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A review on the factors influencing the adoption of new mobility technologies and services: autonomous vehicle, drone, micromobility and mobility as a service

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ABSTRACT

New mobility technologies and services could address a series of transport-related problems such as pollution, congestion, unpleasant travel experiences, as well as first- and last-mile in-connectivity. Understanding the key factors influencing adoption and enablers is critical to the rollout of the new mobility technologies and services. The objective of this paper is to conduct a systematic review of the new mobility technologies and services, especially on autonomous vehicles, drones, micromobility and Mobility as a Service (MaaS). The ultimate goal is to gain a deeper insight into the factors that affect the adoption or preferences of these technologies and services and thus provide policy implications at the strategic level. The results of the review identified several (1) shared, (2) exclusive, (3) opposing and (4) mixed impacts factors that strongly influence the uptake of new mobilities. The synthesised finding will contribute to policy decisions, particularly regarding the sequencing of the launch and development priorities of new mobility technologies and services. To encourage the uptake of new mobility technologies and services, further promotion would benefit from (1) embedding a spatio-temporal perspective, (2) undertaking a careful market segmentation and (3) a careful segmentation of technology and services based on features, application contexts and purposes.

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1. Introduction

New mobility refers to the convergence of new technologies and business models (Slowik & Kamakaté, 2017), which could improve transportation affordability, availability and accessibility while also reducing disparities in transportation provision, usage and pollution (Kamargianni et al., 2016). Currently, extensive research and investments are being made globally in new mobility technologies, services and business models to unlock new value opportunities. New mobility, if properly harnessed, could radically alter people's relationships to vehicles and change our cities.

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The anticipated benefits of new mobility technologies and services cannot be achieved without a comprehensive understanding of key adoption factors (Yigitcanlar et al., 2019). Furthermore, this knowledge would not only provide evidence for engineers to proactively tailor the technologies to encourage higher public acceptance, but also provide evidence for policymakers to understand the current public acceptance and support accordingly the implementation of new forms of mobility. Given its significance, there is a growing number of empirical studies exploring the key factors affecting the adoption of new mobility forms. There are also several review studies on autonomous vehicles (Becker & Axhausen, 2017; Gkartzonikas & Gkritza, 2019; Jing et al., 2020), drones (Kellermann et al., 2020), Micromobility (Fishman, 2016; Liao & Correia, 2020) and Mobility-as-a-Service (Butler et al., 2021; Jittrapirom et al., 2017; Kamargianni et al., 2016). Yet the fact is that each study focuses solely on a specific new mobility technology or service and there are no parallel comparisons. While in practice, there is an increasingly blurred boundary between new mobility technologies and services, such as shared AVs, ride-hailing AVs, electric shared scooters, etc., and this trend makes a synthesised investigation on the instrumental motivators and barriers to adopting new mobilities of unprecedented relevance.

Against this background four new mobile technologies and services have been selected for this study: autonomous vehicles, drones, micromobility and Mobility-as-a-Service (MaaS). The ultimate goal is to explore the factors that affect the adoption or preferences of these technologies and services, and then assess if there are common factors across them. This review is conducted as part of the Horizon 2020 funded project HARMONY[1] to feed the development of the travel demand survey.

Meanwhile, the review aims to answer the following questions: (1) What are the main theoretical frameworks used to explore the adoption of new mobility technologies and services? (2) What are the key factors of adoption for each theme? (3) What are the similarities, differences and relations across the factors affecting the adoption of each one of these themes? (4) What recommendations can be given for future research in order to fill in some of the identified gaps and address future development trends? (5) Could strategies targeting the adoption of new mobility technologies and services as a whole be developed rather than having strategies specific to each technology and service?

The remainder of the paper is organised as follows. After presenting the systematic review method (Section 2), this study reviews the key theoretical and methodological approaches applied in current studies (Section 3). Section 4 discusses the key factors affecting the public's intention to use autonomous vehicle (AV), drone, Mobility as a Service (MaaS) and micromobility (MB). The conclusion pulls together the findings, identifies research gaps and sheds light on future research.

2. Systematic review method

To present a wide coverage of the literature review, the study developed a framework of a systematic review. Referring to previous research approaches (Hosseini et al., 2016), a systematic review was conducted based on three steps, namely online database searching, articles refinements based on abstracts and full articles, keywords co-occurrence analysis. First, to identify potential studies on factors influencing the adoption of autonomous vehicles, autonomous aerial vehicles, Mobility-as-a-Service and micromobility, the study selected references from two databases, Elsevier's Scopus and Web of Science, as these two are the largest scientific peer-review interdisciplinary databases (Rogov & Rozenblat, 2018). The search strings are set as: "Title (autonomous vehicle OR driverless cars or driverless vehicles) and Title (intention AND to AND use) or Title (adoption) or Title (attitudes) or Title (accept)", which are used to identify the literature on the public's intention to adopt autonomous vehicle. Likewise, we repeated this search procedure but replaced the "autonomous vehicle" with "autonomous aerial vehicle" or "drone", "Mobility-as-a-Service" or "MaaS" and "micromobility" or "scooter" or "bike/bicycle" sharing. All the search categories are confined to "Transportation" and document type are limited to "Article". The search was conducted in June 2021. The second step was the refinement of the works by reviewing the abstracts and full-text articles identified in the first step to ensure their relevance. The following inclusion and exclusion criteria were used: (1) the peer-reviewed empirical studies which reflect the first-hand information ranging from 2013 are included; (2) the research subjects are end-users instead of other relevant stakeholders are included; (3) the research aims and scopes are irrelevant to the adoption influencers are excluded; and (4) those studies that only discussed related themes, such as ride-hailing and car-pooling, but not within the four themes are excluded. This step reduced the number of papers from 238 to 62.

To identify the salient research focus and uncover the potential associations among AV, drone, MaaS and MB, a keyword co-occurrence analysis network was conducted based on the rationale that shared keywords imply an intellectual relationship (Noyons, 2001) and an overall structure of knowledge (Lee et al., 2018). Here, the research applied a network analysis software Gephi (https://gephi.org) to assess keywords. The node size in the

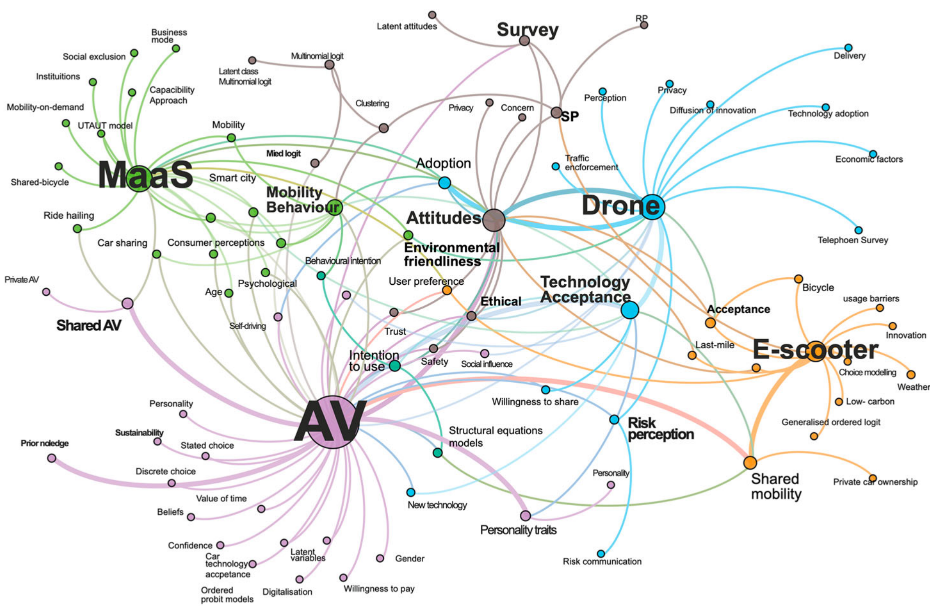


Figure 1. The keywords co-occurrence analysis visualisation, created by Gephi (the size of the nodes indicates the frequency of the keywords, and the colour indicates the cluster to which the keywords belong; node frequencies below 4 are not shown).

network diagram reflects the degree centrality, which serves as an indicator of the keyword occurrence and the level of research attention. As shown in Figure 1, the keywords co-occurrence analysis results provided a preliminary overview of the research focuses. First, except for the four themes, the most representative keywords are Attitudes, Mobility behaviour, Technology acceptance and Survey, which appear 21, 15, 13 and 8 occurrences separately. These occurrences present the key focuses of the selected research. Second, the cluster analysis allows us to identify how each keyword is intensely connected with others. Not surprisingly, it is found that MaaS is linked with AV, drones and Micromobility, and several relevant topics such as Shared mobility. In addition to the four new mobility technologies and services clusters, a fifth cluster is identified, which is a method-based cluster presenting commonly leveraged methods such as SP (stated preference), clustering analysis and logit models. Similarly, several expected associations are also identified among these new mobility technologies and services. For instance, AV, drone and MaaS shared several keywords such as Mobility behaviour, Attitudes, Technology acceptance and Environmental friendliness.

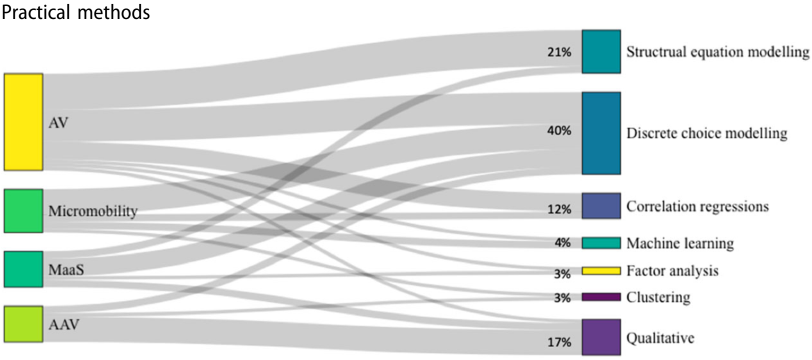
3. Popular theoretical frameworks and modelling approaches

This section elaborates on the theoretical framework studies to explore the adoption of the four themes: autonomous vehicle (AV), drone, micromobility (MB) and Mobility as a Service (MaaS). In exploring the determinants of the adoption of new mobility technologies and services, the most commonly used theoretical frameworks can be classified into three types. The first one generally investigates in reference to three conceptual pillars:sociodemographic characteristics, attitudinal preferences, as well as mobility and travel-related patterns (Eker et al., 2020). Extending from the three pillars, several others have been developed and added, which are built environment (Fishman, 2016; Fishman et al., 2014), psychographics (Clothier et al., 2015; Degele et al., 2018), geography, environment, weather (Campbell et al., 2016; Rosenfeld, 2019), personal traits (Payre et al., 2014), etc. (see Appendix). The second one is developed from the theories of technology (or psychological) acceptance. While the two frameworks are partially in line with several respects, the second framework places more emphasis on the process of technology penetration and relationship between end-users and their self-identity and technology (Wang et al., 2020), and draws on socio-demographic and travel patterns as moderating factors.

As the second framework is not self-evident, here we mainly discuss the second framework (see Table 1), including a family of models: Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology Acceptance Model (TAM), Car Technology Acceptance Model (CTAM), Innovation Diffusion Theory (IDT) etc. Most models within this strand can be traced back to the TRA (Ajzen & Fishbein, 1975) and the TRB (Ajzen, 1985). They both provide a recognised theoretical basis for understanding and predicting consumers behaviour and intention (Jing et al., 2020). Followed by TRA and TPB models, Davis et al. (1989) developed the TAM that attempts to explain a user's intention to adopt technology based on two aspects: perceived usefulness (PU), and perceived ease to use (PEU). Given the consideration of distinct attributes of various technologies, prior empirical studies typically incorporate additional factors to extend the TAM framework. For instance, Choi and Ji (2015) argued that acceptance to AVs may also require trust,

Table 1. The summary of main conceptual frameworks and practical methods.

Concepts Framework Models	The constructs (or beliefs)		Examples of studies
Technology acceptance model (TAM) (Davis et al., 1989)	Perceived usefulness (PU) Perceived ease of use (PEU)	AVs	Choi and Ji (2015) Dirsehan and Can (2020) Panagiotopoulos and Dimitrakopoulos (2018)
		Drones MB	Leon et al. (2021)
		MaaS	Schikofsky et al. (2020) Lopez-Carreiro et al. (2021)
Unified Theory of Acceptance, and Use of Technology (UTAUT) (Venkatesh et al., 2003)	Performance expectancy Effort expectancy Social influence Facilitating conditions	AVs	Manfreda et al. (2019) Zmud et al. (2016) Sener et al. (2019)
		Drones MB	
		MaaS	Ye et al. (2020)
Car Technology acceptance model (CTAM) (Osswald et al., 2012)	UTAUT+ Anxiety Perceived safety Self-efficacy Attitudes towards using technology	AVs	Sener et al. (2019) Zmud et al. (2016)
Innovation diffusion Theory (IDT) (Ryan et al., 2015)	Relative advantage Compatibility Complexity Observability Trialability	AVs	Wang et al. (2020)
		Drones MB	Yoo et al. (2018)
		MaaS	
Mixed methods	TAM + IDT	AV	Yuen et al. (2020a)
	TPB + IDT	E-shared Scooter	Eccarius and Lu (2020)
	UTUAT + TPB	AV	Yuen et al. (2020c)
Practical methods			



perceived risk and personal traits. Schikofsky et al. (2020) found that, beside PU and PEU, emotional factors (e.g. pleasure, fun, enjoyment) should also be integrated into the MaaS adoption framework.

As an extension of TAM, UTAUT was developed to assess the likelihood of success for new technology acceptance and to understand the drivers and barriers of acceptance (Venkatesh et al., 2003). There have been several extensions and modifications. For instance, Manfreda et al. (2019) included extra psychological factors (i.e. perceived risk and perceived satisfaction) into the AV adoption framework based on UTAUT. Based on

UTAUT theory constructs, CTAM framework added variables to these technology adoption models based on automotive technology research to examine an individual's intention to accept car-related technology (Osswald et al., 2012). CTAM proved to be an effective explanatory model for exploring AV adoption factors as it considers the car-exclusive and context-specific factors, such as perceived safety and self-efficacy.

In parallel with the above frameworks that are developed based on TRA and TPB, the innovation diffusion theory (IDT) is another popular framework explaining why individuals choose to adopt or reject an innovation based on their beliefs (Ryan et al. 2015). Considering the relative advantage and complexity of the IDT, several studies (Yoo et al., 2018; Yuen et al., 2020c) applied IDT theory to the TAM. Furthermore, there are several hybrid models used to uncover the adoption determinants, which include TPB and IDT, UTAUT and TPB, TAM and TPB, etc.

A review of these theoretical frameworks leads to three findings: first, although technology acceptance frameworks were initially used to explore attitudes towards emerging technologies, it has gradually been adopted to understand the public's acceptance to new mobility services (e.g. studies by Lopez-Carreiro et al., 2021; Schikofsky et al., 2020), given that new mobilities are progressively adopting an integration of technologies and services, rather than a single form. Second, as mobility technologies and services develop and our knowledge of their characteristics increases, the composition of the constructs will vary. For example, Kapser and Abdelrahman (2020) excluded effort expectations in the UTAUT model when looking at automated delivery vehicles, given the evidence of familiarity with mobile applications. Third, as the context changes, we also need to consider incorporating emerging constructs to capture customers' attitudes. It is found that the prevalence of COVID-19 had a profound impact on mobile behaviour and showed an active and important role in accelerating the consideration of autonomous vehicles (Ribeiro et al., 2022; Said et al., 2021).

With regards to the practical methods and modelling, the commonly used techniques can be summarised into seven types: machine learning, structural equation modelling, discrete choice modelling, correlation or regression analysis, clustering analysis, factor analysis and qualitative analysis. As shown in Table 1, discrete choice modelling and structural equation modelling are widely used in current studies, accounting for roughly 40% and 21%. Machine learning, which relies on large amounts of user data, has emerged as an emerging trend. However, given that many of the new mobility technologies have not been put into use, it is not surprising that there is little research into their application by using the approach.

4. Factors affecting new mobility technologies and services adoption

This section focuses on reviewing the identified factors affecting the adoption of each one of the four themes and thus answering the second research question.

4.1. Autonomous vehicles

Autonomous vehicle (AV) is one that drives itself in "autopilot" mode using a range of new technologies such as GPS, camera, vehicle-to-vehicle communications (V2V) and vehicle-to-infrastructure (V2I) communications. There are various classification standards based on the degree of automation, e.g. SAE J3016 (2021), the most-cited source, defines six levels of driving automation, ranging from No Driving Automation at Level 0 to Full Driving Automation at Level 6. Twenty-seven studies were identified in our systematic review that explore the adoption of AVs. These factors are grouped into socio-demographic characteristics, travel behaviour, geographical-related characteristics and latent variables.

Socio-demographic characteristics show a significant association with AV adoption. For example, males are more likely to own AVs or adopt shared AVs (Haboucha et al., 2017; Payre et al., 2014; Wang et al., 2020); females show less supportive attitudes towards automobile vehicles (Nazari et al., 2018). However, a few studies (Panagiotopoulos & Dimitrakopoulos, 2018) found that females are more likely to embrace AVs. Besides gender, other factors such as household composition (Nazari et al., 2018), car ownership (Liljamo et al., 2018) and residential type (Nazari et al., 2018) are also strongly associated with the willingness to AV adoption. With regard to age, education and income, studies showed mixed results. Some scholars revealed that user groups who are younger (Haboucha et al., 2017; Krueger et al., 2016; Liljamo et al., 2018; Wang et al., 2020), highly educated (Acheampong & Cugurullo, 2019; Roche-Cerasi, 2019) and have higher incomes (Howard & Dai, 2014; Kyriakidis et al., 2015) are more likely to use AVs. It is noteworthy that some factors often come together in the same individuals, e.g. the older licenced drivers (Bansal et al., 2016), men, highly educated individuals who live in densely populated area (Liljamo et al., 2018). However, these findings are opposed to some other studies (Sener et al., 2019; Yuen et al., 2020b; Zmud et al., 2016) that argued that adoption intensions are substantially explained by behaviour trusts (e.g. perceived usefulness) rather than socio-demographic factors.

With regard to travel behaviour, individuals who have long commute distances and high travel times are more likely to use AVs (Haboucha et al., 2017; Kyriakidis et al., 2015). Similar to individuals with high vehicle miles travelled (VMT), they expressed a more positive attitude towards adopting AVs than other respondents (Bansal et al., 2016; Kyriakidis et al., 2015). Individuals with multimodal travel patterns are more open to adopt shared Avs (Krueger et al., 2016). A different study indicated that those who eschew vehicle ownership and have already experienced car-sharing are more likely to adopt AVs (Lavieri et al., 2017).

Geographical differences may also influence AV adoption. For example, compared to Americans, Israeli individuals are more willing to accept AVs, whereas gender plays a more significant role in the choice decision only for Israelis (Haboucha et al., 2017). This may be due to the religious difference between the two countries. Schoettle and Sivak (2014) compared the public views towards AVs in the US, the UK and Australia. The results from the three countries were similar in most regards, with some subtle but noteworthy differences. For instance, although holding a positive attitude towards AVs, the US respondents are more concerned about data privacy and liability compared to the other two countries. Research focusing on four cities in the State of Texas found that Dallas respondents show a higher possibility to become shared AV users due to their higher willingness to adopt ride-hailing (Uber) as an alternative to private vehicles compared to the other three cities (Sener et al., 2019). In terms of residence types, there is no unanimous agreement. Some scholars find that individuals residing in dense areas (Bansal et al., 2016; Liljamo et al., 2018; Roche-Cerasi, 2019) or diverse land use areas (Nazari et al., 2018) are more likely to become AV users. However, some studies (Lavieri et al., 2017; Wang et al., 2020) found that urban and rural respondents have little difference in their willingness to adopt AVs.

Regarding latent variables, respondents' attitudes are strong contributors to the adoption of AVs. In general, people who have positive attitudes toward technologies, e.g. trust in technologies (Choi & Ji, 2015; Dirsehan & Can, 2020), interest in technologies (Bansal et al., 2016; Haboucha et al., 2017; Lavieri et al., 2017; Rahimi et al., 2020; Zmud et al., 2016) or pro-AV sentiment groups (Haboucha et al., 2017), are more likely to use AVs. Some studies also show that people who are concerned about the environment may also be potential users of AVs (Dirsehan & Can, 2020; D. Lee et al., 2019; Nazari et al., 2018). Besides technology considerations and environmental aspects, attitudes towards transportation modes also largely affect the adoption of AVs. Studies reveal that people who are supportive of public transportation (Haboucha et al., 2017) or mobility-on-demand (Lavieri & Bhat, 2019; Nazari et al., 2018) are more willing to use AVs. Worries of privacy (Lavieri & Bhat, 2019; Zmud et al., 2016) safety and self-identity expressiveness (Wang et al., 2020) as well as the driving culture (Haboucha et al., 2017) proved to be the key barriers to the (S)AVs adoption. What is interesting here is that some individuals believe AVs are safer than conventional cars and thus they are willing to adopt them; others are concerned about safety and do not intend to use them (Haboucha et al., 2017; Nazari et al., 2018). Some studies (Choi & Ji, 2015) also revealed that safety is not an important factor for predicting AV adoption.

The strand of applying technology acceptance model families (Choi & Ji, 2015; Dirsehan & Can, 2020; Manfreda et al., 2019; Wang et al., 2020) also provides several innovative insights into unpacking key influencers of AV adoption. Perceived Usefulness and Trust act as significantly positive influencers on behaviour intention among TAM constructs (Choi & Ji, 2015; Manfreda et al., 2019; Yuen et al., 2020c). Social influence, such as valuing someone's positive opinion, can also exert a strong impact on people to use AVs (Sener et al., 2019; Zmud et al., 2016). Surprisingly, Perceived Ease to Use only has a weak influence on people's intention to adopt AVs (Choi & Ji, 2015), which may be due to the fact that the experience with traditional vehicles makes it easier for people to switch to AVs.

Psychological and personal traits perspective extend the understanding of influential factors regarding AVs adoption. In this contribution by Charness et al. (2018), emotional stability and openness to experience are positive influencers while extraversion personalities showed less willingness to use AVs. Other perspectives on personal traits found locus of control and sensation seeking correlate with decision on AV adoption. For instance, the individual with an internal locus control who believe human control and are reluctant to hand over control over others are disinclined to use AV (König & Neumayr, 2017) whereas the individual with an external locus of control who believe that human will always cause accidents, especially those who also experience difficulties with driving, such as vulnerable cohorts, have a greater intention to use AV (Choi & Ji, 2015).

4.2. Drones

Drones (also known as autonomous aerial vehicles or unmanned aerial vehicles) is an aircraft without an on-board human pilot. While the technology per se is not new, the determinants affecting how the public perceives the plethora of emerging civil drone applications, such as parcel delivery and flying taxis, are ambiguous. Twelve studies investigating the adoption of drones were identified in the systematic review, particularly from the perspective of socio-demographics, built environment, unique determinants of technology and latent variables.

Socio-demographic factors are very much related to the public's acceptance of drone. Males hold more positive attitudes towards the adoption of drone than females (Lidynia et al., 2017). In terms of age, younger people have more supportive thoughts on drone than people older than 55 (Reddy & DeLaurentis, 2016). However, Eißfeldt et al. (2020) research showed that the age group of 65 and above also tend to be more likely to accept the application of drones. Further studies are needed to figure out the reason behind this difference. In terms of education, people with high school or lower education generally feel negative about the drones (Leon et al., 2021), which may be explained by their lack of knowledge of drones. Here, it is also worth mentioning that STEM (science, technology, engineering and math) background is not a relevant factor for people to accept drone adoption (Aydin, 2019). Compared to education, prior knowledge of drones plays a greater role, either in terms of affecting the acceptance of flying cars (Eker et al., 2020) or drone delivery (Leon et al., 2021). The more people are informed about the drone applications, the more they hold a supportive attitude towards it (Clothier et al., 2015; Lidynia et al., 2017). Compared to layperson, a good knowledge or a personal user experience has also been found to influence the perceptions of the privacy and risk (Lidynia et al., 2017), and sometimes even the perceived benefits of drones (Tan et al., 2021). The study also shows that a household with children is in less favour of drone's application (Reddy & DeLaurentis, 2016). This could be understood as a concern for children's safety.

Geographically, people residing in the Midwest States in US have negative opinions about drones, while people living in the Western States are more positive (General, 2016). The difference also occurs between countries; for example, people living in Israel are positive about the drone compared to people from the US (Rosenfeld, 2019). Indeed, this difference is, to some extent, caused by cultural bias. For instance, citizens of Germany and Italy are more likely to be concerned about privacy issues arising from drones than in some countries where CCTV is prevalent, such as the UK (Lidynia et al., 2017). Residence type may also affect people's perceptions. The study by Eißfeldt et al.'s (2020) showed that residents in larger cities are more supportive of the drone adoption, which echoes with the IOG's (2016) research in the U.S. that urban residence are likely to adopt drone delivery, while the rural and suburban residence are sceptical. However, other studies also indicated that there is no connection between urban and rural areas (Aydin, 2019).

There are also several unique exogenous and endogenous determinants affecting the degree of drone adoption: (1) application purposes, (2) usage contexts and (3) technology-related features. First, in general, people are more likely to accept the use of drone when it is for the common good. The uses that benefit the society such as public safety and scientific research can be easily accepted (Aydin, 2019). Emergency uses are also on the accepted list (Lidynia et al., 2017). However, recreational uses, commercial uses and hobbies are not in favour of the interviewees (Aydin, 2019; Boucher, 2016). As for military uses, it is somehow debatable. Some research indicates that people can accept police and military usage of the drones (Boucher, 2016), while other studies show the opposite (Clothier et al., 2015). Second, the acceptance of drones varies considerably depending on the varying usage contexts. The study in Singapore found that industrial areas have the highest acceptance, followed by recreational and commercial areas (Tan et al., 2021). Residential areas were the least acceptable usage contexts for drones. Besides, several features associated with drones' technologies were found instrumental for affecting adoption, such as noise degree, overhead flying routes and cameras. It is not surprising to find that the public perceive drones with cameras are mode risky than those without, thus hindering their intention to adopt (Aydin, 2019).

As for latent factors, people's attitudes also have different influences on the adoption of drone s. Some studies show that privacy concerns can be the barrier of drone adoption (Lidynia et al., 2017; Rosenfeld, 2019). However, another study also indicates that this concern about privacy affects people from only rural areas negatively (Yoo et al., 2018). Similar findings were found for concerns about safety and risk issues. While safety is collated to be an important consideration for drones' adoption, the doubts are a little more pronounced among urban populations. What is more, studies also conclude that safety and risk concerns may not be related to the public's acceptance of drone adoption (Clothier et al., 2015; Rosenfeld, 2019).

These differences in people's perception of safety may be due to the different sample regions in different studies. Furthermore, some studies have specifically pointed out that lack of regulation and law enforcement will also put people that are not in favour of drone adoption in the population groups (Leon et al., 2021). Studies show that people with an interest in technology are more positive about drones (Eißfeldt et al., 2020; Yoo et al., 2018). Environmental concerns also play an important role in people's intention of drone adoption. Some people are worried about the counter environmental effect of drone adoption such as noises, pollution and danger to wildlife (Kellermann et al., 2020). While there are positive attitudes and voices that believe in the benefits of drones, such as faster speed, more eco-friendly, and potential economics and environmental gains.

4.3. Micromobility

Micromobility refers to vehicles that are low-speed, small, lightweight and typically used for short journeys (ITDP, 2021), including scoots, monowheels, e-skateboards, shared e-cargo, hoverboard, etc. As shared bicycle and shared e-scooter are two of the most promising (Liao & Correia, 2020) and the fastest growing models, this study particularly reviewed eleven studies on the motivators and barriers to the adoption of these two exemplars.

Similar to other new mobility themes, socio-demographic characteristics strongly affect the usage of micromobility. Specifically, young to middle age males are more likely to adopt shared bicycles (Campbell et al., 2016) and shared cargo bicycles (Hess & Schubert, 2019). Meanwhile, gender differences are evident in some countries. For instance, an empirical study in Mashhad (Iran) found that females who have strong religious background may be hesitant towards using bike-sharing (Abolhassani et al., 2019). Li et al. (2019) found females preferred bike sharing to free-floating ones. However, there are discrepancies in income and education findings. Fishman et al.

(2014) argued that high-income and highly educated population groups are inclined to use shared bicycles in Melbourne and Brisbane, while Campbell and his colleagues (2016) argued that low-income groups with lower education are more inclined to use shared bicycles in Beijing, China. This divergence can be explained by several factors, including cultural differences. To date, with a few exceptions, little research has discussed the adoption factors of E-scooter sharing, as it started penetrating the market since 2015. Typically, young and highly educated population groups have a higher probability of using shared scooters (Aguilera-García et al., 2020; Degele et al., 2018; Eccarius & Lu, 2020).

Several travel behaviour-related factors also significantly affect the choice of micromobility. The population groups that travel shorter distances and prefer cycling and walking have a higher likelihood to use micromobility (Aguilera-García et al., 2020; Campbell et al., 2016; Hess & Schubert, 2019). An unintuitive finding pertaining to shared electric scooters is that people who have a driving licence or own a car are more interested in using scooters in Madrid, Spain (Aguilera-García et al., 2020). Also surprisingly, Bieliński and Ważna (2020) found that the individual who owns (E)-scooter is more inclined to adopt E-scooter sharing service in Tricity, Poland.

In contrast to the AVs and drones, the built environment and weather play stronger roles in influencing the individual's intention to use micromobility. This argument is not surprising given the attributes of most micromobility devices, such as lower speed (20 MPH or less), shorter distance (1.5–2.9 km) and no canopy. Proximity to shared bicycles was found to be a significant factor (Abolhassani et al., 2019; de Chardon et al., 2017; Fishman et al., 2015). Besides, a number of cycling-friendly environmental factors have been found to play an important role in accelerating public adoption of bike-sharing. These factors include good quality pavement and separate cycling lanes (Abolhassani et al., 2019; Hess & Schubert, 2019). Temperature, weather and air quality factors are also found to have a great impact on an individual's intention to use micromobility. For instance, precipitation, wind and heat and poor air quality are factors that hinder the wider adoption of shared bicycles (Campbell et al., 2016; de Chardon et al., 2017).

Several latent variables that encourage or discourage micromobility's adoption have also been identified. Factors hindering broader adoption include privacy concerns (Aguilera-García et al., 2020), safety concerns and perceived difficulty or inconvenience of use (Fishman et al., 2014; Fishman et al., 2015). For instance, the helmet requirement, long sign-up procedure and low accessibility are found to significantly decrease the likelihood to adopt shared bicycles. Besides, individuals who are more concerned about the environment are more likely to use shared bicycles or shared electric scooters (Aguilera-García et al., 2020; Eccarius & Lu, 2020).

4.4. Mobility-as-a-Service

"Mobility as a Service" stands for purchasing mobility services as a package based on consumers' needs instead of purchasing the means of transport (Kamargianni et al., 2016). To explore the key factors of MaaS adoption from a user point of view, 12 studies have been identified view. These factors are then grouped into socio-demographic characteristics, built environment, travel behaviour, personalities and attitudes of the user, as well as the perceived usefulness and social influence.

Socio-demographic characteristics play a significant role in MaaS adoption. In a case study in Manchester, Matyas and Kamargianni (2021) found that age is inversely related with the likeness to use MaaS Package. A study focusing on respondents from the Netherlands shows that younger people between 18 and 34 years old tend to be more willing to adopt MaaS schemes (Alonso-González et al., 2020). Similar conclusions were also drawn from a study in Australia, which indicates that full-time employed young individuals are the potential MaaS users, while older retired individuals are lacking interest in MaaS (Vij et al., 2020). With regards to gender, there are mixed findings. Caiati et al. (2020) found that females are more likely to subscribe to MaaS than males, while Matyas and Kamargianni (2021) found that males have a higher inclination to MaaS adoption than females. Some studies (e.g. Lopez-Carreiro et al., 2021) also suggested the insignificance of gender influencing MaaS subscription choice. Beside age, gender and occupation, educational background is also a key factor for adopting the MaaS. Prior studies (Alonso-González et al., 2020; Zijlstra et al., 2020) found that the population groups that are willing to use MaaS typically have higher levels of education and income. Household composition is also critical to the adoption of MaaS. In general, families with younger kids are less likely to become MaaS users. This may be due to the relatively high demand for vehicle capacity, which limits the choice of public mobility services for households.

In terms of built environment**,** the empirical studies in Netherlands (Alonso-González et al., 2020) and Spain (Lopez-Carreiro et al., 2021) implied that people residing in a higher urbanised area are more willing to use MaaS. However, this is inconsistent with research by Vij et al.'s (2020) in Australia, which showed that in addition to the Sydney metropolitan area, there is a welcoming market for MaaS in remote and rural areas in New South Wales – even more so than in Sydney. Differences in the transport systems of the two countries may be the reason behind these contradictory findings.

Travel behaviour is also an important factor. Some studies (e.g. Lopez-Carreiro et al., 2021) have argued that travel behaviour and attitudes are stronger predictors of MaaS uptake than socio-demographic variables. It is found that respondents' conventional mode choices also largely affect the acceptance of Hoerler et al.'s (2020) study finds that people who use car-sharing more than two times a month are more likely to adopt MaaS. People who have public transport cards and are frequent users of journey planners tend to use MaaS schemes more easily (Alonso-González et al., 2020; Ho et al., 2020; Matyas & Kamargianni, 2019); the same also goes for cyclists. However, in the case of frequent public transport users who are also potential adopters of MaaS, the willingness to pay for MaaS is not that high (Ho et al., 2018). The reason is mainly that public transportation users may overlap with travel cost-sensitive groups who have relatively low income. Besides, people who already use shared mobility services are also more likely to embrace the MaaS schemes (Alonso-González et al., 2020). Conversely, uni-mode users (those who do not like multimodality or intermodality) show less interest in joining MaaS schemes. The least potential MaaS users are the car users, because they usually believe in the necessity of car ownership as a family with children (Alonso-González et al., 2020), or they are just more addicted to private vehicle travel. Schikofsky et al. (2020) also observed that people tend to compare the new travel behaviours with their habitual one in the process of adoption and thus suggested that the transition from the current travel behaviour to one using MaaS should be gradual.

Public attitudes towards new mobility services are also strong factors in the adoption of MaaS. In general, people who develop curiosity about technology and innovations tend to be more open towards MaaS. People who show more concerns about the environment (i.e. pro-environment awareness) are more likely to embrace MaaS as it is seen as a sustainable alternative to current travel options (Hoerler et al., 2020). Privacy is another concern in the application of MaaS, which functions mainly via a digital platform. Personal information leak is always regarded as a potential risk of such services as MaaS (Ye et al., 2020). Beside the attitudes towards technology in general and MaaS in particular, the extended psychological factors such as personality and emotional gains are also raised by scholars. A study in Germany demonstrates that users' hedonic motivations such as the feeling of autonomy, competence and being related to a peer user group play an equal role as the perception of usefulness in MaaS adoption (Schikofsky et al., 2020).

The features of MaaS such as clarity of interface and convenience play great roles in the individuals' decision on adoption. Several surveys argued that the MaaS digital interface should be easy enough to use (Ye et al., 2020), so that it will not become a barrier to MaaS adoption. The degree of flexibility of the MaaS schemes is a very appealing factor that affects people to join the scheme as it supports the individuals' perception about personalised mobility (Schikofsky et al., 2020), as some people hesitate to use MaaS schemes as they are concerned about the ease of use. Key factors affecting the adoption of MaaS are also latent attributes such as the personalities of the users, as well as the perceived usefulness and social influence.

There is an interesting discussion on the role of social influence. It is found that policy recommendations for MaaS adoption may directly convince people to become intended consumers, whereas the effect of users' ratings and feedback on the websites has not been agreed upon, Hoerler et al. (2020) found it to be insignificant, while Caiati et al. (2020) found it to be a strong factor, with similarly important factors being the social network marking share.

5. Discussion and conclusion

New mobility technologies and services have the potential to offer solutions to a series of transport-related problems such as pollution, congestion, unpleasant travel experiences, as well as first- and last-mile in-connectivity. To promote their popularity and implementation, this study focuses on reviewing the key factors affecting the individuals' intentions to adopt new mobility technologies and services (see Table 2) and compares the main theoretical frameworks and analytical methods of previous research.

This review has several interesting observations which will shed lights on further research. First, by synthesising the key factors influencing two new mobility technologies and two new mobility services, we found that there are several (1) shared, (2) exclusive, (3) opposing and (4) mixed impacts factors that strongly influence the uptake of new mobilities (see Table 2). For instance, technology interest and perceived usefulness proved to be important for four themes. With regards to exclusive factors, the pro-AV and locus of control factors are significantly affecting the adoption of AVs. Noise, pollution and danger to wildlife (Kellermann et al., 2020), as well as the type of drone's operations, are found to be of high concern and discourage one's intention of using drone. Regarding micromobility, a wide range of factors (such as cycling-friendly infrastructure, topography,

Table 2. A summary of key factors influencing the adoption of AV, drone, Micromobility and MaaS.

Factor types		Factor	AV	Drone	MB	MaaS
Exogenous factors	Socio-demographic	Gender	(*)	(*)	(*)	(*)
		Age: the young group	(*)	(*)	(*)	(*)
		High level of education	(*)	(–)	(*)	(+)
		High income	(*)		(*)	(+)
		Household with children	(+)	(–)		(–)
	Mobility and travel related patterns	Travel distance: long	(+)			
		Driving frequency: high	(+)			(+)
		Uni-mode preference	(+)			(–)
		Car ownership	(–)	(+)	(*)	(–)
	Geography	Geographical regions	(+)	(+)		
	Built environment	Residence types	(*)	(*)		(*)
		Proximity to services			(+)	
		Bike friendly infrastructure/ topography (e.g. lane flatness)			(+)	
	Weather & environment	Temperature/weather/air quality			(+)	
		Noises, pollution, wildlife		(*)		
	Personal traits		(+)			(+)
		Technology interest	(+)	(+)	(+)	(+)
	Attitudes	Passionate for driving	(–)			
		Environment concern	(+)	(*)	(+)	
		Public transport	(+)			(*)
		Pro-AV sentiment	(+)			
		Safety	(*)	(/)	(–)	(–)
		Security	(*)	(–)	(–)	
		Locus of control	(*)			
		Mobility-on- savviness	(+)			
		Multiple transport mode				(+)
	Technologies acceptance theories related factors	Perceived usefulness (PU)	(+)	(+)	(+)	(+)
		Perceived ease to use (PEU)	(/)		(+)	(+)
		Social influence (SI)	(+)			
		Perceived trust (PT)	(+)			(*)
		Perceived safety	(*)			
		Attitude towards technology	(+)	(+)		(+)
		Facilitating conditions	(+)		(+)	
Endogenous factors		Technology and service-related attributes (e.g. automation levels, noise degree, convenience, price and subscription business models)	(+)	(+)	(+)	(+)

Note: + indicates positive relationship, – indicates negative relationship, / indicates the factor is insignificant, and * indicates there is a mixed finding.

weather/air quality/temperature) are highly related to the intention to use micromobility. MaaS typically shares a similar magnitude of adoption factors but has an additional one – attitudes toward multimodal transport. Notably, observations of contrasting factors (e.g. household with children, car ownership) influencing the acceptance of new mobilities seems to provide more far-reaching insights into our understanding and practical implications. For example, incentives to stimulate increased AV ownership may discourage public interest in the adoption of MaaS, so a rich understanding of the dichotomies between different new mobility technologies and services will help to inform policy decisions on the sequence of launch and development priorities of new mobility technologies and services. Furthermore, in consistent with previous work, this study finds several mixed impacts factors (e.g. age, gender, education, income). This finding highlights the significance of employing some methods such as cluster analysis to capture characteristics of potential adoption groups using multiple factors. In recent years, some studies (Alonso-González et al., 2020; Lopez-Carreiro et al., 2021; Matyas & Kamargianni, 2021) have begun to experiment with cluster analysis to uncover the adoption factors from a multifactorial perspective.

Second, this study classifies the current theoretical frameworks into three types: (1) three pillars and their extension; (2) technology acceptance theory families and (3) exogenous and endogenous factors, which draws a big picture of the key determinants of new mobility adoption. As discussed in Section 3, the theoretical frameworks need to be constructed to reflect the exclusive features of technologies and services, as well as the changes in context (e.g. the COVID-19). Therefore, to better capture the key determinants of new mobility adoption, more effort can be put into developing flexible and theme-specific frameworks by including or excluding several constructs from models such as TAM, UTAUT, CTAM. It would equally be worthwhile to conduct comparative studies using different frameworks and evaluating their effectiveness in predicting acceptance.

Our study also provides some policy implications. First, it is of great necessity to include a spatio-temporal perspective through doing regular surveys (Ho et al., 2018), which will examine how people's attitudes towards and demand for new mobility technologies and services change over time. Being aware of the heterogeneity among areas and doing comparative studies will facilitate the researchers, policy makers and industrial sectors to identify the early trials (neighbourhood, regions) and test the commercially availability, e.g. Vij et al. (2020) identified Melbourne, Canberra and Sydney for the early launch of MaaS through surveying 3985 geographically and demographically representative Australians nationwide. Lopez-Carreiro et al. (2021) also argued that longitudinal study will help industrial sectors to better understand the post-adoption loyalty.

Second, to encourage the uptake of new mobility technologies and services, further promotion would benefit from undertaking a careful market segmentation, leading to the development of targeted strategies for different customer segments. For instance, Lopez-Carreiro et al. (2021) suggested tailored strategies for four MaaS customer segments in reference to a strategy package composed of six main lines of actions. Some barriers, such as high mobility ownership and low technology adoption may be prevalent in several customer groups. Strategies that directly address these barriers can attract a larger group of users (Alonso-González et al., 2020). Besides, a customer-centric approach can help suggest strategies for changing (or expanding) business areas and acquiring new customers (Degele et al., 2018).

Third, we also believe that the equivalent of market segmentation is a careful segmentation of technology and services. The existing studies (e.g. Ho et al., 2020; Matyas & Kamargianni, 2019) have found that the public's attitudes towards the same new mobility technologies and services may vary depending on their attributes (e.g. the automation degree, noise levels, the sign-up convenience degree, payment manners and modes bundles, etc.), application contexts and purposes (e.g. for commuting or leisure travel, for emergency delivery or recreation, etc.). For instance, AVVs have a high acceptance in civil protection, rescue missions and a low acceptance in parcel delivery especially in residential areas (Tan et al., 2021; Eißfeldt et al., 2020). Future studies could consider diverse combinations of new mobilities' attributes, application contexts and purposes, so as to accurately capture the public's attitudes and behavioural intentions.

Note

1. www.harmony-h2020.eu

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Appendix. Selected research summaries on new mobility technologies and services.

Authors	Technology & Service focus	Study area	Sample size	Theoretical framework
Haboucha et al. (2017)	private autonomous vehicles, shared autonomous vehicles	Israel and North America	721	Sociodemographic, attitudinal, travel behaviour
Wang et al. (2020)	private autonomous vehicles	Singapore	353	IDT
Payre et al. (2014)	Fully automated driving	French	421	Sociodemographic, personality traits
Nazari et al. (2018)	private AV, shared AV (car-sharing, ridesourcing, ridesharing and access/egress model)	Washington, U.S.	2727	Sociodemographic, attitudinal, travel behaviour
Liljamo et al. (2018)	AV	Finland	2036	n.a.
Krueger et al. (2016)	shared autonomous vehicles	Australia	453	Socio-demographic, travel behaviour, attributes of new mobilities
Roche-Cerasi (2019)	shared autonomous shuttles	Norway	1419	n.a.
Kyriakidis et al. (2015)	automated technology	International (109 countries)	4886	Sociodemographic, personality traits, travel behaviours, attitudinal.
Yuen et al. (2020a)	AV	Singapore	274	IDT
Zmud et al. (2016)	AV	Austin, Texas, U.S.	556	CTAM
Sener et al. (2019)	AV	Texas cities (Dallas, Houston and Waco)	3097	CTAM
Bansal et al. (2016)	shared AV, private AV	Austin, the U.S.	347	Sociodemographic, travel behaviours, technology-based predictors
Schoettle & Sivak (2014)	automation levels	the U.S., UK, Australia	1533	n.a.
Dirsehan & Can (2020)	AV, fully automated	Turkey	391	TAM
Choi & Ji (2015)	AV	n.a …	552	TAM
Rahimi et al. (2020)	shared mobility, autonomous vehicles	the U.S.	1390	Sociodemographic, attitudinal, travel behaviour
Lavieri & Bhat (2019)	AV ride sharing (or car pooling), ride hailing	the U.S.	1607	Exogenous (sociodemographic, transportation related), attitudinal, endogenous
Manfreda et al. (2019)	AV	Slovenia	382	UTAUT
Charness et al. (2018)	AV	Florida, US	414	n.a.
Acheampong & Cugurullo (2019)	AV, shared AV	n.a …	507	TPB
Howard & Dai (2014)	AV, self-driving taxi	California, US	107	n.a.
Lee et al. (2019)	private autonomous vehicles, shared autonomous vehicles	Isreal and North America	721	Attitudinal
Panagiotopoulos & Dimitrakopoulos (2018)	AV automation	N.A …	483	TAM (extended)

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Authors	Technology & Service focus	Study area	Sample size	Theoretical framework
König & Neumayr (2017)	AV automation	Australia	489	n.a.
Lavieri et al. (2017)	mobility-on-demand services AV	Washington, U.S.	1832	Sociodemographic, attitudinal, travel behaviour
Nair et al. (2018)	AV (with or without drivers)	Washington, U.S.	1365	Sociodemographic, attitudinal, travel behaviour
Yuen et al. (2020)	AV	Seoul, Korea	526	IDT
Matyas & Kamargianni (2021)	MaaS package types: basic, urban & extra	Greater Manchester, UK	475	Sociodemographic, mobility usage and ownerships
Alonso-González et al. (2020)	MaaS pooled on demand service (ridesharing)	Netherland	1077	Sociodemographic, mobility characteristics, technology characteristics,
Ho et al. (2018)	MaaS service bundle	Sydney, Australia	252	Mobility characteristics
Caiati et al. (2020)	MaaS service bundle	Amsterdam& Eindhoven, Netherland	1078	Social influence, socio-demographic, transportation related characteristics
Ye et al. (2020)	MaaS service	Anting New Town, China	600	UTAUT
Vij et al. (2020)	Ride hailing on-demand service	Australia	3895	Sociodemographic, attitudinal, travel behaviour
Matyas & Kamargianni (2019)	MaaS service bundle	London, UK	1068	Sociodemographic, travel behaviour
Schikofsky et al. (2020)	MaaS service	Germany	1067	TAM
Ho et al. (2020)	MaaS service bundle	Sydney, Australia and Tyneside, UK	290	Sociodemographic, mobility characteristics
Hoerler et al. (2020)	carsharing	Switzerland	995	Sociodemographic, mobility characteristics
Zijlstra et al. (2020)	MaaS service	Netherlands	1547	Sociodemographic, mobility characteristics, built environment
Lopez-Carreiro et al. (2021)	MaaS service	Spain	1000	TAM
Eißfeldt et al. (2020)	drone applications (10 types)	Germany	832	Sociodemographic, built environment
Reddy & DeLaurentis (2016)	drones	U.S.	400	KAP (Knowledge, attitude, practice)
Aydin (2019)	40 drone applications	U.S.	153	KAP (Knowledge, attitude, practice)
Office of Inspector General (2016)	Drone delivery	U.S.	1465	Socio-demographic, travel behaviour
Clothier et al. (2015)	drones	Australia	510	Sociodemographic, psychographic
Lidynia et al. (2017)	drone applications	Germany	200	Demographic
Boucher (2016)	drone applications	Manchester, UK; Milan, Italy	focus groups	n.a.
Yoo et al. (2018)	drone parcel delivery	the U.S.	296	IDT
Eker et al. (2020)	flying cars	84.3% U.S., 16.7% worldwide	692	Sociodemographic, attitudinal, perceived behaviour patterns
Leon et al. (2021)	drone delivery	U.S.	617	Tam
Tan et al. (2021)	drone applications	Singapore	1050	KAP (Knowledge, attitude, practice) model
Rosenfeld (2019)	drones	Isareal & US	US = 115, Israel = 125	n.a.
Hess & Schubert (2019)	e-cargo bike sharing	Basel, Switzerland	301	Social practise theory

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Authors	Technology & Service focus	Study area	Sample size	Theoretical framework
Campbell et al. (2016)	electric bike sharing	Beijing, China	1188	Sociodemographic, environment and weather, travel purpose
Abolhassani et al. (2019)	bike sharing, bike sharing system	Mashhad, Iran	92	Sociodemographic, services attributes
de Chardon et al. (2017)	bike sharing systems	Europe and North America	75	BBS Performance matrix
Fishman et al. (2014)	bike sharing	Melbourne and Brisbane, Australia	372	Sociodemographic, built environment, mobility ownership
Fishman et al. (2015)	bikes sharing membership	Melbourne and Brisbane, Australia	372	Sociodemographic, built environment, mobility ownership
Li et al. (2019)	bike sharing, free-floating bike sharing	Kunming, China	552	Sociodemographic, travel behaviour, attitudinal
Aguilera-García et al. (2020)	Moped scooter-sharing, Shared mobility	Spain	430	Sociodemographic, mobility and travel related, attitudinal, service features
Eccarius & Lu (2020)	E-scooter sharing	Taiwan	471	TPB & IDT
Bieliński & Ważna (2020)	E-scooter sharing, e-bike sharing, e-cargo bike	Tricity, Poland	633	n.a.
Degele et al. (2018)	E-scooter sharing	Germany cities	53000	Sociodemographic, travel behaviour, psychographic