2	1	2	2	2	2	**11**
35	Home alone and Wired	1	3	1	2	3	2	**12**
11	Slow is beautiful	1	3	1	2	3	2	**12**
9	Altermobility	1	3	1	3	2	2	**12**
41	Scenario 1—Lower Carbon Emissions Motor Vehicles 2030	2	1	2	2	2	2	**11**
10	Proxymobility	1	3	1	3	2	3	**13**
16	Eco-city	1	3	3	2	2	2	**13**
27	Sharing is the new black	1	3	2	2	3	2	**13**
37	Scenario 2	1	3	3	2	2	2	**13**
42	Scenario 2—Increased Active Travel 2030	1	3	3	2	2	2	**13**
17	Electri-city	1	3	3	2	2	3	**14**
30	Viga	1	3	3	2	2	3	**14**
6	Sub-optimal scenario C	1	3	3	2	2	3	**14**
19	Shared Transition pathway	1	3	3	2	3	2	**14**
2	Slowing but growing	1	3	2	3	2	3	**14**
12	Data world	1	3	3	2	2	3	**14**
52	Shared mobility	1	3	2	2	3	3	**14**

13	Digital nomads	3	3	2	2	3	2	**15**
28	What you need is what you get	3	3	3	2	2	2	**15**
43	Scenario 3—Towards Sustainable Transport 2030	1	3	3	3	3	3	**16**
46	The 3R Scenario: Adding Shared Mobility	3	3	2	2	3	3	**16**
47	Driving Ahead	3	3	2	3	2	2	**15**
49	Digital Divide	3	3	2	2	3	3	**16**
3	Wild card - Low probability	3	3	2	3	3	3	**17**
5	Sub-optimal scenario B	3	3	3	2	3	3	**17**
14	Minimum Carbon	3	3	3	3	3	3	**18**
24	AV in bloom	3	3	3	3	3	3	**18**
7	Sub-optimal scenario D	3	3	3	3	3	3	**18**
20	Smart transition pathway	3	3	3	3	3	3	**18**

Legend: x_i^j= 1 current stage without relevant changes, 2 moderate changes, 3 significant changes

Changes related to automation (A) and shared mobility (B) seem to be the drivers of alterations in future mobility: there are scenarios in which a distinction may be made by the expected level of automation (A) if the total score is relatively high (equal to or above the median of 12) and scores for sharing mobility (B) is above the average.

Scenarios with an overall lower value (below 12) show the same pattern, i.e., the scenarios with the lowest total scores foresee the tangible future without a higher level of automation. This suggests that these are *key themes*, which may determine the clustering of previously created scenarios into new and more comprehensive ones.

In other words, by the study of interconnections, values of $x_i^C; x_i^D; x_i^E; x_i^F$ depend primarily on the alterations of x_i^A and x_i^B.

S2 Scenario building: Based on S1, four categories may have been distinguished (Table 5).

Table 5. Identification of categories based on evaluation values

No.	Aggregated evaluation value	Evaluation value x_i^j						Description
		j=A	**j=B**	**j=C**	**j=D**	**j=E**	**j=F**	
I	$6 \leq X_i \leq 7$	1	1	≤2	1	1	1	Most of the themes indicate a constant state, except Electrification (C), which may indicate a slight advance.
II	$8 \leq X_i \leq 11$	2	1	≤2	≤2	≤2	≤2	A slight development of Automation (A) is foreseen in each case, without changes in Sharing mobility (B). No significant changes are foreseen in other themes (at least one of them indicate moderate changes).
III	$12 \leq X_i \leq 14$	1	3	$2 \leq C \leq 3$	$2 \leq C \leq 3$	$2 \leq C \leq 3$	$2 \leq C \leq 3$	Automation (A) indicates no development, while Sharing mobility (B) is going to highly dominate. Other themes indicate some development, incl. the value of 3 in one or two of them.
IV	$15 \leq X_i \leq 18$	3	3	$2 \leq C \leq 3$	$2 \leq C \leq 3$	3	$2 \leq C \leq 3$	Automation (A), Shared mobility (B) and Social attitude (E) indicate significant changes in each case and one or two further themes promise moderate changes.

Legend: A=Automation, B= Shared mobility, C= Electric vehicles, D=Congestion, E=Social attitude, F=GHG emission

In scenarios in category I ($X_i \leq 7$) researchers (Brenden et al. 2017; Zmud et al. 2013; Marletto 2014, 2019; Milakis et al. 2017; Shergold et al. 2015, Zmud et al., 2014, Banister, 2013, Fulton, 2017) forecast potential realities without AVs and predict almost the same state of vehicle ownership and road transport dominance as nowadays, ($x_i^B = 1$) . This is attached to lack of improvements in terms of the level of congestion ($x_i^D = 1$) and environmental problems (x_i^F =1). Only a slight further development and spread of electric vehicles can be detected in these scenarios. These scenarios predict potential future urban mobility in Europe, some of them particularly in the Netherlands (Milakis et al. 2017), Sweden (Brenden et al. 2017), Norway (Julsrud, 2015) and outside Europe (Asia – Banister, 2013; in the United States – Zmud, 2014; Fulton, 2017). In sum, this is the category of a traditional transport system with no significant changes, hereinafter it is named scenario *Grumpy old transport*.

Scenarios in category II ($8 \leq X^j \leq 11$) describe a minimal transformative change (i.e., a slow or moderate reduction of existing urban transport problems) (Brenden et al. 2017; Zmud et al. 2013; Kane and Whitehead 2017; Shergold et al. 2015, Zmud et al., 2014; Banister, 2013; Fulton, 2017; Julsrud, 2015; Rohr, 2016). In addition, a moderate development of automation ($x_i^A = 2$) and spreading of sharing are expected. The geographical scope of slow transition scenarios is mainly Europe, but some scenarios refer to Asia (Zmud et al. 2013; Banister, 2013) and the United States (Zmud et al., 2014; Fulton, 2017). This is the category of a traditional transport system with a moderate or slow transition towards automation and shared vehicle use, hereinafter this is the scenario *At an easy pace*.

Reducing the number of privately used vehicles plays a key role in scenarios in category III ($12 \leq X^j \leq 14$) (Schippl et al. 2016; Kaufmann and Ravalet 2016; Keseru et al. 2018, Banister, 2013, Julsrud, 2015, Rohr, 2016; Kane and Whitehead, 2017; Shergold et al. 2015; Ecola et al. 2016). The increasing role of shared mobility (x_i^B =3) is predicted. Shared mobility scenarios are considered for Europe and, in two cases, Asia (China – Ecola et al. 2016; India – Banister, 2013). Most researchers analyse the role of automation in the context of shared mobility, but some scholars (Ecola et al. 2016; Keseru et al. 2019) predict unchanged levels of automation ($x_i^A = 1$). Social attitudes are slightly or largely changing ($2 \leq x_i^E \leq 3$). In other words, this is the category with a vision of a radical shift towards sharing mobility with a low penetration of automation, hereinafter this is the scenario *Mine is yours*.

Scenarios in category IV ($15 \leq X^j \leq 18$) forecast a highly advanced system. The two main characteristics are the prominent role of high automation and shared mobility ($x_i^A = 3$; $x_i^B = 3$) (Marletto 2019; Milakis et al. 2017; Brenden et al. 2017; Banister, 2013; Fulton, 2017; Rohr, 2016). These visions provide a largely changed picture of future mobility as, due to the emergence of electric propulsions ($2 \leq x_i^C \leq 3$), automation and sharing, environmental problems are widely resolved ($2 \leq x_i^F \leq 3$). Alongside Europe and Asia (Banister, 2013), a vision for Australia has also appeared (Kane and Whitehead 2017). This is the vision of the dominance of sharing-based transport solutions with a high level of automation, hereinafter this is the scenario *Tech-eager mobility*.

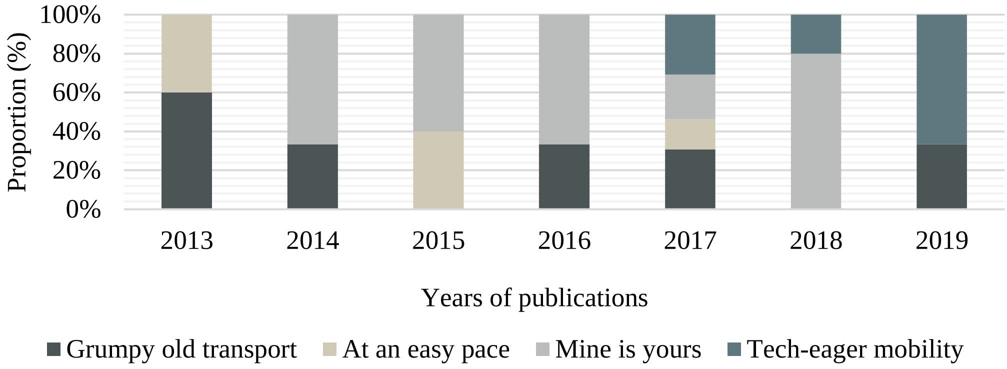
IV.3.3 General characteristics of scenarios

The proportion in terms of the number of existing scenarios included of the scenarios formulated indicates their relevance: 'Mine is yours' shows 35%, 'Grumpy old transport' 19%, 'Tech-eager mobility' 17% and 'At an easy pace' 29%. Although the analysis is merely qualitative, shared mobility is suggested to shape urban mobility transition in the future. However, the proportion of scenario 'Grumpy old transport' is also significant whilst forecasting no transformative changes.

The period analysed in the existing scenarios is diverse, therefore, the uncertainty of predictions regarding tangible future (the 2030s) is relatively high. Among the scenarios for 2030, the proportion of scenarios formulated presents minimal alteration. The dominance of 'Mine is yours' remains remarkable (35% of the visions belong to this group), but the importance of 'Grumpy old transport' declines to 18%, and the proportion of 'Tech-Eager mobility' is slightly higher (18%).

Publication dates of scenarios are summarized in Fig 4. Over the last few years, a remarkable shift in findings can be seen. The results show that the role of the scenarios supporting the 'Grumpy old transport' future was greater in the earlier publications than after 2016. Scenarios forecasting future potentials of shared mobility is nearly equally relevant in the analysed years. Visions related to 'Tech-eager mobility' only appear in post-2016 literature.

Figure 4. Years of publications



IV.3.4 Description of scenarios

The scenarios formulated are described in terms of mobility challenges and socio-economic issues, as follows.

IV.3.4.1. Grumpy old transport

The Grumpy old transport scenario forecasts an urban transport system very similar to the current one, in which the use of privately-owned cars is the most conventional way of private mobility (Zmud et al., 2014; Banister, 2013; Milakis et al., 2017). Shared mobility services are attractive only to a narrow segment (Julsrud, 2015; Fulton, 2017). The dominant groups are generation Y and Z, and the use of shared services is not expected to become widespread (Brenden et al., 2017; Marletto, 2014, 2019). Even with automation developments, no breakthrough is expected, and the sale of vehicles at the current automation level (SAE 2 or 3) remains constant (Zmud et al., 2013; Fulton, 2017).

Challenges in transport

Due to private car ownership, the level of vehicle kilometers travelled increases, and overcrowded roads continue to be a common issue (Zmud et al., 2014; Banister, 2013; Milakis et al., 2017). The 'ever-increasing' presence of private cars contributes to congestion, whilst inadequate infrastructure and obsolete mobility services (public transport with no serious innovation) make passenger transport difficult in larger cities. The basic capacity of the urban transport system is further strained by urbanization processes (Milakis et al., 2017). Due to excessive traffic, the burden on the environment caused by industry continues to grow (Marletto, 2014, 2019). If this scenario is realised, the contribution of the transport sector to environmental pollution will be challenging.

Socio-economic factors

In general, slow transition is mainly due to consumer behaviour. Travellers prefer convenience-oriented ways of fulfilling mobility needs (Fulton, 2017). Comfortable, seamless mobility, even with the negative effects of congestion, seems to be dependent on using cars (Brenden et al. 2017; Zmud et al. 2013). Individual car ownership is consistently regarded as a status symbol in many countries, and travellers consider shared mobility as a useful possibility only until they can afford to own a car (Fulton, 2017; Milakis et al., 2017). Lack of communication between stakeholders and decreasing 'coopetition' are typical. Due to consumers' reluctance, the government and transport companies do not see any major benefits from the rapid improvement of mobility services. Progressive legislation and supportive policies are lacking, so the rise of any innovative mobility solutions is dismissed; automation is available for only the elite class (Zmud et al., 2013; Fulton, 2017).

IV.3.4.2. At an easy pace

In this scenario, some moderate changes can be detected. Although the dominant transport mode remains privately-owned cars (complemented by public transport) (Brenden et al. 2017; Zmud et al. 2013), progress towards change in vehicle propulsion varies. The role of EVs is increasing significantly, but, at the same time, the role of shared mobility is improving slowly (Kane and Whitehead 2017; Shergold et al. 2015). Further, the spread of automation is slow, and faster development is expected only in the USA (Zmud et al., 2014; Fulton, 2017), China and Japan (Fulton, 2017; Banister, 2013). Due to excessive use of cars, environmental and traffic problems remain serious and unsolved.

Challenges in transport

Transport problems continue to be significant, but some measures strive to reduce their impacts. Zone restrictions are introduced to mitigate congestion in urban traffic. Some forms of employment, such as flexitime, home-office and the emergence of home-based positions are able to reduce the amount of travel required. This would also result in a slight reduction in congestion (Zmud et al. 2013; Banister, 2013). Due to the increase in the use of EVs, GHG emissions are less likely to increase (Brenden et al., 2017; Julsrud, 2015).

Socio-economic impacts

Leading players in industry are still the oil companies and car manufacturers (Zmud et al., 2013; Zmud et al., 2014). The market share of electric and self-driving car manufacturers is expected to grow (Rohr, 2016; Fulton, 2017). Willingness to change mobility habits is increasing, but not explicitly towards sustainable modes. Due to general improvement in living standards, more and more people can afford to buy a car (Shergold et al., 2015; Julsrud, 2015). The need for comfortable and meaningful travel is growing, other options are used only when there is no alternative.

IV.3.4.3. Mine is yours

In this scenario, major changes may be predicted. The sharing-based economy business model has immense market-shaping power (Julsrud, 2015; Schippl et al., 2016). The role of shared mobility dominates transport modes. Further, the spread of EVs and the decline of the manufacture of vehicles with traditional propulsion are typical (Kaufmann – Ravalet, 2016; Keseru et al., 2018). The large-scale development of automation does not appear. Shared mobility and EVs reduce some traffic problems and the negative impact of transport on environment is diminished (Shergold et al., 2015; Ecola et al., 2016).

Challenges in transport

The increase of shared mobility reduces transport problems (Julsrud, 2015; Schippl et al., 2016). In addition, other modes, such as public transport, cycling and walking are integrated, enabling door-to-door travel. The importance of alternative micro-mobility vehicles (e.g., e-bikes and e-scooters) is also increasing (Ecola et al. 2016; India – Banister, 2013). To establish high-quality and integrated solutions, significant developments in rail and public transport services are needed (Rohr, 2016; Kane and Whitehead, 2017). The role of private cars has hugely decreased. To minimize carbon emissions, urban traffic is shaped by strong regulations: car-free areas as well as zero-emission zones are created (Shergold et al. 2015; Ecola et al. 2016).

Socio-economic impacts

A significant proportion of commuters uses shared vehicles; however, the role of public transport is further reinforced (Ecola et al., 2016; Keseru et al., 2019). This can be achieved through major infrastructure and service improvements (for instance, by the implementation of MaaS). In addition to traditional industry players, car-sharing and ride-sourcing companies become more powerful and the role of producers of EVs is growing, whilst oil company penetration is minimized (Ecola et al., 2016; Kane and Whitehead, 2017). Users accept the alterations, prefer sharing economy solutions; they become open to new mobility options, and less and less eager to owning cars (Banister, 2013; Julsrud, 2015). Consequently, several automotive companies may leave the market. The environmental consciousness of the whole of society increases, resulting in a decreased need for mobility (Kane and Whitehead, 2017; Shergold et al. 2015). Due to strong individualization and flexible employment, the boundaries between private life and work disappear, but this benefits the transport sector. Travellers can reduce travel demand to decrease travel time and costs, and this attitude can greatly relieve the already optimized transport system (Ecola et al., 2016; Kaufmann and Ravalet, 2016; Keseru et al., 2018).

IV.3.4.4. Tech-eager mobility

This scenario predicts the most intense transition. Technological advances affect the transport process as well as travel behaviour. Vehicles with a high level of automation will have become widely available. AVs and EVs go hand-in-hand; both technologies are highly advanced, strengthening each other's market position (Marletto 2019; Milakis et al. 2017). However, public transport remains one of the most effective means of transport. Transport is completely environmental-friendly and traffic problems are minimized owing to shared and autonomous vehicles (Milakis et al. 2017; Brenden et al. 2017).

Challenges in transport

Although AVs are widespread, transport is predicted more likely to be mixed in the near future when conventional and autonomous vehicles run on the same road at the same time (Marletto 2019; Milakis et al. 2017). AVs are connected, resulting in optimised traffic flow, travel time and minimised congestion. Even though total kilometers travelled increase, the transport infrastructure is not overloaded, as a consequence of the shared use of AVs (Milakis et al. 2017; Brenden et al. 2017). In addition, the role of public transport remains significant, although its importance is somewhat reduced as a consequence of shared mobility services, especially in last-kilometer travel. Even if travellers use AVs in a non-sharing form, the number of cars per household is also likely to decline, as only one AV can meet the needs of a whole family (Banister, 2013; Fulton, 2017; Rohr, 2016). The spreading of AVs may also contribute to land use change. As less parking space is needed, current parking lots can be used for other purposes (e.g., green areas, non-motorized transport modes). Pedestrian traffic has also increasing importance due to the reorganization of the infrastructure (Rohr, 2016; Kane and Whitehead 2017). As a consequence, the impact of transport on the environment is reduced.

Socio-economic factors

The market is dominated by EV and AV manufacturers and sharing companies in cooperation with public transport (Marletto 2019; Milakis et al. 2017). Supportive policies allow the smooth application of technology. Changes predicted have the greatest impact on travel behaviour. Travellers switch to low emission mobility forms; they are less likely to own cars and even be licensed drivers (Brenden et al. 2017; Fulton, 2017). They appreciate integrated and ICT-based mobility solutions (MaaS applications, e-ticketing, real-time information, etc.). Moreover, the productivity of travellers is increased using AVs (Rohr, 2016; Kane and Whitehead 2017; Fulton, 2017). The divide between private and professional spheres could be blurred; employees can work from anywhere without wasting time driving a car (Marletto 2019; Milakis et al. 2017). Overall optimal time control reduces the need for fast transport, which can positively influence users' perception of each transport mode.

IV.4 Conclusion

In this paper, the methods and outcomes of a literature review concerning the tangible future (until the 2030s) of urban mobility are summarized. With a systematic literature review, employing 10 keywords and 8 search engines, 62 recently published papers discussing the emerging trends and the innovations of the future of urban mobility have been analysed. In sum, 52 scenarios outlining the possible future state of mobility have been identified and evaluated by a complex method. Based on the context analysis, a multi-criteria scenario analysis with six themes (role of automation, sharing mobility, electric vehicles, congestions, GHG emissions and social attitudes) that, according to the literature, significantly affect the future paths of urban mobility, has been applied. On this basis, answers to the research questions posed in the Introduction are as follows:

- Based on context analysis, *the spread of shared mobility solutions, electrification, and automation of vehicles are the technological solutions that shape the future of urban mobility.* Scenario analysis proved that key themes are shared mobility and automation along which four distinguishable directions of alteration (scenarios) are created for 2030.

- Based on the context and scenario analysis, *opportunities to reduce GHG emissions, road traffic congestion, and travelers' ambivalent attitudes are the key current issues that thematize current transportation research.*
- Based on the SLR, 52 scenarios have been identified in the literature that can be arranged in a matrix in line with the key themes (progress of automation and spread of shared mobility services). As result, four scenarios that synthesize researchers' current forecasts have been formed: 'Grumpy old transport', 'At an easy pace', 'Mine is yours', 'Tech-eager mobility'. The scenario 'Tech-eager mobility' is dominated by sharing-based transport solutions with a high level of automation. The scenario 'Mine is yours' is led by sharing mobility with low penetration of AVs. The scenario 'At an easy peace' is based on traditional transport modes with slow transition towards shared mobility and the massive use of AVs. And the scenario 'Grumpy old transport' represents no relevant changes. Based on the scenarios formed, the transition towards higher automation and shared mobility will be rather slow. *By the 2030s, the most likely scenarios are 'At an easy pace' and 'Mine is yours'. This means that only an incremental advance, such as a slow shift towards self-driving, electric and shared vehicle use can be predicted.*

It has to be underlined here that due to the limited number of papers presenting future mobility scenarios, only 16 scientific papers could be used to identify complex scenarios. Other key limitations of this study are different scope, timeframe, aims, and methods applied in the papers analysed.

Bearing this in mind, the next step of this research is the review of other sources, particularly the visions of urban and mobility planners (e.g., in the standardised approach in sustainable urban mobility plans provided by common European guidelines) to understand what professionals forecast. Furthermore, as social aspects are significant in the spread of urban mobility innovations, another research direction is modelling the factors influencing the acceptance of emerging mobility solutions. Moreover, the recent impact of the COVID-19 crisis indicates that previous assumptions and mobility planning criteria need to be reconsidered. This suggests that the research community quickly has to formulate new scenarios or identify potential mobility pathways to let decision-makers reconsider policies that are the basis of financial programs for the upcoming years.

V IMPACTS AND POTENTIAL OF AUTONOMOUS VEHICLES IN TOURISM

Reference: Miskolczi, M., Kökény, L., Ásványi, K., Jászberényi, M., Gyulavári, T., Syahrivar, J. (2021). Impacts and potential of autonomous vehicles in tourism. *Deturope*, 13(2): 34-51.

Abstract: Autonomous vehicles (AVs) are developing rapidly, but the deeper understanding of tourists' attitudes towards AVs is still little explored in social sciences. Bearing this in mind, this study aims to identify the expected changes in tourism arising from the technology, and the openness towards AV-based tourism services. For this, an online data collection (n = 671) has been completed. Prior to the data collection, a literature review was conducted to identify and categorise the changes expected from the spread of AVs. Based on the results, tourists would be willing to give up control to the AVs in a foreign environment, and so to pay more attention to the environment. The majority of respondents would be also open to participating in AI-based city tours, especially those with the "Extraversion" and "Openness to Experiences" personality types, based on Big Five Theory. Findings can serve as a basis for practitioners in preparing for the technology and for further analysis of attitudes towards tourism-based AV services (e.g., modeling of technology acceptance).

Keywords: autonomous vehicles (AVs), tourism service development, attitudes towards autonomous vehicles, tourism consumer behavior

V.1 Introduction

Nowadays, one of the biggest issues of passenger transport is to find a balance between economic sustainability, environmental regulations, and even travelers' satisfaction (Tromaras et al., 2018; Bagloee et al., 2016). Automation is one of the promising technologies of Industry 4.0 that can transform many industries, including tourism and passenger transport (Fagnant & Kockelman, 2015). According to optimistic (pre-pandemic) estimates, 27 million AVs are expected to be on the roads by 2030 in Europe, and 40% of passenger kilometers will be performed by AVs (PWC, 2018). Despite this radical improvement, there are several unanswered questions (legal – e.g., Glancy, 2015; moral and sectorial – e.g., Miskolczi et al., 2021, De Sio, 2017; social – Bissell et al., 2020) around the technology. Most of the literature on AVs consider primarily the technical feasibility (Run & Xiao, 2018; Zhao et al., 2018) as well as the general advantages and disadvantages of spread (Nielsen & Haustein, 2018; Du & Zheng, 2021).

In our study, we especially concentrate on the attitudes towards the use of AV for tourism purposes. Our research aims to reveal how tourists with different consumer habits relate to AV-based tourism services that we have identified in the literature. In our empirical research, the correlation between the subjects' personality type and AV attitude has also been analyzed. There are only a few papers (e.g., Tussyadiah & Zach & Wang, 2017; Cohen & Hopkins, 2019) that analyze the impact of AVs on tourism which reinforces the relevance of our research objective. Findings revealed a generally positive attitude towards AV-based tourism services. According to respondents' assumptions, AVs would improve the tourism experience, as their use would allow for a more convenient way of visiting the destination and its attractions.

Our study is structured as follows: In section 2, the basic definitions of AV technology and the results of previous research related to our research topic are discussed. The process and results of empirical research (Section 3) are interpreted along with three main topics (Section 4): tourism habits of subjects, attitudes towards AV-based tourism services, and the correlation between personality types and openness to AV technology. Finally (in section 5), we answer our research questions and make suggestions for the application of AV in tourism.

V.2 Theoretical background

V.2.1 Definitions and levels of automation

A significant part of transport is realized due to tourism motivations. Therefore, such disruptive innovations as automation in passenger transport might also affect tourism (Jászberényi & Munkácsy, 2018). Nowadays, the main objective of transport development initiatives is to reduce the number of accidents caused by human error, which currently accounts for 90% of road accidents (Menezes et al., 2017). Automation determines the replacement of processes by machines that previously required human intervention (Fagnant & Kockelman, 2015; Nikitas et al., 2017).

Automation is an incremental innovation in transport. To define the nature of this phenomenon, the SAE[9] (Society of Automotive) framework developed by the National

[9]https://www.sae.org/news/press-room/2018/12/sae-international-releases-updated-visual-chart-for-its-%E2%80%9Clevels-of-driving-automation%E2%80%9D-standard-for-self-driving-vehicles

Highway Traffic Safety Administration (NHTSA[10]) should be interpreted, which is structured as follows:

- **Level 0: "No Automation":** Conventional way of using a vehicle without any automation.
- **Level 1: "Driver Assistance":** Only the human driver controls the vehicle, but there are some supporting functions (e.g., cruise control).
- **Level 2: "Partial Automation":** The human driver controls the vehicle, but advanced driving assistance systems (ADAS) (e.g., lane-centering, IPAS[11]) are available.
- **Level 3: "Conditional Automation":** The human driver is still responsible for controlling the vehicle, but the continuous monitoring of the environment is no longer required; AI performs all driving operations. On the other hand, in the case of special traffic situations, human drivers must take back control over the machine. Currently, the most advanced vehicles achieve this level of automation (Honda company's new development – Sensing Elite Traffic Jam Pilot[12]).
- **Level 4: "High Automation":** The vehicle manages all driving functions and controls itself under certain conditions (e.g., adequate 5G coverage of the operating zone).
- **Level 5: "Full Automation":** The vehicle possesses and maintains all driving functions completely (without zone restrictions).

V.2.2 General forecasts and socio-economic impacts of automation

The impacts of AVs from different aspects have been addressed by several researchers in recent years. Researchers primarily examine how the spread of AVs changes the *mobility patterns and space utilization in an urban environment* (Bagloee et al., 2016; Madigan et al., 2017; Tokody & Mezey, 2017), the *role of car use in the future of passenger transport* (Zmud et al., 2013; Arbib & Seba, 2017; Lagadic & Verloes & Louvet, 2019) and the

[10] https://www.nhtsa.gov/
[11] Intelligent Parking Assist System
[12] https://hondanews.com/en-US/honda-corporate/releases/release-e86048ba0d6e80b260e72d443f0e4d47-honda-launches-next-generation-honda-sensing-elite-safety-system-with-level-3-automated-driving-features-in-japan

travel experience (Prisecaru, 2016; Clements & Kockelman, 2017; Marletto, 2019; Syahrivar et al., 2021).

V.2.2.1. Altering mobility patterns

As technology evolves, travelers' mobility habits could change significantly. Studies addressed some remarkable benefits of automation like the increased usefulness of travel time (e.g., decreasing traveling time and widening of activities during mobility – Kyriakidis et al., 2015; Platt, 2017) and the environmental and economic benefits of automation (e.g., less energy consumption, lower travel costs – Bagloee, 2016). Research on urban and transport development (Freudendal-Pedersen et al., 2019; Schipper, 2020) emphasizes that, with the widespread use of AVs, urban traffic flows could improve, fewer parking spaces will be needed, thus reducing the environmental impact of the sector.

Research also suggests that the emergence of AVs may also widen the range of people who were previously unable to travel alone (e.g., without a driving license, due to health problems, etc.). Sivak and Schoettle (2015) surveyed 1,500 people in the UK, Australia, and the United States. The most important findings are that 60% of the people involved in the research had a positive attitude towards technology (high willingness to try AVs). Platt’s (2017) research in Canada examined different aspects of AVs. Results proved that frequent travelers are more receptive and families with young children are the most distrustful (they consider it too risky to hand over the driving tasks to the machine). The analysis of the general impacts, such as socio-economic externalities (e.g., altering of consumer preferences, labor market reorganization), are currently the most important and unanswered issues around the technology.

V.2.2.2. Altering car usage and perception of the machine

Research on travel psychology and behavior suggest that driving a car represents the dominance of the person in a certain micro-community (e.g., family, friends) and enhances confidence (Urry, 2004). In contrast, at the level of full automation, these psychological benefits (e.g., driving experience, enjoying gear shifting, controlling the vehicle, etc.) might disappear. At SAE level 4-5, there will be no need for a driver’s license, which could also weaken the prestige of automobiles. Research highlights that constantly evolving automation makes car use simpler and more comfortable, which can guide travelers to this means of transport, i.e., the importance of other environment-conscious modes (e.g., public transport) might be decreased in the long run (Currie, 2018). One of the most important issues regarding AVs is the road safety and data security. Although increased road safety is one of the major benefits of automation, research has shown (Xu et al., 2018; Liljamo et al., 2018) that there is noteworthy mistrust in fully automated vehicles, primarily due to uncertainty and the lack of in-depth knowledge about the machine.

V.2.2.3. Altering travel experience

Another significant influencing factor can be the novelty of the driving experience. Pitcher (2011) highlights that the usage of AVs seems to be easy to learn, easy to operate, and does not require meaningful efforts. Other research stresses the negative impacts of self-driving cars on driver experience. It has been revealed that individuals who seek complex and intense sensory experiences, tend to drive at a higher average speed (Becker & Axhausen, 2017) and keep a shorter tracking distance (Payre et al., 2014). Obviously, this cannot be provided by the usage of self-driving cars; the human driver becomes a passive observer at higher levels of automation (SAE Level 4-5). Individuals who are stick to intense driving experiences would be less likely to prefer a complete handover of driver's responsibilities, as this would reduce the intense sensory experience they require (Gardner & Abraham, 2007). It is also worth pointing out that a self-driving car may enhance the sense of freedom by serving special mobility needs such as a "moving living room, or office" and new activities on board.

Table 1. General issues regarding autonomous vehicles (SAE Level 4-5)

Altering mobility patterns	**Altering car usage and AI-human interaction**	**Altering travel experience**
1) Widening of activities during mobility	1) Easier to use a car, extending functionality	1) Elimination of driving experience - or becoming a unique service
2) Extending segment, individuality	2) Cybersecurity, legal and ethical issues	2) Compensation of drivers - extending on-board services while traveling
3) Environmental benefits		
4) Economic and social consequences		

Source: Authors' own editing based on the literature review

V.2.3 Impacts of AVs on tourism services

Although previous research analysing the impacts of AVs in tourism is limited, several possible consequences can be identified. During the transition period (on a lower level of automation - SAE Level 2-3), mobility opportunities may change (e.g., easier approaching a more distant destination with a car equipped with ADAS), but more radical tourism-related alterations can be predicted on the full level of automation.

Based on this, we focus on exploring the potential effects of SAE level 4-5 automation. The possible changes in the field of tourism are interpreted along with three main topics: *tourism alterations that can be associated with the handover of driving tasks*, *the increasing accessibility, and the new (possible) applications of vehicles for tourism purposes*.

V.3.1. Handover of driving tasks during tourism-related travel

At the level of full automation, the lack of the need for a driver's license barriers for travelers who, due to their age or health constraints, would not be able to travel alone for tourism (Anderson et al., 2014). This consumer group becomes more independent and flexible in their mobility and could reduce their social isolation (IFMO, 2016; Koul & Eydgahi, 2018). Based on forecasts, the spread of AVs could increase travel demand by about 11% in the next decade (Sivak & Schoettle, 2015). Research also emphasize (Cohen & Hopkins, 2019) that passengers can embark on *new activities while traveling* (e.g., relaxation, admiring the environment) instead of driving. Decreasing travel time can also change travel mode preferences, making AVs more attractive than other modes of transport, such as rail transport or aviation. Door-to-door mobility can also reduce travel time compared to public transport, which may lead to a reduction in the use of public transport (IFMO, 2016). The use of AVs also offers an additional option for people who have a driving license but are reluctant to drive to a foreign destination. When sitting in an AV, it is not necessary to be aware of the driving rules of the destination (e.g., left- and right-hand traffic), thus, the *unknown environment will no longer be a limiting factor* (Cohen & Hopkins, 2019).

V.3.2. Increasing accessibility of destinations and attractions

As a result of the optimized traffic realized by AVs, travel speed increases and travel time decreases, allowing tourists to travel longer distances in the same time interval (Bagloee et al., 2016). Due to the constant travel speed, route and travel time planning is more reliable and predictable (Kim et al., 2015). Tourists will also be able to *reach more distant and previously little-visited attractions*, giving AVs the opportunity to reach new destinations and attractions (Cohen & Hopkins 2019). In the light of the expected changes, AVs can replace the role of conventional shuttle buses and taxi services, thus, completely repositioning the importance of the means of passenger transport (Bainbridge, 2018).

V.3.3. New (possible) applications of AVs for tourism purposes

With the spread of automation, new AV-based services might also emerge in tourism. There may be a need for using conventional vehicles (human-driven) if this is no longer possible at the destination visited. On the other hand, testing self-driving cars on SAE Level 4-5 in places where technology is not yet widespread can also appear as travel motivation (Ásványi et al., 2020). With the application of AVs, a *new way of sightseeing (AutoTour)* could be created (Bainbridge, 2018). This would work on a similar principle to hop on – hop off bus tours in cities but could also replace walking tours. AutoTour services might be more flexible since the route can be easily configured in real-time, along with tourists' preferences. At the same time, the service raises sustainability issues. Tourism habits, the behavior might be radically changed due to the emergence of AVs. Tourists – who were previously responsible for driving and monitoring the environment – can drink alcohol since they are released from these obligations. Evening tours and parties become more attractive in urban spaces and might decrease the responsible attitude of visitors (Bainbridge, 2018). In the early stages of diffusion, there may also be an increasing demand for a *test (experience) "driving" of AVs*. Since the *interior design of AVs can be modified*, vehicles can offer new (tourism-related) services that might affect MICE tourism, hospitality, and the hotel industry. Passengers in specially designed AVs can *sleep while traveling*, so passengers may not need to book accommodation as they do not have to stop for a rest during a long-distance trip (Cohen & Hopkins, 2019).

Table 2. Impacts of AVs on tourism

Handover of driving tasks	Increasing accessibility	Possible applications of vehicles for tourism purposes
1) Extension of consumer group	1) Optimized traffic flow - better route and time management	1) Driving a car/try an AV as a tourism attraction
2) Enhancing activities that can be carried out while traveling	2) Better accessibility of distant destinations and attractions by road transport (AVs)	2) AutoTour service with MI tour guide
3) Increasing travel comfort, relieving stress arising from special travel conditions (e.g., right- or left-handed traffic)	3) Redefined passenger transport - decreasing role of conventional means of transport	3) Radically changing tourism behavior
		4) Advanced interior design of AVs - moving hotel room, meeting room

Source: Authors' own editing based on the literature review

V.2.4 Research gaps identified by the literature review

Based on the literature review, the following key findings and research gaps have been identified that determine the empirical phase of our research:

- The literature on the diffusion of AVs is extensive, based on which we have synthesized the general impacts into three main categories: Altering mobility patterns (1), Altering car usage and perception of the machine (2), and Altering travel experience (3).
- Nevertheless, sector-specific analyses are limited, especially the literature on tourism impacts. Based on the journal articles identified, a new framework of expected tourism impacts has been developed (see Table 2).
- No empirical research on the impact of self-driving cars on tourism has been found, nor did any other research consider factors other than traditional sociodemographic variables. This confirmed the relevance of our study and the application of the Big Five Personality Trait to extend the segmentation of tourists who are open to using AVs.
- In the light of these, the empirical research investigates attitudes towards possible, tourism-related AV applications identified in the literature: namely, the willingness to hand over the driving tasks in a foreign environment to better observe the surrounding, the openness to use AVs for sightseeing, the intention to

use AI-based tour guiding (AutoTour service) and AVs for experience driving, and the openness to do new activities while traveling (instead of driving – recreation, sleeping, conduct meetings).

V.3 Data and methods

Data collection has been carried out online, between October-December 2020, and resulted in 671 responses. The number of subjects involved in the survey exceeds the expected size of exploratory marketing research (Malhotra, 2009) and so the outcomes can be approved and utilized for further analysis.

Based on the literature review, we have formulated three research questions (RQs):

- **RQ1:** *How do tourists relate to the use of AVs at the level of full automation?*
- **RQ2:** *Which of the AV-based tourism services identified in the literature are attractive among tourists?*
- **RQ3:** *What personality types are open to AV-based tourism services?*

Respondents who regularly take part in trips for tourism purposes were included in the analysis. Respondents had to associate with the pre-COVID19 period during the completion of the survey. With our questions, the tourism and mobility habits, the personality type of the subjects based on the Big Five Personality Traits (Table 3) framework have been identified.

Table 3. Main characteristics of Big Five Personalities based on and Gosling et al. (2003) Komarraju et al. (2011)

Category	**Main characteristics**
Extraversion	sociable, energized by social interactions, outgoing
Conscientiousness	organized, self-disciplined, duty conscious
Agreeableness	high empathy, altruist, high trust
Neuroticism	experience a lot of stress, anxious, vulnerable
Openness to Experience	curious, creative, out of the box behaviour

Source: Authors’ own editing

A Likert scale ranging from 1 to 7 has been applied to explore attitudes towards AV-based tourism services. During the analysis, mean values above 4 were considered positive (i.e., represents openness to tourism-based services). In addition to the basic descriptive statistics (e.g., mean, standard deviation, mode, median), the Kruskal-Wallis test has been employed to identify significant differences among variables. The strength of the test was assessed based on the Eta-squared test suggested by Tomczak and Tomczak (2014).

V.4 Results

V.4.1 Sociodemographic characteristics of the sample

By gender, the sample is relatively balanced: of the 671 people surveyed, 56.3% are women and 43.3% are men. The sample consists of subjects of all age groups. The largest proportion (27%) is in the 18-29 age group, followed by the over-60 age group (25%). The 30-39 age group has a slightly lower proportion (21%), while the 40-49 age group is represented by 15% and the 50-59 age group (12%). Most of the respondents live in the capital (40.2%), 29.4% in other cities, 17.4% in county seats, and 12.7% in villages.

V.4.2 Tourism-related consumer and mobility habits

Subjects' tourism-related consumer habits have been analyzed in terms of travel frequency (1), way of organizing travel (individual travel or package tour) (2), travel motivations (most preferred tourism product) (3) and means of transport used to travel to (4) and from the destination (5).

1. Based on the results, 6.5% of the total sample make several trips a month or more per year. 27.6-27.6% of respondents travel for tourism purposes every six months or every year. In addition, a further 24.8% travel every few months.
2. The majority of respondents (80.2% of the total sample) organize their trips individually; package tours are not common among subjects.
3. In terms of motivation, the most popular tourism activities are recreation (26%), urban and cultural tourism (17%), wellness (15%), and VFR (visiting friends and relatives) (13%). The share of other tourism products (e.g., MICE, active tourism, festival tourism, niche elements) is below 10%.
4. The majority of tourists use their cars (68.2%), but airplanes (44.2%), trains (32.8%), and buses (27.7%) are also common ways to reach the destinations. A negligible proportion of tourists rent a car (6.2%) or use carpooling services (1.7%).
5. At the destination, the vast majority of subjects travel by car (64.9%), use public transport (50.9%), or approach attractions on foot (53.8%). Relatively few people

rent a car (17.4%) or decide to use shared mobility services (e.g., carsharing) (2.3%), or micro-mobility vehicles (2.9%).

V.4.3 Attitudes towards tourism alterations based on AV use

Based on the attitudes towards AV-based tourism services, the following findings have been revealed.

Respondents were asked how much they would prefer to use self-driving cars to pay attention to the environment rather than driving. Based on the responses, there is openness towards AVs in this context (Mean: 4.45; Median: 5). Tourists also stated that they would be willing to give up control to the machine in a foreign environment (Mean: 4.52, Median: 6). However, there is also a sense of caution among tourists, as they are less open to leisure activities (e.g., sleeping, reading, etc.) while traveling in an AV (Mean: 3.55, Median: 3). When asked whether tourists would use AVs for sightseeing, there was also a high proportion of positive responses (Mean: 4.51, Median: 5). The willingness to visit more distant destinations and to use AVs in a foreign environment also scores above 4. Tourists would be open to a tourist service in which the machine (AI) would be the tour guide (AutoTour) (Mean: 4.64, Median: 5). The openness towards experience driving with AVs is particularly positive (Mean: 4.77, Median: 5). The intention to use extended AV-based services (e.g., mobile meeting room – Mean: 4.21, Median: 5; interior for sleeping – Mean: 4.05, Median: 4) is slightly lower but above 4. Standard deviation values are below 2 in every case. The most frequent element in every case is 5, which also indicates a high degree of openness.

Table 4. Correlation between travel frequency and possible application of vehicles for tourism purposes

Item	Monthly or often	A few times a year	Twice a year	Annually	Less frequently	H statistics	Eta^2
Openness to do sightseeing conducted by an MI-based tour guide (*AutoTour*).	4.73 (1.84)	4.83 (1.81)	4.49 (1.82)	4.57 (1.86)	3.55 (1.90)	22.787***	0.03
Openness to use AVs that suitable to conduct meetings.	4.21 (1.85)	3.69 (1.91)	3.42 (1.86)	3.44 (1.94)	3.06 (1.85)	16.429**	0.02

Openness to use AVs which has an interior design for sleeping.	4.14 (1.96)	3.84 (1.98)	3.67 (1.88)	3.57 (2.12)	3.25 (2.03)	9.466*	0.01
Openness towards tourism services that include "driving" experience (*test driving*) with AVs.	5.04 (1.75)	4.98 (1.82)	4.79 (1.68)	4.74 (1.82)	3.91 (1.91)	19.531**	0.03

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

Source: Authors' own editing based on empirical research

Based on Kruskal-Wallis test, significant correlations between travel frequency and the attitude toward AV-based tourism services have been revealed (Table 4). Among those who travel more frequently for tourism purposes, the openness to use AVs is significantly higher. The effect size based on Eta^2 is low (below 0.06) in all cases.

V.4.4 Big-Five personality traits and tourism preferences

- Based on the results, respondents of the "*Extraversion*" category typically stay more than 3 nights in the destination visited. No significant difference by gender compared to the total sample has been detected. By age, the 18-29 age group is found in a higher proportion in this category (40%). A significantly higher proportion of subjects belong to this category who are interested in urban and cultural tourism.
- The segment of "*Agreeableness*" has a higher share of longer trips (7-8 days), during which the demand for VFR tourism and active tourism products dominates. No significant difference by gender is observed compared to the overall sample. The proportion of age group 30-39 is slightly higher here (42%) than in the total sample.
- The group of "*Conscientiousness*" is also made up of subjects who prefer shorter trips of 1-3 nights. By gender, men are in a higher proportion in this category. By age, no significant difference has been found. Among respondents of the category "*Neuroticism*", trips of 3-4 days are the most common. In addition to VFR tourism, MICE tourism is also a popular travel motivation among them. No differences have been revealed by age and gender.
- The highest proportion of subjects belonging to the "*Openness to Experiences*" prefer long trips (7-8 days). Female respondents make up a larger proportion of

this group (66.6%). Among them, urban tourism, active tourism, and visiting festivals are the most popular reasons for traveling.

Table 5. Correlations between the measured items and personality traits based on Big Five theory

Item	A	B	C	D	E
Openness to use AVs to pay more attention to the surroundings.	0.090*				0.258***
Openness to carry out additional activities (*reading, entertainment, etc.*) during the traveling by AVs.	0.094*	0.090*	-0.095*	-0.107*	0.241***
Openness to use AVs in special traffic situations (*e.g., right- or left-hand traffic).*					0.191***
Intention to use AVs while sightseeing.					0.273***
Willingness to visit more distant destinations when using AVs.				-0.098*	0.208***
Openness of AV use in unfamiliar environments.	0.083*				0.213***
Openness to do sightseeing conducted by an MI-based tour guide (*AutoTour*).	0.198***				0.243***
Openness to use AVs that suitable to conduct meetings.	0.137***			-0.089*	0.232***
Openness to use AVs which has an interior design for sleeping.	0.133***				0.188***
Openness towards tourism services that include "driving" experience (*test driving*) with AVs.	0.228***	-0.120**		-0.118**	0.279***

*Notes: ***: p<0.001; **: p<0.01; *: p<0.05. Abbreviation to the table: A – Extraversion, B – Agreeableness, C – Conscientiousness, D – Neuroticism, E – Openness to Experiences*

Source: Authors' own editing based on empirical research

Correlations between personality traits and attitudes towards AV use for tourism purposes have been found (Table 5).

Based on the test statistics, subjects within the category of "*Extraversion*" (A) are significantly more positive with each alternative of tourism-related AV usage (Table 6).

Results revealed that there is also a significant correlation between “*Neuroticism*” (D) personality and lower attractivity of tourism-related AV services. Among respondents of “*Extraversion*” (A) and “*Agreeableness*” (B) categories, the idea of experience driving is the most attractive, whereas the same service is the least attractive among subjects who belong to the “*Neuroticism*” (D) category. It can be concluded that respondents of the “*Conscientiousness*” (C) category seem to be less open to using AVs for tourism purposes. Among tourists of the “*Openness to Experiences”* category (E), the evaluation of each tourism-based alternative is significantly positive. In this category, the most attractive services are also the idea of test driving as well as sightseeing with AVs.

V.5 Discussion and conclusion

This research aimed to explore the potential impacts of SAE Level 4-5 autonomous vehicles in the field of tourism. As a result of the literature review, we have created three categories (*handover of driving tasks, increasing accessibility of destinations, new (possible) applications of AVs for tourism purposes*) that synthesize the potential tourism alterations resulting from the use of AVs. Empirical research has revealed the attitudes of 671 respondents towards AVs for tourism purposes.

Based on the results and in relation to the research questions (RQs), the following conclusions have been drawn:

RQ1: *How do tourists relate to the use of AVs at the level of full automation?*

Based on respondents' attitudes towards services, there is a generally positive (all mean values above 4) attitude towards the analysed applications of AVs in tourism.

RQ2: *Which of the AV-based tourism services identified in the literature are attractive among tourists?*

Based on the evaluations, the openness to use AVs for sightseeing and AI-based guided tours (AutoTour service) is particularly noteworthy. Tourists would also be open to using AVs while staying at the destination (e.g., for sightseeing). Subjects see an opportunity to use AVs to better observe the environment and to immerse themselves in the tourist experience instead of driving.

RQ3: *What personality types are open to AV-based tourism services?*

Higher openness can be detected among the 18-29 age group, who are taking longer trips (3-7 nights), and in the “*Extraversion*” and “*Openness to Experiences*” segment. This segment of tourists especially prefers urban and cultural tourism. It should be noted that the results show lower openness among subjects with other personality types (e.g., “*Neuroticism*”).

The main added value of our research is that we have explored the potential impacts of AVs on tourism, on which very few studies and international publications have been done before. In addition to the demographic data, we also specified the attitudes of the respondents based on different personality types, which is also a unique approach in the social studies of AVs and can be useful for better market segmentation. Although our empirical research is not based on a representative sample, it proposes relevant inputs for further research on tourism development, as a significant proportion of respondents regularly participate in tourism trips and mainly organize their trips individually, thus we have explored the view of an important consumer segment.

The attitude analysis concerning AVs provides a basis for further empirical research in social sciences (e.g., modeling the technology acceptance of AVs in tourism, more detailed elaboration of AV-based tourism service elements) and help to prepare for the technology revolution for practitioners in tourism.

VI AUTONOMOUS VEHICLES (AVS) IN TOURISM – TECHNOLOGY ACCEPTANCE FROM THE TOURISTS' PERSPECTIVE

Reference: Miskolczi, M., Munkácsy, A., Földes, D., Jászberényi, M., Syahrivar, J. (2022). Autonomous vehicles (AVs) in tourism – technology acceptance from the tourists' perspective. *Turizmus Bulletin (accepted)*[13]

Abstract

Autonomous vehicles (AVs) are expected to radically shape consumer preferences and services in tourism. On the basis of a comprehensive literature review and an empirical research project, this paper introduces an extension to the Technology Acceptance Model (TAM) to better understand the adoption of self-driving cars for tourism purposes. The new model (TAMAT: Technology Acceptance Model of Autonomous vehicles for Tourism purposes) confirms some under-explored impacts of tourism-related variables, such as Openness to Tourism Usage and Unusual Surroundings, as well as the Adherence to Conventional Use on the Intention to Use self-driving cars. The empirical research is based on online data collection (n = 646) and applies Covariance-Based Structural Equation Modelling (CB-SEM) to reveal impacts and significant paths between variables. Findings indicate that the opportunity of using self-driving cars for tourism and unusual environments have a positive, while adherence to conventional car use has a negative impact on the intention to use self-driving cars. The results can be used for introducing AV-based services in tourism seamlessly.

Keywords: automation, autonomous vehicles (AVs), technology acceptance model (TAM), tourism, systematic literature review (SLR), structural equation modelling (SEM)

VI.1 Introduction

The impact of automation in passenger transport has been growing steadily in recent years. In autonomous vehicles (AVs), driving tasks are being incrementally taken over by artificial intelligence (AI) (BAGLOEE ET AL. 2016). As of 2021, according to the SAE (Society of Automotive Engineers) framework, vehicles in SAE2 (partial

[13] This article was submitted to the journal in Hungarian. The translation presented here is identical to the original paper, no changes have been made to the content.

automation) and SAE3 (conditional automation) are available (SAE INTERNATIONAL 2021).

Automation might have a great influence on passenger transport by 2030 (MISKOLCZI ET AL. 2021), which also affects traveling habits and tourism. Radical alterations in tourism services (e.g., guided tours, sightseeing opportunities), as well as in individual mobility are predicted (TUSSYADIAH ET AL. 2017; PRIDEAUX AND YIN 2019; COHEN AND HOPKINS 2019; COHEN ET AL. 2020; HE AND CSISZAR 2020).

The technology acceptance of AVs is primarily based on the extension of traditional Technology Acceptance Model (TAM) (DAVIS 1986) or Unified Theory of Acceptance and Use of Technology (UTAUT) (VENKATESH ET AL. 2003) with a particular focus on consumer characteristics (e.g., LEICHT ET AL. 2018; ZHANG ET AL. 2019; SYAHRIVAR ET AL. 2021). However, the potential use and impacts of AVs in tourism have so far received little attention. Previous research has mainly focused on rural tourism (RIBEIRO ET AL. 2021) or the willingness to rent self-driving cars for tourism purposes (TAN AND 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. Accordingly, 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) is applied in this study, which regards only self-driving cars here.

For answering the research question, an online survey has been conducted in Hungary. The endogenous variables of the TAM model (VENKATESH AND 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, as well.

The paper is structured as follows: In Section 2, a literature review on the technology acceptance of AVs is introduced. Methodology is described in Section 3 with the stages of empirical research highlighted. 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.

VI.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 the 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 AND 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 AND 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 AND BALA 2008) and UTAUT2 (VENKATESH ET AL. 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 theories (OSSWALD ET AL. 2012; KOUL AND EYDGAHI 2018).

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

Figure 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 19 relevant records after the exclusion of 13 duplicated records. The papers have been analyzed according to seven aspects.

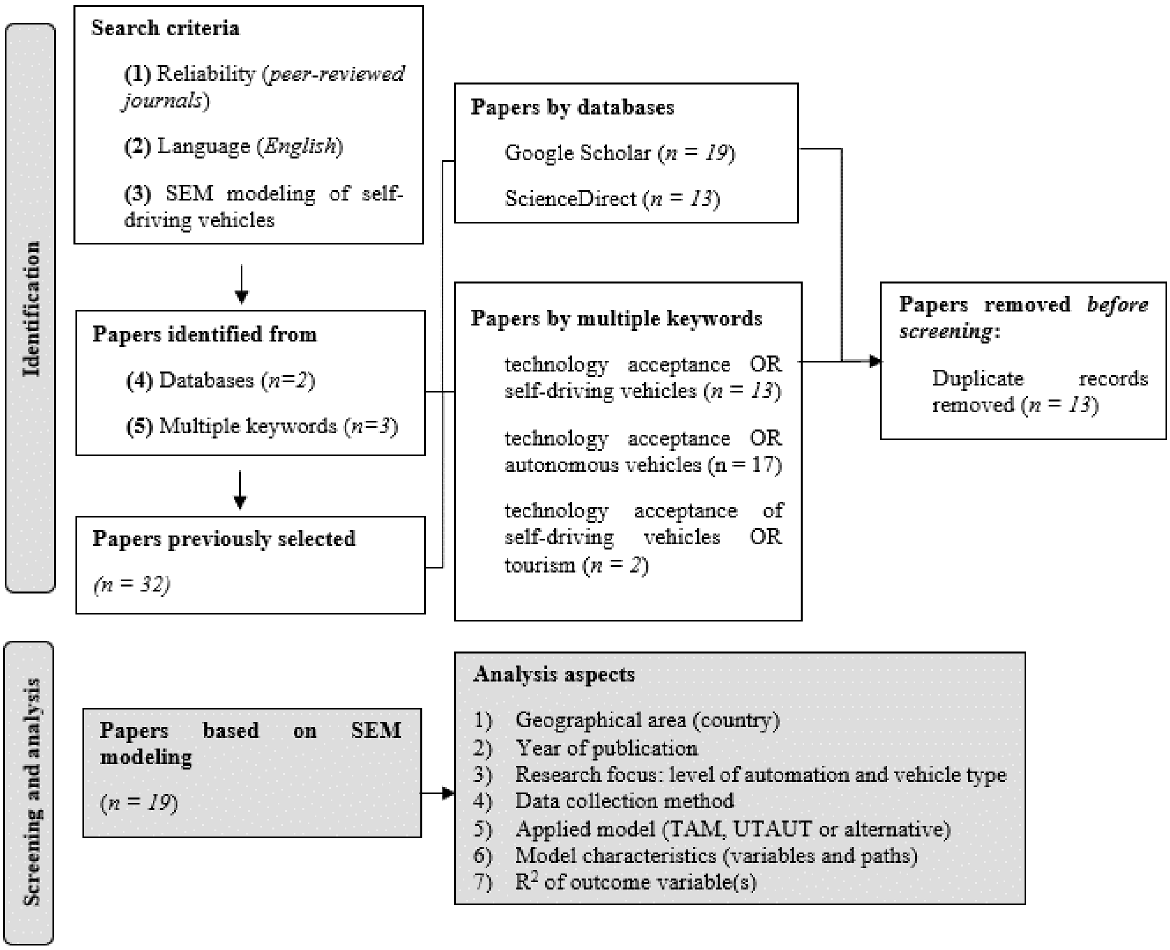


Figure 1. Flow diagram of the literature review, own editing

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) (Figure 2) or employ only some exogenous variables and create new (hybrid) ones. 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 AND 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).

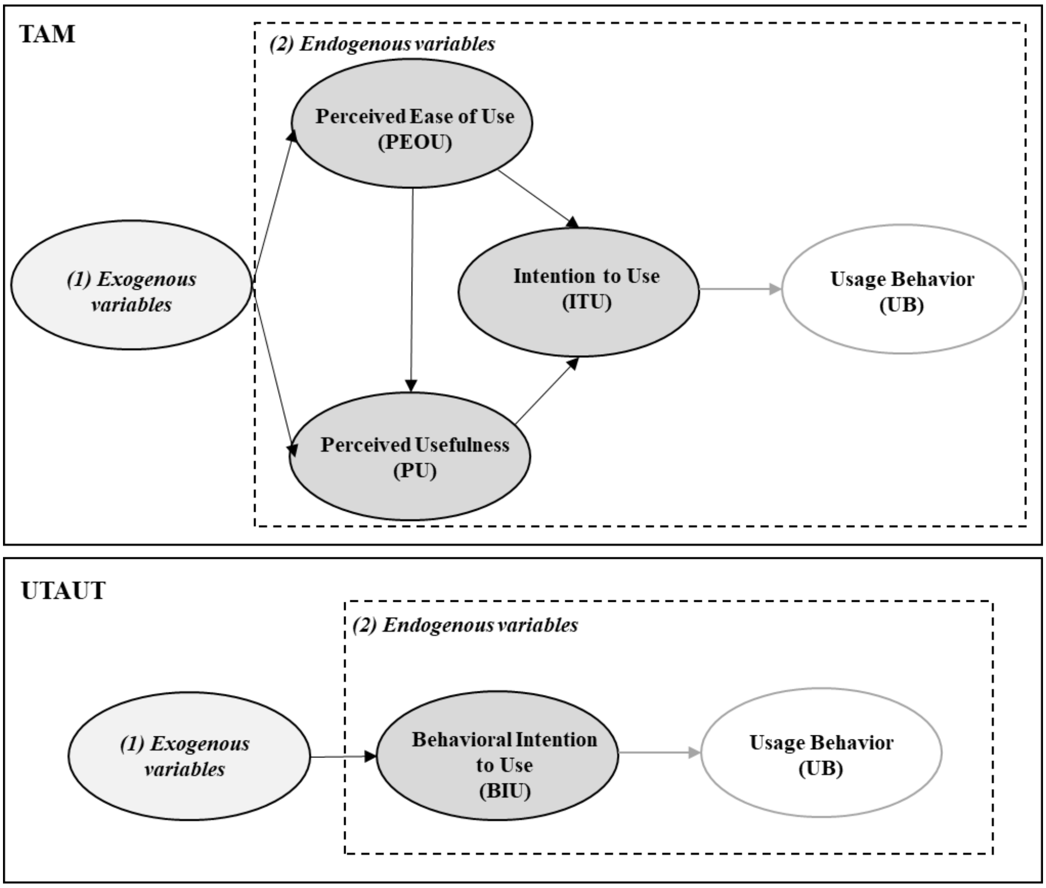


Figure 2. Exogenous variables applied in TAM and UTAUT, own editing

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

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

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) modelling, own editing

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*

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*

Most papers report findings from Asia, the United States, and six papers have been found from Europe (UK, France, Germany, Hungary, Greece, Turkey). All papers were published between 2018 and 2021, which also proves the novelty of the research field. Online and offline surveys are the common data collection methods with some exceptions, where respondents shared their opinions after having tested the vehicle. Data collections were generally conducted online and among the adult population (aged 18–70). In some cases, a specific target group (e.g., college students – DU ET AL. 2021; employees working at a truck accessory manufacturer – KOUL AND EYDGAHI 2018) has been involved. Based on sample size, the typical number of elements is below 400, which is only exceeded by two surveys (KESZEY 2020; SYAHRIVAR 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 ($\geq 0{,}67$).

As a synthesis of the literature review, five categories of new variables may be identified:

(1) Impacts of media usage and reference group opinion: The analysis of reference group opinion (e.g., PANAGIOTOPOULOS AND DIMITRAKOPOULOS 2018), the impact of technology-related information on the user attitude (e.g., mass media and/or social media – ZHU ET AL. 2020; DU ET AL. 2021) or the technology image (YUEN ET AL. 2021). These variables have a positive effect on the Intention to Use (ITU).

(2) Issues about the operation: Impacts of perceived risks of technology use. Trust as a variable is often included in the models (e.g., PANAGIOTOPOULOS AND DIMITRAKOPOULOS 2018, CHEN 2019, DIRSEHAN AND CAN 2020, KARNOUSKOS 2020, RIBEIRO ET AL. 2021), and it is closely related to perceived self-safety (XU ET AL. 2018), the visibility of operation (YUEN ET AL. 2021), and the perceived sustainability (DIRSEHAN AND CAN 2020). Variables of this category have a negative effect on the ITU.

(3) Perceived benefits of use: User enjoyment (CHEN 2019), economic benefits of use (KESZEY 2020), efficacy and relative advantage (LEE ET AL. 2019). These perceived benefits positively influence the ITU.

(4) Consumer traits: Years of driving experience (KOUL AND EYDGAHI 2018), the desire for the different levels of control (BUCKLEY ET AL. 2018; SYAHRIVAR ET AL. 2021), and vehicle ownership (LEE ET AL. 2019). This type of variable has a significant impact on endogenous variables and negatively affects ITU.

(5) Tourism perspectives: Only two papers included tourism-related extensions. Performance expectancy and hedonic motivation, namely the pleasure or enjoyment of using AV (TAN AND 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.

VI.3 Methodology

The main stages of empirical research are presented in Figure 3.

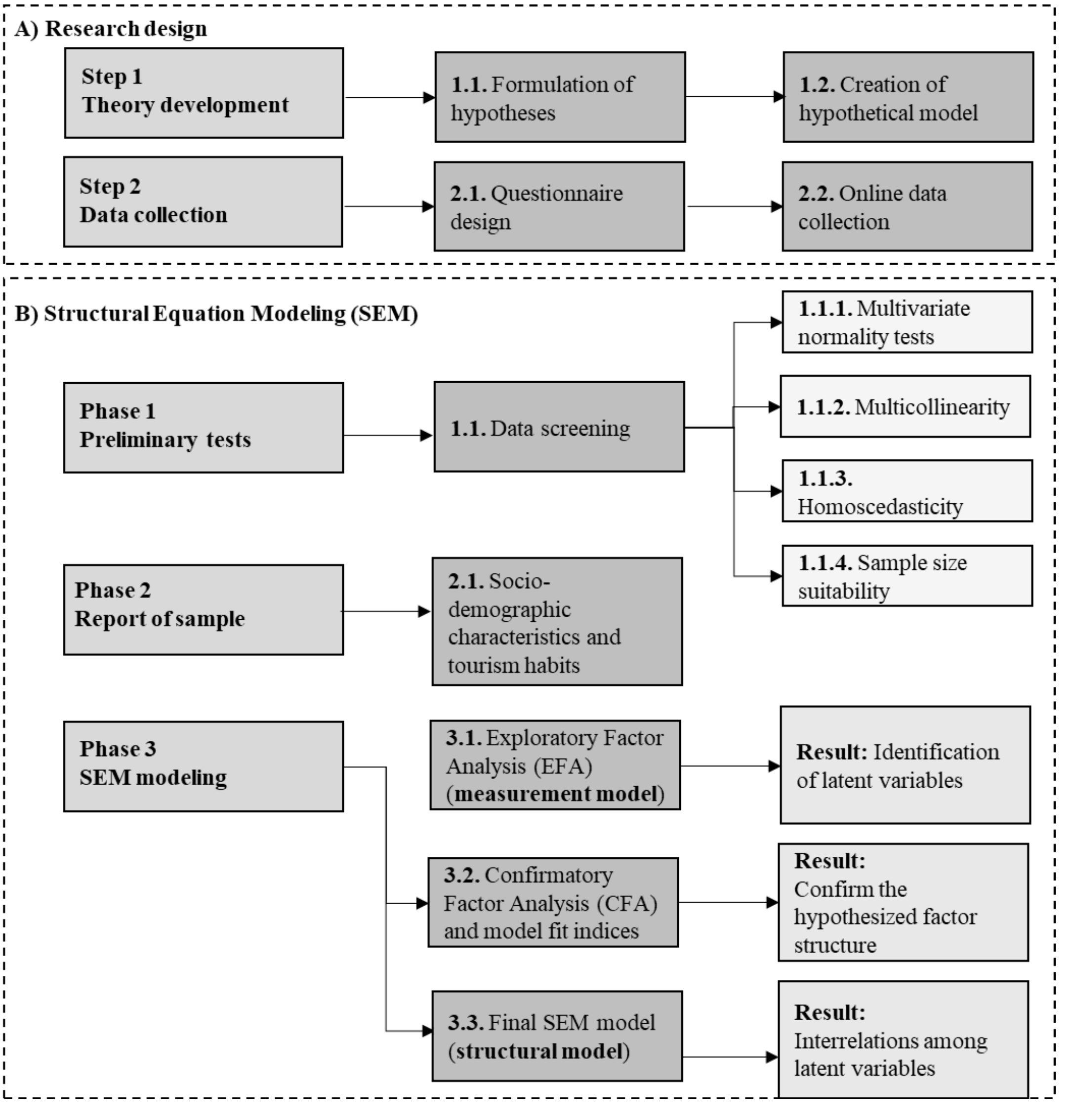


Figure 3. Empirical research, own editing

Two main stages can be distinguished:

A) Research design:

Step 1: Based on the literature review, hypotheses and a hypothetical model are formulated.

Step 2: Online data collection is conducted to test the attitude of respondents towards AV-based tourism services.

B) Structural Equation Modeling (SEM): There are three widely accepted steps in CB-SEM (KLINE 2011 HOYLE 2011) along which the analysis is summarised:

Phase 1: Preliminary tests are run to exclude outliers, and to 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 final structural model are analysed.

VI.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 AND LIN 2020; RIBEIRO ET AL. 2021) that tourism perspectives might have a significant impact on ITU.

A new (extended) theoretical model has been created (Figure 4) based on HAIR ET AL. (2011). The hypothetical paths (H_n, n = 1..13) between exogenous (ξ_n, n = 1..3) and endogenous (η_n, n = 1..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 wide range of tourism-related aspects.

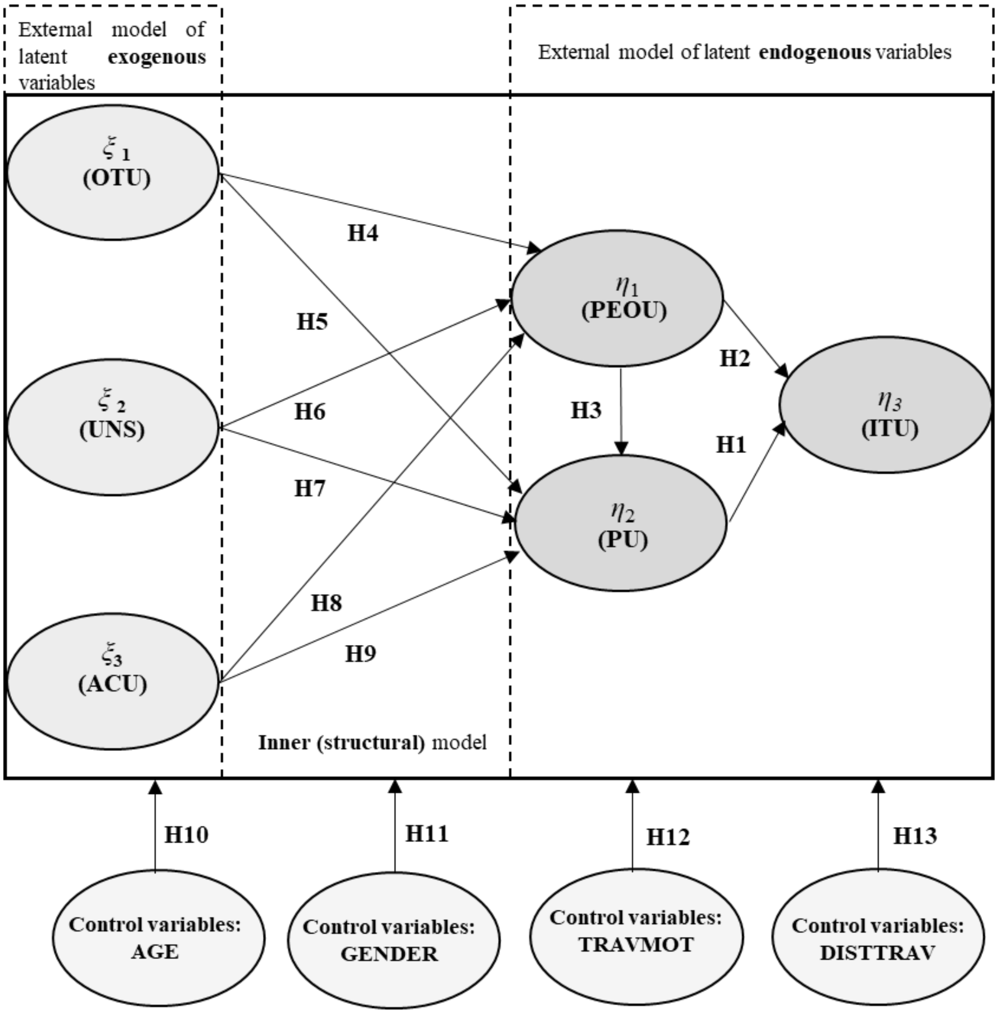


Figure 4. The theoretical model of TAMAT, own editing

Endogenous variables

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

- **H1:** *Perceived Usefulness (PU) has a positive impact on the Intention to Use (ITU).*
- **H2:** *Perceived Ease of Use (PEOU) has a positive impact on the Intention to Use (ITU).*
- **H3:** *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.

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 AND HOPKINS 2019). Fewer resting stops would be enough, which could alter 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 AND 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 AND 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).*

Unusual surrounding

The environment significantly affects mode choice (LEVINSON AND WYNN 1963; CERVERO AND KOCKELMAN 1997). Spatial diversity, namely the dissimilarity of the traveler's surroundings (e.g., narrow streets in old towns) is associated with lower intention to drive a car (CERVERO AND KOCKELMAN 1997; BOARNET AND SARMIENTO 1998; POTOGLOU AND KANAROGLOU 2008). Spatial design characteristics such as the density of built environment, unusual street characteristics or traffic rules also decrease car usage (MCNALLY AND KULKARNI 1997; HESS ET AL. 1999), mainly in the case of recreational traveling (MEURS AND HAAIJER, 2001).

During tourism trips, travelers 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, 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).*

Adherence to conventional use

The anxiety over the loss of conventional use has a major impact on the intention to use AVs. LILJAMO ET AL. (2018) argued that only 5% of their sample was willing to give up driving activities completely, and less than 20% clearly agreed that AVs would increase travel comfort and experience. Stronger desire for control, especially among those using their own cars, decreases the positive attitude toward self-driving cars (BERGMAN ET AL. 2017; LEE ET AL. 2019, SYAHRIVAR ET AL. 2021).

Accordingly, the impact of ownership preferences and attachment to manual control should be 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).*

Control variables

DIXON ET AL. (2020) highlighted that men are less concerned with risks related to the use of self-driving vehicles. RÖDEL ET AL. (2014) and HULSE ET AL. (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.

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

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

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 use AVs:

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

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.

The 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 AND TOPOLŠEK 2014). For the analysis, IBM SPSS Statistics 25, and IBM SPSS AMOS 26 software was applied.

VI.5 Results

Phase 1 – Preliminary tests

Preliminary tests suggested by the literature (JARRELL 1992; OSBORNE AND OVERBAY 2008) have been conducted to ensure that this dataset is suitable 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 ET AL. 2019). 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 exceed the thresholds (VIF > 4.0, tolerance ≤ 0.2) (HAIR ET AL. 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 by using scatter plots suggested by GASKIN AND HAPPELL (2014). Results supported 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 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 on the sample.

Phase 2 – Report of sample

Table 3 represents sociodemographic characteristics of the sample ($n = 646$) applied for structural equation modelling. Although the sample is not fully representative, it is heterogeneous in terms of sociodemographic characteristics. Female respondents are over-represented. 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, where approx. 18% of the population live) is higher than in the total population, but residents from other regions (urban, rural) are also involved.

Table 3. Sociodemographic characteristics, own editing

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 summarises the tourism characteristics that are assumed to be the control variables of the model: respondents were asked which tourism products they are mostly 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 are below 10%.

The largest proportion of respondents who travel by car for tourism purposes choose this transport mode for distances of 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 more than 1000 km by car. The data show that only 6.08% of car users use their vehicles for very short journeys (up to 100 km).

Table 4. Tourism habits, own editing

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%*
Distance travelled (DISTTRAV)	*≤ 100 km*	*6.08%*
	≤ 300 km	*18.63%*
	≤ 500 km	*23.83%*
	≤ 1000 km	*25.94%*
	more than 1000 km	*25.52%*

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 AND 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, 6 factors as latent variables are created, see in Table 5.

Table 5. List of remaining observed variables (items) and related latent variables (factors) after data screening and EFA, own editing

	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 traveling.*	*5.35*	
PU_4	*I find it useful in self-driving cars that I can carry out other activities (e.g., work, entertainment) while traveling.*	*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 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*	

	Observed variables		*Latent variables (constructs)*
Code	***Items***	***Mean***	***Name***
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 as a life goal to be achieved.*	*5.66*	

To prove the construct reliability as 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.

Table 6. Correlation matrix and the square root of the AVEs, own editing

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).

Factor loadings should exceed the threshold of 0.8 (PREACHER AND MACCALLUM 2003; GASKIN AND HAPPELL 2014). As Table 7 shows, all constructs also 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.

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

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*

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 should be analyzed based on some of the most important fit measures suggested by FALK AND MILLER (1992), SCHERMELLEH-ENGEL ET AL. (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 studies the fit improvement of the hypothetical model concerning the fit of the model (KLINE 2015; HOYLE 2012). Based on the results, all fit indices provide a good fit, since metrics are within the accepted thresholds.

Table 8. Fit indices, own editing

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).

The nomological validity – which is 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 considered adequate (FALK AND 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). Figure 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)

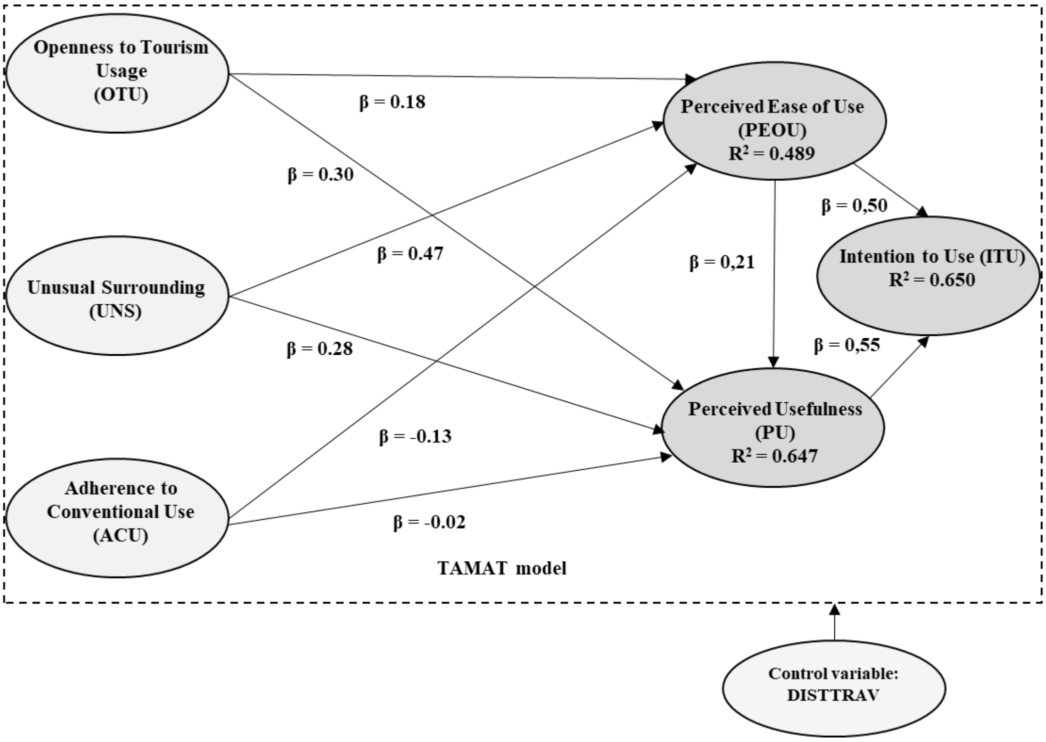


Figure 5. Relationships between variables in the TAMAT model

Figure 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 explains **48%** of the variance of PU (moderate level).

Table 9. Direct effects of paths, own editing

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).

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 (β = 0.21), and PEOU (β = 0.5) and PU (β = 0.55) together have a positive effect on ITU.
- OTU also has a positive impact on both endogenous variables (PEOU – β = 0.18; PU – β = 0.3) of TAM. OTU represents the attitude towards the expected changes in conventional tourism services with the spread of self-driving cars.
- UNS represents a so far under-researched aspect in the technology acceptance of AVs. Findings proved that the environmental motives positively affect PEOU (β = 0,47) and PU (β = 0,28). An important finding is that spatial diversity reduces the demand for car use in the case of recreational traveling 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 (β = -0,13) and PU (β = -0,02) of AVs. A new finding related to this phenomenon is that the two preferences together 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 (Figure 6.).

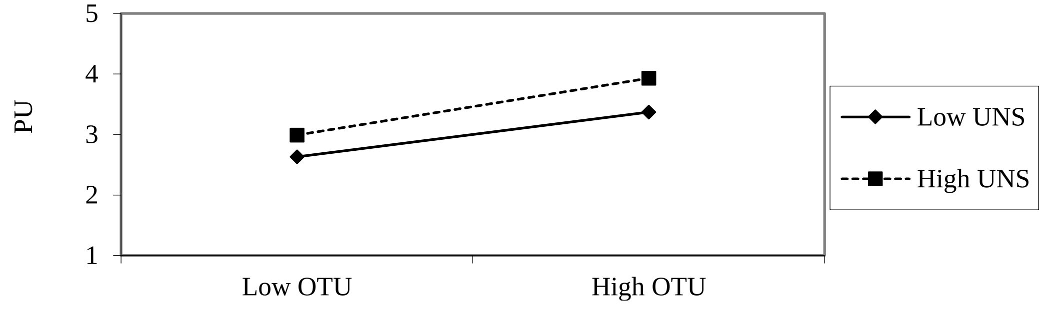


Figure 6. Moderation effect of UNS on the relationship between OTU and PU, own editing

The interaction between ACU and UNS proved that ACU dampens the positive relationship between UNS and PEOU (Figure 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.

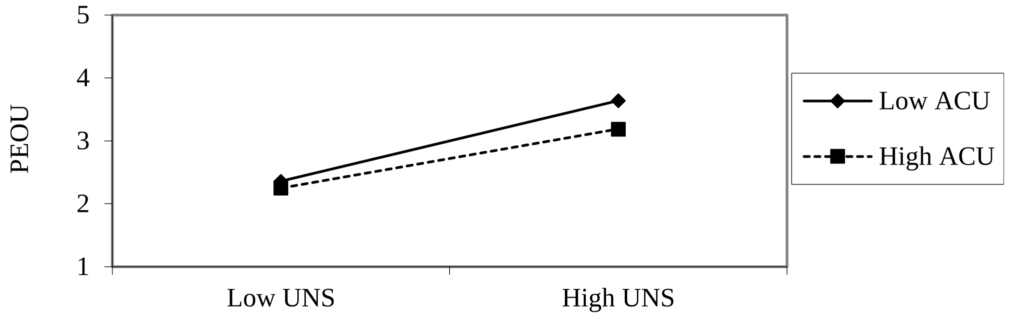


Figure 7. Moderation effect of ACU on the relationship between UNS and PEOU, own editing

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 (less than 500 km).

VI.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 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 TAMAT model employs endogenous variables (Perceived Ease of Use – PEOU, Perceived Usefulness – PU, Intention to Use – ITU) of TAM (DAVIS 1986), which is the most frequently used (11 out of 19 reviewed research) 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 analysis, we applied covariance-based structural equation modeling (CB-SEM), a popular method for determining technology acceptance of different phenomenon. Considering the model characteristics, in addition to the direct effects of our hypothetical model (H_1-H_9), moderating and multigroup effects (H_{10}-H_{13}) have also been analyzed. Since all the fit indicators and R^2 values expected for CB-SEM modeling 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.

Results proved that tourists would be open to using AVs for traveling from home to the destination and for sightseeing. Tourists also welcome the extension of the car interior for tourism purposes (e.g., mobile hotel room, meeting room). In unfamiliar environments, there is a more positive attitude towards self-driving cars, which further strengthens the potential of technology in the tourism sector.

Overall, the usability of AVs for tourism could greatly increase the adoption of self-driving cars. Results also proved that tourists who insist on the conventional use of automobiles are less open to the use of self-driving cars, and this attitude is not affected by the trip purpose.

It can be concluded that self-driving cars primarily 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. It is advisable to create an action plan for the sector, defining measures for a smooth technology adoption. The sector needs to prepare for the transformation of some professions (e.g., tour guide, coach, and taxi drivers), sub-sectors, and services (food service, hotel industry, attraction management) as soon as possible, to minimize social and economic externalities.

A limitation of this research is that the online data collection can only reach a restricted segment of the population. With the spread of AVs, it is required to complement the attitude studies with data collections based on real experience with self-driving cars. Another interesting path of further research could be the development of technology acceptance models focusing on specific sub-fields of the sector or consumer segments. For this, the TAMAT model presented could provide a basis and could support the implementation of AVs in the tourism sector.

VII CONCLUSION

In my research, the main socio-economic impacts of automation, the future role of AVs in urban passenger transport, and the implications of their uptake in the tourism sector have been explored. The relevance of my research question was supported by the findings of the research conducted, since several previous studies on the socio-economic impacts of automation (e.g., Clements – Kockelman 2017; Hussain – Zeadally 2018) or the technology acceptance of AVs (e.g., Zhu et al. 2020; Keszey 2020; Syahrivar et al. 2021) were identified, but empirical research on tourism impacts is very limited so far. Only the forecasts of Cohen and Hopkins (2019), Cohen et al. (2020), and the empirical findings of Tan and Lin (2020) and Ribeiro (2021) considered some tourism-related factors in connection with AV acceptance in tourism, which served as a basis for identifying research gaps and conducting my empirical research.

VII.1 Responses to research questions

Research question*: How does the spread of highly automated (SAE 4-5) vehicles affect the tourism sector, especially the mobility for tourism purposes, and conventional tourism services?*

Response to the research question*:* Based on the research, the spread of autonomous vehicles could transform the way destinations are approached (e.g., the modal share of cars might increase, fewer resting stops would be enough, and opportunities to observe the environment might be improved while travelling), as well as mobility and tourism consumption patterns within a destination (e.g., new ways to discover the destination – AI tour guide, AutoTour services, etc.). In addition, it has been revealed that the ability to use AVs for tourism purposes and the foreign environment have a positive impact on the intention to use.

As a result of the research, the four sub-questions (Q1, Q2, Q3, Q4) were answered as follows:

- **Q_1:** *With the spread of self-driving vehicles, what socio-economic changes can be expected?*

Response to Q1: Based on the research, four key categories of socio-economic impacts have been identified, namely the changes in the need for human resources (e.g., the changes in the labour market (e.g., some professions are no longer needed), in industrial revenue from traditional vehicle-usage (e.g., insurance market, oil industry, tertiary sector – tourism), in social habits (e.g., growing digital dependence), and in the social and environmental sustainability (e.g., growth of car usage, overtourism).

- **Q_2:** *What major trends shape urban mobility in the tangible future, i.e., until the 2030s and what role will self-driving vehicles have in this alteration?*

Response to Q2: The urban transport of the future will be shaped by automation, the spread of shared mobility, alternative vehicle propulsion (electrification), and social attitudes. The analysis has led to the creation of four scenarios (Grumpy old transport, At an easy pace, Mine is yours, Tech-eager mobility). Findings suggested that urban passenger transport is expected to undergo a slow transformation by 2030 and this will be driven by the spread of automation and shared mobility services.

- **Q3:** *How might tourism services change with the spread of self-driving vehicles and how do tourists relate to these potential changes?*

Response to Q3: The research indicated that with the spread of AVs in the tourism sector, the impact of technology can be divided into three areas (e.g., handover of driving tasks during tourism-related travel, increasing accessibility of destinations and attractions, new applications of AVs for tourism purposes), in relation to which positive consumer attitudes can be identified.

- **Q4:** *What drives tourists to adopt self-driving cars for tourism purposes?*

Response to Q4: Based on the empirical research, a new model called Technology Acceptance Model of Autonomous vehicles for Tourism purposes (TAMAT) has been created. Three new, tourism-related variables have been identified that significantly affect the intention to use AVs. Consumers are open to the use of AVs for trips outside their usual environment (positive impact of the Unusual Surrounding variable), and the possibility to use AVs for tourism-related consumption (e.g., sightseeing) can greatly increase the intention to use them (positive impact of the Openness to Tourism Usage variable). It should be stressed, however, that the attachment to traditional vehicle use (the Adherence to Conventional Use variable) negatively affects technology acceptance even in the case of tourism trips.

VII.2 Theoretical contributions

Both my secondary and empirical research have led to new theoretical and methodological insights.

In *Paper 1*, the novelty of the literature review reported is the *impact assessment* and the identification of the socio-economic, sectorial, and moral issues associated with the spread of AVs. Results also point to the negative externalities connected with the phenomenon, thus, emphasizing some still unanswered questions regarding the technology in different sectors, including tourism.

In Paper 2, the *new qualitative analysis method* I have developed can be considered a new methodological outcome of my research. Employing this qualitative analysis framework, the metadata of papers can be categorised, and the key themes of scenarios can be evaluated using a unified evaluation methodology. The scenario analysis method developed can be used for the systematic analysis of scenarios presenting current transport trends and socio-economic phenomena. On the other hand, the method is also suitable for the qualitative analysis of other thematic scenarios, as it consists of steps that can be applied regardless of the topic while offering a transparent analytical framework. Applying the scenario analysis and building method; *four scenarios have been created* for the future of urban passenger transport by 2030. The four new scenarios (Grumpy old transport, At an easy pace, Mine is yours, Tech-eager mobility) can serve as a basis for defining urban passenger transport prospects in future studies by 2030.

In Paper 3, I have *typified how the technology could change tourism consumption and thus how tourism services could be altered* (e.g., handover of driving tasks, increasing accessibility, possible applications of vehicles for tourism purposes). Empirical results revealed that the *positive attitude is stronger in a different transport environment and among subjects who are more frequently participate in tourism trips*. A particularly positive attitude has also been observed in relation to the idea of sightseeing and test driving with self-driving vehicles. These results further reinforce the importance of technology in tourism and indicate that the sector needs to prepare for technological changes to attract tourists and improve the tourism experience in the near future. Related to this analysis, a new result is that I have revealed *openness towards AVs based on the Big Five personality types*. In addition to adding a new aspect to attitude research on AVs, the results may provide important inputs for further investigation of the role of psychosocial cues in intention to use.

In Paper 4, a *new synthetisation of research papers presenting the technology-acceptance of AVs* has been created along with a 7-point analysis, which is helpful for comparing technology acceptance studies and thus focusing on under-analysed aspects. During a structural equation modeling, a *new technology-acceptance (TAMAT) model has been created* which is the first technology acceptance model specialized for AVs that considers the impact of *environmental factors*, the *tourism applicability of AVs* while also considering the *distorting effects of the desire for manual* control and *individual ownership* preferences. My findings suggest that the risk of manual loss of control and the weakening demand for shared mobility is an unresolved issue that has a major impact on the technology acceptance and sustainable use of AVs. Previous research has not investigated these aspects in the context of technology acceptance; thus, this is an important theoretical contribution of my research.

Overall, my dissertation has made a significant contribution to exploring the social and sectorial changes associated with autonomous vehicles, especially in terms of tourism, which has been a marginal issue in previous research.

VII.3 Practical implications

My research findings provide an insight into the technological issues that society will face and thus help professionals to react to the expected impacts of the spread of AVs.

For cities and local governments, the results of my research are worth considering. As I have described the main social drivers of technology diffusion, my results can provide important input for determining the feasibility of urban development projects related to automation. My results are particularly relevant in the case of large cities with high tourist flows (e.g., capitals with a rich built heritage and cultural experiences).

For the automotive industry, results can also be useful in developing urban and transport strategies along with the key trends identified. The scenarios created can be used for urban mobility planning as categories into which municipalities can be classified according to their readiness for innovative transport solutions (e.g., shared mobility, self-driving vehicles). The empirical results on the social acceptance of autonomous vehicles can have a direct impact on the ongoing development of self-driving vehicles and the infrastructure, as well as on the development of related policy, regulatory and official frameworks. Considering the key findings of my research may be critical to attracting future consumers.

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, especially in the field of urban tourism (e.g., sightseeing by self-driving car) and the sector must prepare for the expected penetration of the technology. Personality traits can be used to better target marketing campaigns to increase the intention to use AVs and AV-related tourism services. It is also of particular importance to developing in the near future tourism development strategies that also analyse the impacts of automation, for which the main conclusions of my research can serve as a good basis.

VII.4 Limitations and future research directions

There are limitations to my research. In the empirical research, subjects reported their attitudes based on the pre-pandemic period. Therefore, the distorting impacts of COVID19 on travel habits and tourism-related consumption should be considered in future research. The persistence of the effects of the pandemic is also an open question, and it would be worthwhile to examine the effects of COVID19 in the context of technology acceptance. Furthermore, the pandemic has also influenced the development of technology, raising the question of whether changes in the development paths presented in the scenarios will be affected by the pandemic. It is also important to continuously monitor the development of automation and artificial intelligence and, in this context, to track changes in consumer attitudes and the identified tourism-related impacts on technology acceptance.

All this justifies further exploration of the topic, for which the research results, methods presented in my thesis can provide a useful background. Although the research focused primarily on socio-economic aspects, my results can also be a starting point for technical developments outside my research area. As several vehicle development priorities have been identified, my research results offer ideas for vehicle engineers to consider. For transport engineers, the expansion of self-driving vehicles in tourism could also offer exciting research opportunities, as my results suggest that the development of infrastructure for accessing attractions with AVs could become a priority in the near future.

Besides, I also intend to continue working on the following research topics related to my doctoral research in the near future:

- Investigating the applicability of self-driving vehicles for Hungarian destinations. The research would focus on the analysis of the cooperation between shared mobility service providers and tourism operators (e.g., self-driving cars for tourists, included in sightseeing packages).
- Explore opportunities for cooperation between tour companies (e.g., Hop-on Hop-off) and automotive companies to develop the details of an AutoTour service based on self-driving vehicles.

- A consumer attitude analysis based on real experiences (e.g.: participation in living lab surveys) to verify the validity of the variables I have identified that influence the technology acceptance of self-driving vehicles.
- My aim is also to broaden the scope of my current research area and analyse the social impact of other AI-based solutions in tourism. In my future research, I would like to focus on the consumer perception of different levels of AI, and the thematization of the effects of AI-based devices on consumption patterns and machine-human interaction.

For a thorough exploration of these research topics, it is advisable to involve experts from different subfields of transport and tourism (e.g., traffic engineers, companies developing self-driving vehicles, tour operators, tour guides). It is also important to further investigate consumer preferences on a representative sample of the Hungarian population by gender, age, and place of residence to get a more detailed picture of the possible future applications of AVs.

VIII VIII REFERENCES

The bibliography of journal articles presented in this dissertation is formatted according to the requirements of the journal in which the articles were published. In other parts of the dissertation (Chapters I, II, VII), the APA citation format has been followed.

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