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Predicting Mobility as a Service (MaaS) use for different trip categories: An artificial neural network analysis

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A B S T R A C T

Mobility as a Service (MaaS) has gained popularity as a means of sustainable urban transport which makes the understanding of MaaS use critical for its design and promotion. Studies have contributed to the growing understanding of MaaS, its design features, and consumers' willingness to pay for MaaS in general, without recourse to the differences in traveling for work, social and general purposes. This paper develops and tests models to predict MaaS use by applying artificial neural network analysis, following the cross industry standard process and data mining framework. It also estimates separate models for social, general, and work trips, using 33 input variables reflecting network externality, transaction cost, behaviour, institutional, environmental concern, personal travel, and socio-economic factors. Data are collected from a survey of 331 Australians. The study reveals different sets of socio-economic factors, the impact of Covid-19, and personal travel factors as key predictors of MaaS use for general, social, and work trips with an average prediction accuracy of 68%, 68%, and 75% respectively. The findings can be used to inform strategies and policies on how to attract a user base with respect to socio-economic and personal travel factors for promoting MaaS use.

1. Introduction

Mobility as a Service (MaaS) is an innovative and multimodal delivery of personal transport by integrating different modes of transport, auxiliary services, and all the functions from trip sourcing to completion into a single digital platform (Jittrapirom et al., 2017; Arias-Molinares and García-Palomares, 2020; Hensher et al., 2021). It brings together public transport, car share, bike share, ride share operators and other services and transaction fulfillment providers to create a seamless solution for meeting the mobility need of individuals (Bushell et al., 2022). Examples of notable MaaS schemes include Whim in Finland, Ubigo in Sweden, and Swa Augsburg in Germany (Reck et al., 2020; Hensher et al., 2021). Despite the growing interest in MaaS, there are very few successful MaaS business models in the market (Hensher et al., 2021).

The potential policy and practice impacts of MaaS include a decline in car ownership (Sochor et al., 2018), a change in travel behaviour from vehicle ownership to service-based models (Wong et al., 2020; Hensher et al., 2021), and an increase in the efficiency and utilization of transport resources and networks (Wong et al., 2017; 2020) to achieve sustainable policy goals and objectives (Reck et al., 2020; Hensher and Mulley, 2021). The assumptions underlying these short-, mid- and long-term impacts of MaaS are the acceptance and diffusion of MaaS among travellers. As a relatively new concept and a digital innovation at the early stage of supply and

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demand diffusion, there is a need to evaluate user acceptance of MaaS to address the critical question of whether MaaS is scalable as a viable mobility model or will remain as "a niche offering" (Hensher and Mulley, 2021). Several researchers have responded to this need.

To promote research and the conceptual understanding of MaaS, scholars have provided definitions and descriptions of MaaS and its prospect (Jittrapirom et al., 2017); taken a user perspective to propose MaaS integration taxonomy (Lyons et al., 2020); suggested different design options (Reck et al., 2020) and systematically analyzed the emerging literature (Butler et al., 2021; Santos and Nikolaev, 2021). Experimental studies, for example, use discrete choice modelling to understand user's willingness to pay for MaaS (Hensher et al., 2021), choices between subscriptions and payment service bundles, and the role of cost savings on MaaS uptake (Ho et al., 2021). Other studies rely on specific theories to explain the demand side latent variables that influence users' intention to adopt MaaS (Alonso-González, 2020; Schikofsky et al., 2020; Zijlstra et al., 2020; Matyas and Kamargianni, 2021) or surveys to understand consumers demand and willingness to pay for MaaS (Vij et al., 2020). Some researchers have taken a qualitative approach to explore the socio-technical factors such as attitude, car dependency, trust, uncertainties about service characteristics, value, and cost that either facilitate or inhibit MaaS uptake (Smith et al., 2018; Alyavina et al., 2020; Matyas, 2020) as well as the service attributes including simplicity, accessibility and flexibility that potential users are likely to value the most (Sochor et al., 2016). Overall, extant studies have developed a growing understanding of MaaS.

In this paper, we take a different angle by appropriating a range of variables drawn from the transaction cost, network externality, behavioural, institutional, sustainability, and socio-economic theories including the impact of Covid-19, delving into the purpose of travel, i.e., whether it is for social, general, or work travel, and developing neural network based predictive models to explain MaaS use. This is a significant undertaking as one of the key objectives of MaaS is to offer users mobility services that meet their specific travel needs (Hensher et al., 2021). Furthermore, a common dilemma in rolling out innovation for mass adoption is the difficulty in predicting its adoption rate and determining the factors that affect it, which highlights the need for and potential value of MaaS predictive models.

The paper, therefore, aims to develop predictive models and identify the factors that explain MaaS use for social, general, and work trips. Social trips are linked to mobility needs where the primary goal is to satisfy the hedonic needs of individuals, such as entertainment, visiting families and friends. Work trips are about the travel to earn and learn that are often necessary, routine and sometimes unavoidable (Turcotte, 2011). General trips are related to travelling to meet everyday demands of life such as picking up groceries, visiting doctor, post office and other errands. These distinctions are important because they may affect the efficiency, comfort and safety needs and concerns of travellers (Turcotte, 2011), and the strategies and policies that are needed to increase the respective MaaS use rates. It is thus important to empirically verify whether the predictors vary across different types of trips.

This study develops the models to predict the intention of individuals to adopt MaaS for three trip types using artificial neural network (ANN). ANN is an artificial intelligence technique for simulating the way that human brains store and process information (Morris et al., 2004; DeTienne and DeTienne, 2017; Nguyen et al., 2020). It is preferred in this study over conventional statistical techniques due to its advantages of providing higher predictive accuracy and better optimizing solutions by exploring both linear and non-linear relationships between dependant and independent variables (DeTienne and DeTienne, 2017). ANN can also enable to effectively deal with data discontinuities and nonlinear transformations and identify the variables that contribute to a solution and those that do not (Morris et al., 2004; DeTienne and DeTienne, 2017). The cross industry standard process and data mining (CRISP-DM) framework (Nguyen et al., 2020) is followed to guide the design of the ANN predictive models.

The model can be used to better understand how to attract a larger user base and how other mobility stakeholders can better respond to changes in behavioural, socio-technical, and institutional factors that influence MaaS use. These contributions are important to MaaS stakeholders in rolling out commercial MaaS models. The empirical results add to building a cumulative knowledge base addressing the critical question of MaaS scalability and how it can be achieved. The paper also contributes to the application of ANN in predicting mobility modal shift.

The rest of the paper is organized first by reviewing the related studies to identify the conceptual foundation of variables used in the predictive model. This is followed by a description of variables, the data and the ANN procedure. Section 4 presents the results, followed by a discussion of contributions of this paper. The last section concludes the paper with a summary of findings and limitations.

2. Literature review

There are growing studies on investigating MaaS use for improving the mobility of people (Butler et al., 2021; Santos and Nikolaev, 2021). These studies have been conducted for exploring the MaaS use behaviour of individuals with the intention to identify the relevant factors through survey, experiment, interviews, or systematic literature review. Table 1 presents a sample summary of such studies.

Survey-based studies focus on investigating the preference of individuals on MaaS use, leading to the identification of the critical factors for MaaS use. Alonso-González et al. (2020), for example, examine the attitude of individuals to MaaS use with respect to mobility integration, transport modes, mobile applications, and willingness to pay in the Netherland. This study shows that individuals who are young, highly educated, living in more dense urban areas, having no children, and depending more on online information for travel are likely to adopt MaaS. Vij et al. (2020) investigate the consumer demand and willing to pay for MaaS in Australia. The study shows that there is a market for MaaS in Australia and consumers prefer pay-as-you-go schemes to bundled schemes in MaaS implementation. Schikofsky et al. (2020) explore the motivation for MaaS use through analyzing the survey data in Germany. The study reveals that autonomy, competence and relatedness affect hedonic motivation and hedonic motivation, perceived usefulness, perceived ease of use, and habit schema congruence are positively associated with MaaS use. Matyas and Kamargianni (2021) examine

Table 1
A summary of the MaaS use studies.

References	Research variables	Data analysis method	Findings
Alonso-González et al. (2020) [Survey]	Age, education, gender, income, household composition, employment, degree of urbanization	Latent class cluster analysis	Individuals who are young, highly educated, living in more dense urban areas, having no children, and depending on travel information for travel are likely to adopt MaaS.
Schikofsky et al. (2020) [Survey]	Perceived usefulness, Perceived ease of use, Habit schema congruence, hedonic motivation, competence autonomy, relatedness	Partial least squares analysis	Autonomy, competence, and relatedness affect hedonic motivation. Hedonic motivation, perceived usefulness, perceived ease of use, and habit schema congruence are positively associated with the intention to use MaaS
Vij et al. (2020) [Survey]	Consumer demand and willingness to pay	Latent class cluster analysis	There is a market for MaaS in Australia. Consumers prefer pay-as-you-go schemes to bundled schemes.
Matyas and Kamargianni (2021) [Survey]	Socio-economic factors including age, gender, income, education, travel behaviour, MaaS offerings	Latent class cluster analysis	Socio-economic factors including age, gender, income, education and travel behaviour affect the intention of individuals to purchase MaaS packages
Sochor et al. (2016) [Experiment]	Transportation smorgasbord, simplicity, improved access and flexibility, and economy	Statistical analysis	A holistic approach focusing on serving users' needs and capitalizing on synergies between public and private actors is required to develop MaaS.
Ho et al. (2018) [Experiment]	Maas offerings, car ownership, bundle prices, individual characteristics	Mixed-logit analysis	MaaS bundle price and car ownership directly affect MaaS use
Brezovec and Hampl (2021) [Experiment]	Transport mode, contract termination modes, modes of access, bundle price	Choice-based conjoint analysis	Bundle price and bundle features significantly affect the MaaS use
Caiati et al. (2020) [Experiment]	Individual preferences and service characteristics	Mixed logit analysis	Service characteristics, especially the price of the monthly subscription, and the social influence variables have an important effect on the subscription intention
Hensher et al. (2021) [Experiment]	MaaS bundle uptake, choice made between PAYG and bundles, private car use	Discrete-continuous choice analysis	The use of MaaS bundles reduces the use of private cars
Smith et al. (2018) [Interview]	Scope, usage, access, business model, competence structure and brand value	Thematic analysis	Three emerging MaaS scenarios have been identified including market-driven, public-controlled and public–private.
Alyavina et al. (2020) [Interview]	Car dependence, trust, human element externalities, value, and cost	Thematic analysis	The success of MaaS as a sustainable travel mode depends on changing attitude to car ownership and using public transport as a backbone of MaaS models
Matyas (2020) [Interview]	Attitude, MaaS modes, safety, trust, service characteristics, and administration	Thematic analysis	MaaS plays a positive role in helping change behaviours on multi-mode transport use and reduce private vehicle dependence
Lyons et al. (2020) [Literature review]	User perspective, MaaS conceptualization, MaaS integration taxonomy	Document analysis	A MaaS behavioural schema is provided to illustrate potential consideration and use of MaaS from the user perspective
Butler et al. (2021) [Literature review]	Reduced vehicle kilometres travelled, increased trip awareness, reduced parking, reduced vehicle ownership, and improved social equity	Document analysis	Reduced vehicle kilometres travelled, increased trip awareness, reduced parking, reduced vehicle ownership, and improved social equity directly affect the MaaS use of MaaS.

the preference of individuals for purchasing MaaS packages in Greater Manchester. The study finds that socio-economic factors including age, gender, income, education, and travel behaviour of individuals affect the intention of individuals to purchase MaaS packages. These studies above provide insights on the relevant factors that can affect the intention of individuals to adopt MaaS.

Experiment-oriented studies concentrate on exploring the choice behaviour of individuals in their selection of specific MaaS bundles, resulting in the itemization of the critical factors to the use of MaaS. Sochor et al. (2016), for instance, investigate travel behaviour and related changes from a 6-month field MaaS operational test with respect to the transportation smorgasbord concept, simplicity, improved access and flexibility, and economy. The study reveals that a holistic approach focusing on serving users' needs and capitalizing on synergies between public and private actors is required to develop MaaS. Ho et al. (2018) explore MaaS use using mixed-logit analysis with respect to the willingness of individuals to pay in Sydney. The study shows that MaaS offering price and car ownership are critical to the adoption. Following the same data analysis approach, Caiati et al. (2020) examine the relationship between MaaS bundles, pricing schemes and extra features and MaaS use in the Netherlands. The study reveals that service characteristics, especially the price of monthly subscription, and social influence variables, socio-demographic profiles of individuals, and travel related characteristics significantly affect the use of MaaS. Brezovec and Hampl (2021) investigate the use of e-car sharing and e-scooter sharing as part of MaaS bundles using choice-based conjoint analysis for improving mobility in Austria. The study finds that bundle price and bundle features directly affect MaaS use. Hensher et al. (2021) explore MaaS use bundles and their impact on private car use in Sydney based on discrete–continuous choice analysis. The study reveals that MaaS use bundles reduces the use of private cars. All these studies reveal that there are various factors from different perspectives that affect the intention of individuals to adopt MaaS.

Interview-aligned studies centre on understanding the perception and preferences of users in their adoption of MaaS, leading to the identification of the expectation and requirements of users on MaaS design and implementation. Smith et al. (2018), for example, explore how MaaS could be developed and how public transport might be affected in West Sweden. The study finds that there are three emerging MaaS scenarios including market-driven, public-controlled, and public–private with two critical roles such as MaaS integrators and MaaS operators that public and private can play in MaaS development. Alyavina et al. (2020) investigate the factors underpinning the uptake and potential success of MaaS as a sustainable travel mechanism. The study reveals that the success of MaaS as a sustainable travel mode depends on changing the attitude of users to car ownership and using public transport as a backbone of MaaS models. Matyas (2020) probe the potential ways that MaaS could help encourage behavioural change and understand the barriers to using alternative transport modes. The study shows that MaaS plays a positive role in helping change behaviours on multi-mode transport use and reduce private vehicle dependence. The studies above reinforce existing findings and show that users play an increasingly critical role in the design and implementation of MaaS for smart mobility.

Systematic literature reviews have been conducted for identifying the enablers and barriers to MaaS use (Lyons et al., 2020; Butler et al., 2021). The study finds that lack of appeal to older generations, public transport users, and private vehicle users, attractiveness of digital platforms, and user willingness to pay are critical to the uptake of MaaS. It shows that the development of MaaS depends on public–private cooperation, business support, service coverage, shared vision, and data and cybersecurity. Furthermore, the study reveals that MaaS use can provide individuals and communities with significant benefits, including reduced vehicle kilometres travelled, increased trip awareness, reduced parking, reduced vehicle ownership, and improved social equity (Bushell et al., 2022). Promoting such benefits can further improve MaaS use.

The discussion above shows that existing studies have explained what might affect MaaS use. These studies identify a variety of variables, including demographic characteristics of individuals, behavioural attributes, transaction cost factors, network externality issues, and social dimensions that all affect MaaS use. One distinguishing characteristic of these studies is that they focus on building an explanation for the behaviours of individuals in their preferences to MaaS use. Most experimental studies neither test theories nor offer explanatory power statistics, while most empirical studies draw from a limited range of theories and variables for exploring the use of MaaS. Most of these studies have not attempted to predict the intention of individuals to MaaS use under various circumstances.

Existing studies provide useful insights in understanding the preference and intention of individuals for the use of MaaS and for identifying potential variables for predicting the MaaS use with respect to different purposes of using MaaS for mobility. Social, work, and general trips serve different purposes and may have different trip frequency, destination, duration, time of travel (peak and off-peak hours), travel distance and travel time. With the growing recognition of the importance of MaaS for improving mobility and the rapid development of information and communication technologies, there is an increasing need for predicting the MaaS use behaviour of individuals for different travel needs. Such prediction can help MaaS stakeholders to formulate targeted strategies and policies to improve the uptake of MaaS.

Furthermore, most existing studies apply statistical and econometric modelling techniques, such as latent class cluster analyses, partial least squares and discrete modelling or qualitative thematic analysis to analyse the data and explore the preference of individuals and their choice behaviours with the availability of specific MaaS bundles. There is a lack of studies that focus on the development of specific prediction models for investigating the relationship between various variables and MaaS use with respect to specific purposes of travelling using machine learning techniques, such as ANN or decision trees, which are very different approaches in data analytics.

3. Methodology

3.1. Survey and participants

The study aims to identify the factors that predict MaaS use for social, general, and work trips. To achieve this objective, the relevant data is collected using a survey. The study is approved by the university human research ethics committee. The online survey is hosted on Qualtrics platform and administered by Qualtrics's Sample Management Service to recruit and distribute the survey to a nationally representative sample. The selection criteria of the survey participant include those who are 18 years or older and live in Australia.

In addition to the usual socio-economic data, the survey also collects information on the participants' perception of MaaS use. 551 responses are collected. 173 responses fail to respond to the primary constructs of the survey, which indicates person-level missingness (Newman, 2014). They are therefore removed from the dataset. In addition, to ensure the quality of the data received from Qualtrics, two data integrity checks are used in the survey for identifying potentially careless responses. 47 responses that do not pass the integrity checks are removed. The resulting 331 valid responses are more than the minimum required sample size for reliable predictions to be generated from ANN.

According to the Australian Bureau of Statistics (ABS), "To be 95 % confident that the true value of the estimate will be within 5 percentage points of 0.5, (that is, between the values of 0.45 and 0.55), the required sample size is 385." (ABS, 2021). Our sample of 331 is close to the expectation. Our sample is comparable with the sample size of 252 in Ho et al. (2018) and 290 in Ho et al. (2021), and larger than the sample size of 105 in Mulley et al. (2020).

To check if the sample is representative, the chi-square test is conducted to compare the demographic profile of respondents with the ABS census (ABS, 2021). The results as presented in the Appendix show that gender, age, and car ownership of respondents are in line with the Australian population distribution. This implies a good representation of the population in terms of age and gender distribution, although the education and income levels of the respondents in the sample are higher than the population.

Table 2 presents an overview of the demographics of the respondents. 58.9 % of participants are female, 49.5 % aged between 25

Table 2
Profile of respondents.

Measure	Item	Frequency (%) (N = 331)	Respondents who intend to use MaaS		
			Social trip (n = 179)	General trip (n = 165)	Work trip (n = 141)
Gender	Male	136 (41.1 %)	70	70	59
	Female	195 (58.9 %)	109	95	82
Age	18–24	17 (5.1 %)	13	12	15
	25–44	164 (49.5 %)	110	102	94
	45–64	89 (26.9 %)	40	33	27
	65+	61 (18.4 %)	16	18	5
Qualification	Primary	4 (1.2 %)	2	1	2
	Secondary	82 (24.8 %)	37	37	22
	Certificate/Diploma	112 (33.8 %)	58	53	37
	Bachelor degree	96 (29.0 %)	60	55	59
	Postgraduate degree	37 (11.2 %)	22	19	21
Marital status	Single	103 (31.1 %)	58	59	50
	Married	196 (59.2 %)	110	95	84
	Divorced/ Separated	32 (9.7 %)	11	11	7
Children	0	195 (58.9 %)	89	81	61
	1	61 (18.4 %)	40	37	33
	2	48 (14.5 %)	38	35	37
	3 or more	27 (8.2 %)	12	12	10
Weekly income	$999 or less	155 (46.8 %)	66	69	48
	$1,000 - $2,999	147 (44.4 %)	97	82	79
	$3,000 or more	29 (8.8 %)	16	14	14
Employment	Employed	179 (54.1 %)	118	101	103
	Unemployed/Job seeker	69 (20.8 %)	40	38	31
	Retired	64 (19.3 %)	16	20	2
	Others	19 (5.7 %)	5	6	5
Car ownership	Yes	279 (84.3 %)	147	127	112
	No	52 (15.7 %)	32	38	29
Public transport seasonal ticket	Yes	95 (28.7 %)	68	65	58
	No	236 (71.3 %)	111	100	83

and 44, 26.9 % aged between 45 and 64, 84.3 % own a car, 40.2 % have a university degree, 59.2 % are married, 54.1 % are employed, 46.8 % has weekly income less than $1,000. 54.1 % of participants have the intention to use MaaS for social trips, 49.8 % and 42.6 % would like to use MaaS for general trips and work trips respectively.

3.2. *Dependent variable*

The dependent variable of this study is the use of MaaS for three different types of trips: (a) work; (b) social; and (c) general. These variables are initially measured using the 5-point Likert scale ranging from 'Never' to 'Very Often'. In preparing the variables for this study, the 5-point Likert scale measures are recoded into a dichotomous variable. For each item, responses that are 'Never' and 'Rarely' are recoded into 'No', while responses that are 'Sometimes', 'Often', and 'Very Often' are recoded into 'Yes'.

3.3. *Predictor variables*

To identify the predictor variables to be used in this study, the findings of previous studies summarized and discussed in section 2 are used, including network externality, transaction cost, behaviour, institutional, environmental concern and demographic characteristics.

3.3.1. *Transaction and service costs*

The transaction cost theory (Coase, 1937; Wang et al., 2012; Yigitbasioglu, 2014) hypothesizes that there is cost associated with every transaction, such as negotiation cost, contract cost, etc. These costs vary depending on the mode of transactions since transactions between suppliers and customers, business-to-business or within a firm entail different costs. In this study, it is hypothesized that an individual choosing to use MaaS will incur two transaction costs: (a) resources (effort, time and cost) that might be involved in searching, choosing and using MaaS; and (b) resources (effort, time and cost) that might be involved in redressing the problem that might be encountered using MaaS (Alyavina et al., 2020). In addition to the transaction cost, this study also examines the influence of the comparative cost of getting the same mobility service from a private car (Wang et al., 2012; Yoo et al., 2020). According to the Law of Demand in economics, the price of a good or the cost of a service is expected to have a significant effect on consumers' purchase decisions. These measures are recorded using a 5-point importance scale.

3.3.2. Network externality

There are various platform-related factors including positive, negative and indirect network externalities (Tucker, 2008; Huang et al., 2018; McLeay et al., 2018). The direct network externalities are the benefit or cost brought by the size of the network (Hong et al., 2021). Such benefit or cost depends on the level of openness of web-based service platforms (Gebregiorgis and Altmann, 2015; Hong et al., 2021). There are various factors, including platform portability and usability, simplicity, and flexibility that affect MaaS use (Sochor et al., 2016; Matyas 2020). MaaS studies have also highlighted the importance of operational, information, and transactional integration (Lyons et al., 2020) and collaboration among service providers (Bushell et al., 2022). In this study, direct network externality is measured using two items: (a) 'The number of people that are using a MaaS platform increases its attractiveness' (positive network externality), and (b) 'If more people shift to use MaaS, it becomes less attractive to me' (negative network externality). These measures are recorded using a 5-point Likert scale.

The indirect network externality is related to the value of the core product or service caused by an increasing number of adopters (Shim et al., 2018; Hong et al., 2021). It results from the scale effect, as platform architecture can offer a wide portfolio characterized by easily interchanged modules (Cenamor et al., 2017; Hong et al., 2021), which can improve the quality of products and services while reducing prices. Indirect network effects can positively influence the valuation of the platform from the perspective of individual organizations (Shim et al., 2018; Hong et al., 2021). In this study, indirect network externality is measured using 'The number of transport service providers that are working to make their services available on the MaaS platform increases its attractiveness' and recorded using a 5-point Likert scale.

3.3.3. Institutional factors

To facilitate transactions, digital platforms require the appropriate architecture, design, governance, and regulations to maximise public trust (Tomaino et al., 2020) and minimise friction in the delivery of products and services (Ruggieri et al., 2018, Hirschhorn et al., 2019). In the area of MaaS, studies have indicated that consumers' safety, trust, and service administration concerns can either facilitate or inhibit the acceptance and success of MaaS (Alyavina et al., 2020; Matyas, 2020). These concerns can be closely related to the public or private or public–private partnership approaches for developing MaaS (Smith et al., 2018) and highlight the importance of MaaS platform ownership and governance (Smith et al., 2018; Brunswickera and Schecterb, 2019). In this study, a consumer is assumed to be concerned about the safety and security of a system when deciding to use MaaS (Alyavina et al., 2020; Matyas, 2020). This concern is closely related to the governance and regulation of the system and is measured using six items: (a) 'Government should oversee MaaS service provision' (government oversight); (b) 'MaaS safety are properly regulated' (safety regulation); (c) 'MaaS data protection are properly regulated' (data protection); (d) 'MaaS geographic coverage and accessibility are properly regulated' (geographic coverage); (e) 'A MaaS platform shares users' data with third parties by offering rewards in exchange' (data monetisation); and (f) 'A MaaS platform should be owned by a government (public) transport service provider' (public ownership). These measures are recorded using a 5-point Likert scale.

3.3.4. Behavioural factors

According to the widely used Theory of Planned Behaviour (Ajzen and Fishbein, 1977), the behaviour of an individual is assumed to be influenced by his/her intention, which in turn, is influenced by his/her attitude, social norm, and his/her perceived behavioural control. From exploratory MaaS studies, car dependence and attitude have been identified as important variables in influencing users' willingness to pay for or use MaaS (Vij et al., 2020; Alyavina et al., 2020; Matyas, 2020). In this study, attitude and perceived behavioural control are considered and measured using: (a) 'MaaS could help reduce car ownership' (attitude); and (b) 'I have the skill to use a MaaS digital platform' (perceived behavioural control). In addition, one item is used to measure the construct of relative advantage in innovation adoption (Karahanna, 2002; Choudhury and Karahanna, 2008): 'MaaS is a great way to have access to transport without owning a private car'. These measures are recorded using a 5-point Likert scale.

3.3.5. Environmental concerns

There is a common perception that MaaS is a more sustainable approach to address the growing mobility needs of modern society (Giesecki et al., 2016; Hirschhorn et al., 2019) although this depends on the future development of MaaS to use public transport as a backbone and to change car ownership attitude (Alyavina et al., 2020). One major aspect of more sustainable transport services is having a smaller footprint on the environment. In this regard, a consumer who has a greater concern for the environment is expected to be more likely to adopt MaaS. This study uses two measures of environmental concerns: (a) 'I am concerned about environmental issues because of the consequences for me' (egoistic environmental concern); and (b) 'I am concerned about environmental issues because of the consequences for humanity' (altruistic environmental concern). These measures are recorded using a 5-point Likert scale.

3.3.6. Travel pattern and options

An individual's travel pattern has been found to significantly influenced his/her choice of travel mode (Scheiner, 2010; Ding et al., 2017; Matyas, 2020; Chen and Deng, 2022). Similarly, the intention to adopt MaaS is hypothesized in this study to be influenced by the travel pattern of the individual and his/her travel choices. Two principal travel attributes are used in this study: (a) 'On average, how long do you travel per day?' (Distance travelled) and (b) 'What is your average travel time per day?' (Travel time). Travel distance is recorded using seven categories: <10 km, 10–20 km, 21–30 km, 31–40 km, 41–50 km, 51–60 km and > 60 km while travel time is recorded using 5 categories: <30 min, 31–59 min, 1–2 h, 2.1–3 h and > 3 h). These variables are assumed to have a significant influence on the travel costs associated with the choice between using MaaS or private vehicle travel. In addition to the travel costs, this study also examined six constraints on the choice sets of the consumers due to ownership and accessibility: (a) driving license; (b) car

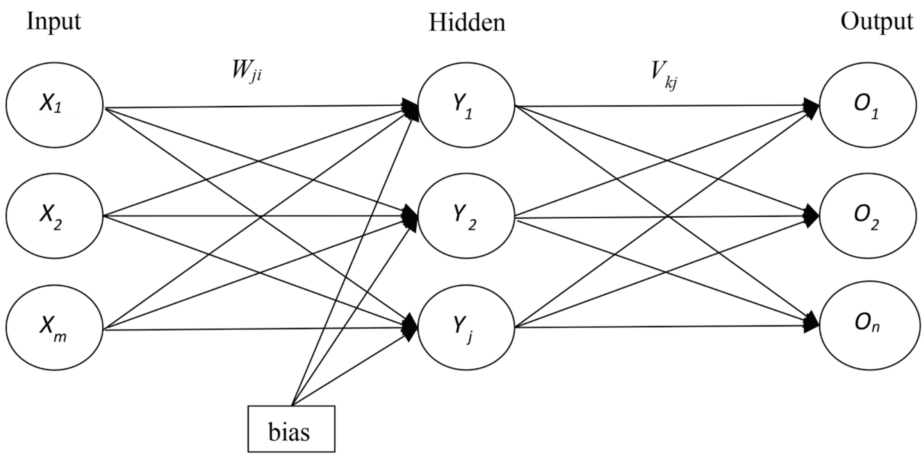

Fig. 1. Architecture of ANN.

ownership; (c) multiple car ownership; (d) bike ownership; (e) car sharing membership; and (f) public transport seasonal ticket. These measures are recorded using the binary "Yes" and "No" categories.

3.3.7. Socio-economic influences

According to the consumer choice theory in economics and marketing, a consumer is assumed to choose the best option that will maximise his/her utility, given a set of choices and his/her budget constraint. In empirical analyses, the consumer's budget constraint and his/her taste and preference are often captured indirectly by his/her socio-economic characteristics (McCarthy and Tay, 1998; Chowdhury et al., 2016). Therefore, seven socio-economic characteristics are included in this study: consumer's age, marital status, gender, children, employment status, education and income.

3.3.8. Covid-19 impact

The Covid-19 pandemic has significantly changed the travel behaviour of many people, including their work trips, social trips and general travel. These changes also include changes to their travel mode, with a shift from using public transportation to private transportation (Eisenmann et al., 2021; Das et al., 2021), which may be pertinent to their intention to adopt MaaS. Therefore, this study uses an item to measure the impact of Covid-19: "Post-Covid, how likely are you going to change your mode of transportation preference from your pre-Covid habit?" for the three different types of travel. This measure is recorded using a 5-point Likert scale.

3.4. Data analysis

3.4.1. CRISP-DM framework

To guide the development and deployment of the predictive models in this study, the CRISP-DM framework is followed. The CRISP-DM is a systematic framework that outlines six steps for designing machine learning models (Nguyen et al., 2020). The first step requires transforming the business objectives into a machine learning problem. This study aims to identify the factors that predict MaaS use for social, general, and work trips. Therefore, the problem the study deals with requires the development of three separate models to predict the key factors of using MaaS for social, general, and work travel respectively.

The second step involves identifying the data source and variables related to the problem. 33 predictor variables identified from the review of existing studies as detailed in section 3.3 are extracted from the survey.

The third step in the CRISP-DM framework is preparing a reliable dataset before model building. To generate consistent and reliable predictions, ANN requires a minimum sample size of at least 50 times the number of prediction classes or at least 10 times the number of predicting attributes (Haykin, 2009). In this study, there are 33 predicting attributes for predicting the dependent variable which is measured using two prediction classes (Yes and No) in each ANN model, this means the sample size should be at least 100.

The fourth step is related to developing the predictive models. The ANN analysis (see next section) is conducted in SPSS 26. Using the IBM-SPSS Perceptron Neural Network, three predictive models are formulated with the use of a two-stage ANN for each dependent variable. The use of the two-stage ANN can facilitate the selection of the key predictors for different purposes of MaaS use in an effective manner. The first-stage ANN model contains all 33 predictor variables as inputs and one of the three dependent variables as output. To compute the relative importance of all predictors, the tenfold cross validation technique with 70 % of the data for training and 30 % for testing is used. This produces the top ten predictors which are then applied as input variables to the second-stage ANN for predicting the same dependent variable. After another ten folds cross validation with 70 % of the data used for network training and the remaining 30 % for testing, the relative importance of all ten predictors is calculated and ranked. This process is repeated for all dependent variables.

The relative importance of the factors is measured by how much the predicted output value varies with different values of the independent variables (Chong, 2013; Duan and Deng, 2021). It is used in the sensitivity analysis to compute the normalised importance as the ratio of the relative importance of each variable with its highest relative importance and represented in percentage.

In all ANN models, the independent variables with categorical measures are treated as factors, while those with scale measures are treated as covariates. To obtain better model performance, all inputs and outputs are normalized to the range [0, 1]. In the hidden and output layers, sigmoid is used as an activation function. All ANN models have one hidden layer, with the number of hidden neurons generated automatically by SPSS (Sharma, 2019).

The fifth step involves measuring the performance of predictive models. To assess the predictive accuracy of the models, the root mean square of error (RMSE) and the percentage of incorrect predictions of both training and testing data sets for ANNs are used. The lower the value of RMSE and the percentage of incorrect predictions, the better the predictive performance of the model (Nguyen et al., 2020).

The last step includes generating insights to inform decision-making, which is described in the Discussion section.

3.4.2. ANN procedure

ANN is a machine learning technique for simulating the way that human brains store and process information (Leong et al., 2020). A typical neutral network is made up of several hierarchical layers, including the input layer, hidden layers, and output layer, as shown in Fig. 1. Each layer contains neurons that are interconnected with neurons of another layer. The first step in the ANN analysis is to decide the number of hidden layers. In the technology adoption context, one hidden layer is sufficient for representing any continuous function (Duan and Deng, 2021). To quantify the relationship between the factors and the use of MaaS in this study, the feedforward backpropagation multiplayer perceptron is used, where the signals are fed forward from the input layer through the entire network to the output layer. The inputs to each neuron are multiplied by its synaptic weights and summed, and this signal is transformed to the output value using a nonlinear activation function (Leong et al., 2020).

The ANN models used in this study is formulated as follows. Given a set of input neurons X (X_1, X_2, … X_m), the weights of the input neuron i ($i = 1, 2, 3 \ldots m$) to the hidden neuron j are represented by W_{ji}. The weights of the hidden neuron j to the output neuron k ($k = 1, 2, 3 \ldots n$) are represented by V_{kj}.

For the j-th hidden neuron,

$$netj = \sum_{i=1}^{m} W_{ji}x_i\,, yj = \mathrm{f}\,(netj) \tag{1}$$

For the k-th output neuron,

$$netk = \sum_{j=1}^{j+1} V_{kj}y_j,\; ok = \mathrm{f}\,(netk) \tag{2}$$

The dependent variable in this study uses the binary categorical measure. As a result, the sigmoid function is used as an activation function for both hidden layer and output layer (IBM, 2012). A typical sigmoid function with a parameter β is presented in (3). In the learning process, for a specific input pattern, an output o_k is generated by the network, which is matched to the desired response of every neuron d_k. In addition, the weights are altered to minimise the error. The subsequent pattern is forwarded. The weight adjustment formula for output layer weights V is computed using (4) whereas the hidden layer weights W is calculated using (5) in which d_{pk} and o_{pk} signify the desired and the real output of neuron k respectively for input pattern p. The weights are continually revised until the sum square of error (SSE) as in (6) across all training patterns is minimised under some predefined levels of tolerance (Leong et al., 2020).

$$f(net) = \frac{1}{1 + e^{-\beta net}} \tag{3}$$

$$V_{kj}(t+1) = v_{kj}(t) + c\beta(d_k - o_k)o_k(1 - o_k)y_i(t) \tag{4}$$

$$W_{ji}(t+\ 1) = w_{ji}(t) + c\beta^2 y_j(1 - y_j)x_i(t)(\sum_{k=1}^{k+1}(d_k - o_k)o_k(1 - o_k)v_{kj} \tag{5}$$

$$\mathrm{SSE} = \frac{1}{2P}\sum_{p=1}^{P}\sum_{k=1}^{K}(d_{pk} - o_{pk})^2 \tag{6}$$

ANN offers several advantages in building predictive models (Chong, 2013; Duan and Deng, 2021), including the ability to capture both linear and nonlinear relationships between independent and dependent variables (Nguyen et al., 2020), formulate models without the pre-assumption of particular distributions of sample population (Chong, 2013), and produces high model prediction accuracy (Leong et al., 2020). With the use of ANN in this study, predictive models can be built based on the theoretical knowledge for predicting the future use of MaaS for social, general, and work travel with high predictive power.

The ANN used for the analysis in this study is IBM's Multilayer Perceptron Neural Network, which is suitable for the purpose of the research because it offers flexibility about the specifications of dependent variables as *"scale, categorical, or a combination."* and to identify hidden layers, non-linear patterns and connections that would have otherwise been impossible to detect (IBM, 2012).

4. Results and discussion

Although Australia has stopped making cars in 2017, the car culture is deeply ingrained into the Australian lifestyle. Figures from Budget Direct show that after peaking in 2013, the new car market has been declining, especially since 2017. While there are several reasons for this decline, including a decline in youth licensing (Delbosc, 2017), our result seems to suggest that there might be a gradual shift in Australian's view of car ownership as 58 % of survey participants in this study believe that MaaS could help to reduce car ownership and 74 % think that MaaS is a great way to have access to transport without owning a private car.

However, when it comes to actually shifting to MaaS, only 44 % of participants would use MaaS on a regular basis if it becomes available. Of these potential users, 75 % will use MaaS for satisfying the hedonic needs of individuals such as entertainment, visiting family and friends (social trips), 72 % for travelling to earn and learn (work trips), and 66 % for meeting everyday demands of life such as pick groceries, visit doctor, post office and other errands (general trips).

This study develops and tests predictive models with three different output variables: social trips, general trips and work trips. To assess the robustness of the predictive ability of each ANN model, the tenfold cross-validation procedure as discussed in section 3.4 is followed. The RMSE and the percentage incorrect prediction of all training and testing data sets are computed. The results indicate that the models are reliable in capturing the relationship between the predictors and the dependent variables. Specifically, the percentage of correct prediction of MaaS use for general, social, and work trips are averaged at 68 %, 68 % and 75 % respectively. The average cross validated RMSEs in all ANN models for both training and testing data are quite small, with values from 0.344 to 0.462. Further, the standard deviation values that range from 0.014 to 0.023 for training and testing data in all models show that the errors in the ANN models are relatively small (Leong et al., 2020).

4.1. Top ten predictors for MaaS use

Fig. 2 presents a summary of the top ten predictors of MaaS use for social trips, general trips, and work trips. Based on the order of importance, the predictors of MaaS use for social trips are employment, Covid-19 impact, children, age, income, public transport seasonal ticket, marital status, travel length, travel time, and qualification. Predictors for MaaS use for general trips are Covid-19 impact, age, car ownership, children, public transport seasonal ticket, employment, travel length, income, marital, and travel time. Predictors for MaaS use for work trips are age, employment, Covid-19 impact, children, qualification, income, marital, travel time, travel length, and public transport seasonal ticket.

Based on these results, we can infer that the preferences are slightly different for different types of trips. For example, car ownership is a top ten most important predictor for general trips but not for social and work trips, and public transport season ticket holding is more influential in MaaS use for social and general trips than MaaS use for work trips. Therefore, different strategies are needed to increase the demand during peak hours when most trips are work trips and off-peak hours when most trips are social and general trips. In particular, different marketing promotion, product, placement and pricing strategies may be needed to target the different market segments for different types of trips.

Regardless, it is important to note that although the relative importance of each variable across the three models may be different, a relatively consistent set of predictors are identified as important irrespective of the purpose of the travel. The important socio-economic factors are age, income, employment, marital status, children, while the important personal travel factors are travel length, travel time, public transport seasonal ticket and change of travel mode due to Covid-19. Education is one of the top ten important predictors for two of the three types of trips while car ownership is one of the top ten important predictors for general trips.

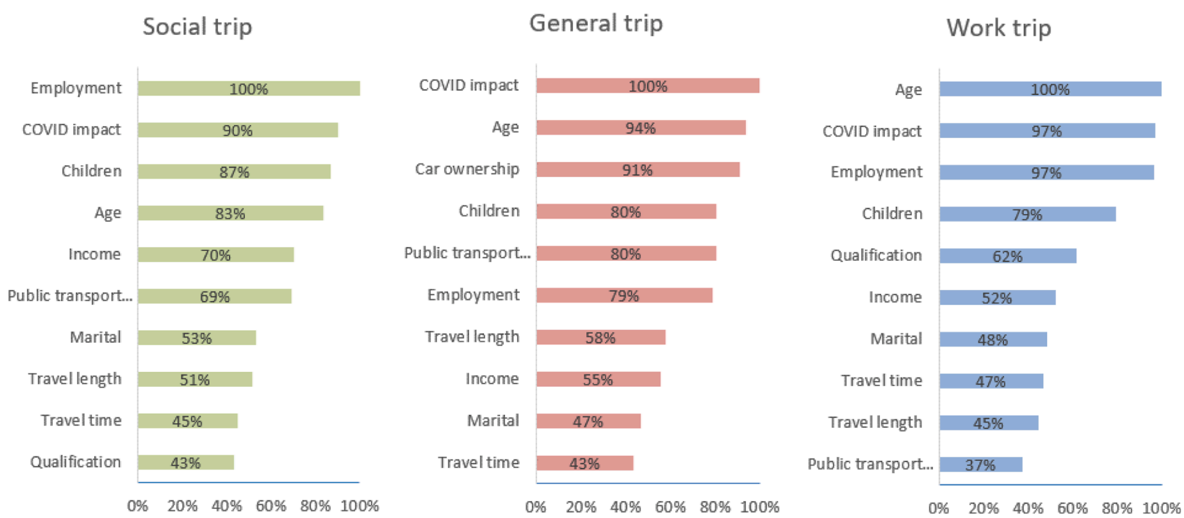

Fig. 2. Top ten relative importance of predictors for MaaS use.

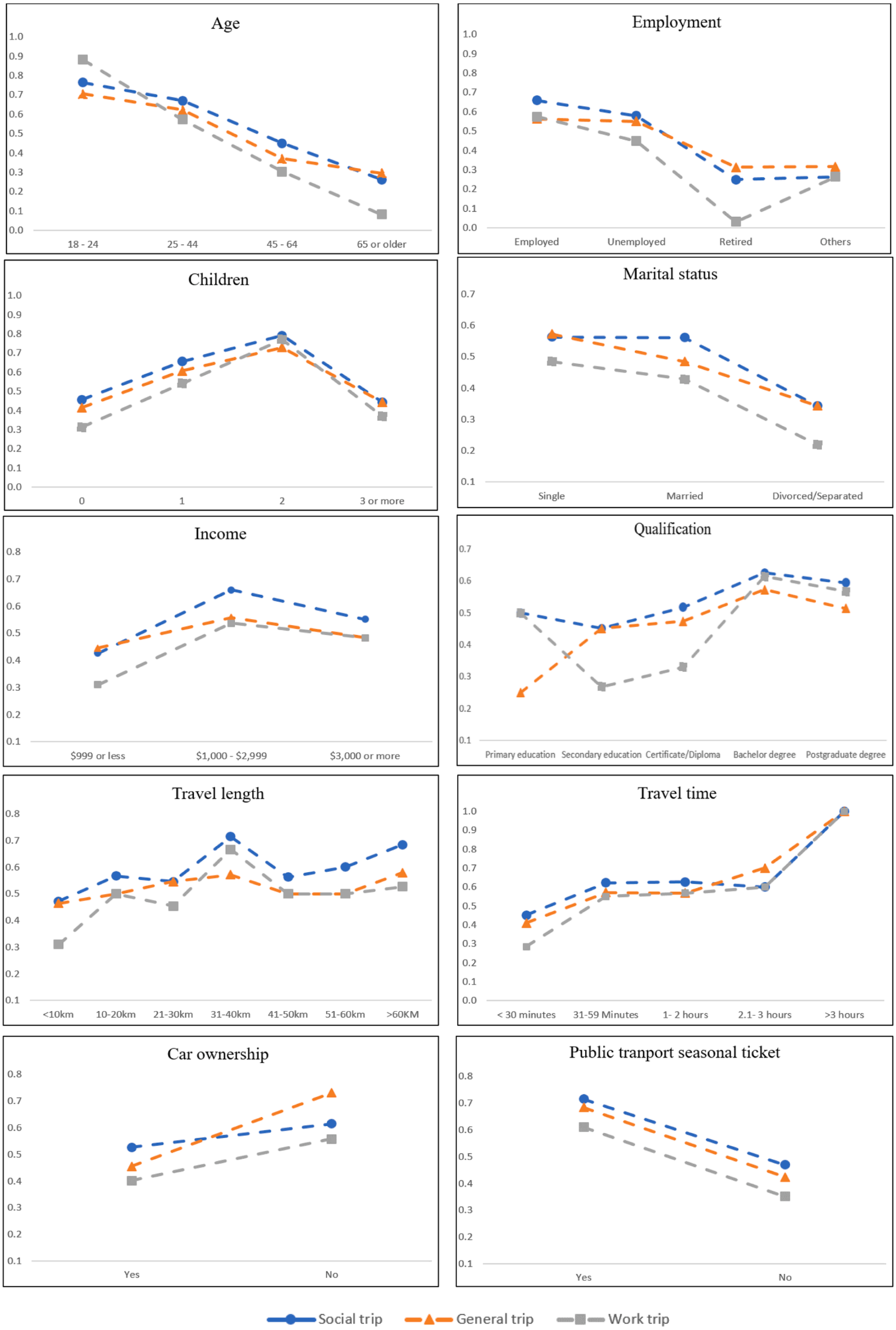

Fig. 3. Comparison of the mean MaaS use intention by key predictors.

4.2. Effects of key predictors

The findings above suggest that out of 33 predictor variables discussed in section 3, socio-economic, Covid-19 impact, and travel pattern and options are the key predictors of MaaS use for general, social, and work trips. To better understand the effects of the above key predictors, the mean MaaS use rates for different levels of the predictors are calculated for each predictor and shown in Fig. 3.

4.2.1. Socio-economic influences

The overall finding from the socio-economic factors is consistent with innovation acceptance and MaaS research where younger (Anshari et al., 2016; Caiati et al., 2020), single (Alonso-González et al., 2020), educated (Zijlstra et al., 2020), and employed (Matyas and Kamargianni, 2021), are most likely to accept innovation. In addition to these results, car ownership is negatively associated with MaaS use for all three types of trips although it is ranked in the top ten only for general trips. This result is expected as car ownership will increase the likelihood of travelling by private cars rather than using active transport, ride-share services or public transport.

Age is the top predictor of MaaS use for work trips and thus has normalised importance (i) of 100 %, the second top predictor for general trips ($i = 94$ %) and is ranked fourth ($i = 83$ %) in predicting MaaS use for social trips. As the age of the respondent increases, a decreasing trend of using MaaS for social trips, general trips and work trips is observed. This finding is in line with Ho et al. (2018) and Caiati et al. (2020) in which younger generations are found to be more interested in MaaS subscription than other age categories. Older people have been travelling in their private cars for a longer time than the younger generation, thus may be more difficult to change their habit and switch to using MaaS (Schikofsky et al., 2020). Another reason could be the close association and the frequent use of smartphones among younger people (Anshari et al., 2016) which facilitate the use of MaaS. Older people also may have a lower propensity for performing complex decisions that are typical in many MaaS services.

Employment status is the top predictor for MaaS use for social trips ($i = 100$ %) and third highest ranked predictor for work trips, with a relative importance of 97 %. When predicting MaaS use for general trips, it is ranked sixth ($i = 79$ %). As shown in Fig. 3, employed people are the most likely to use MaaS compared to unemployed and retired people. This result is expected as employed people usually make more trips and more regular trips because work trips tend to be more frequent and structured in terms of origin–destination, time of travel, transport modes, etc (Matyas and Kamargianni, 2021). Therefore, there is a greater benefit of switching to more efficient or economical ways of travelling.

As shown in Fig. 3, the effect of the number of children on MaaS use is non-linear. The number of children in the household is ranked third in predicting MaaS use for social trips ($i = 87$ %), and fourth in predicting MaaS use for both general trips ($i = 80$ %) and work trips ($i = 79$ %). Specifically, households with two children are more likely to use MaaS compared to other groups. Relative to respondents without children, respondents with one or two children may have a more structured lifestyle and travel demand, which may facilitate the use of MaaS. On the other hand, when a household has three or more children, they are less likely to use MaaS. This could be explained by an increase in the demand for private cars due to their convenience increases as the number of children increases (Ho et al., 2018).

Marital status also has varying effects on MaaS use for different types of trips. Relative to married respondents, married respondents are less likely to adopt MaaS for social trips but more likely to adopt MaaS for general and work trips. The latter result is consistent with previous findings that single, younger, and more educated respondents are likely to adopt new technology (Alonso-González et al., 2020). It should be noted, however, that marital status and its relationship with the number of children nowadays are more complex, including a higher prevalence of same sex marriage, child adoption, single parenthood, etc. These varying interactions may have contributed to the non-linear results in marital status and number of children. More research needs to be conducted to explore the effects of different lifestyles on the decision to use MaaS.

Income ranks 5th in predicting MaaS use for social trips ($i = 70$ %), 8th in predicting general trips ($i = 55$ %), and 6th in predicting work trips ($i = 52$ %). As shown in Fig. 3, income has a non-linear effect on MaaS use. Those with a weekly income of $1,000 - $2,999 are most likely to use MaaS compared with the higher and lower income groups. The finding is consistent with (Hall et al., 2018; Alonso-Gonzalez et al., 2020; Caiati et al., 2020) who suggest that people with middle to high income are the current public transport users and are more open towards accepting alternative on-demand services to complement their public transport usage.

Educational qualification is the 10th most important predictor for MaaS use for social trips ($i = 43$ %) and the 5th most important predictor for work trips ($i = 62$ %). Respondents having a university degree are more likely to be MaaS users. This result is consistent with the finding of Zijlstra et al. (2020) that a higher level of education is associated with better abilities to adopt new ideas and concepts.

4.2.2. Covid-19 impact

Survey participants are asked about their likelihood of changing the mode of transportation post-Covid. The ANN model identified that the likelihood of people changing their post-Covid mode of transportation preference plays a key role in predicting MaaS use across the three trip purposes. It is ranked first for predicting the MaaS use for general trips ($i = 100$ %), and second for both work trips ($i = 97$ %) and social trips ($i = 90$ %). More than two-thirds of the participants indicate that they are either unlikely or uncertain to change their transportation mode for social trips (64 %), general trips (68 %) and work trips (75 %). These results imply that temporary disruptions are not likely to establish habits and most participants feel that they will still maintain their pre-Covid-19 preferences for transportation. This finding is inconsistent with studies that have reported a modal shift from public to private transport due to the health risks associated with Covid-19 (Das et al., 2021). However, we believe that this effect could be temporary and might wither away as more people get vaccinated and the public health risk associated with Covid-19 becomes under control.

4.2.3. Travel pattern and options

Besides socio-economic characteristics, the travel patterns and options of the respondents are also important in determining their intentions to adopt MaaS. As shown in Fig. 3, the effect of travel length on MaaS use is highly non-linear, with a peak around 30–40 km. This result is especially prominent in work trips. This distance may correspond to a round trip from the outer suburbs to the city centre. It also corresponds to a round trip travel time of around 2–3 h, which may also explain the finding that travel time is positively related to the MaaS use. In the city of Melbourne, for example, many of these trips are undertaken by train, which may also explain why public transport season ticket holders are more likely to adopt MaaS, as evident in Fig. 3.

Compared to respondents living in the city centre and inner suburbs, residents living in the outer suburbs have a greater incentive to adopt MaaS because their trips tend to be longer in both travel distance and travel time. Therefore, the perceived benefits are greater for a more efficient and seamless mobility format and scheme that will facilitate the train access using different modes such as car-share and bike-share. Also, relative to residents in the outer suburbs, residents in the inner suburbs may be less likely to take public transport for their daily commute because many public transport services, especially train services, will become congested by the time they reach the inner suburbs. The above challenge is mainly due to the radial transport network and commute trips in major cities like Melbourne and Sydney. Under the existing system, the outer suburbs will house relatively more of the early adopters of MaaS.

5. Contribution

This study makes significant contributions to research and practice. The theoretical contributions are mainly-two folds. First, this research contributes to the existing MaaS research by adding the knowledge of key factors that predict the MaaS use for different purposes of travel. MaaS is designed to meet specific travel needs of individuals (Hensher et al., 2021). Existing MaaS use studies, however, do not differentiate among different trips with travel purposes. This study addresses this significant omission in the literature by identifying the predictors of MaaS use for social trips, general trips, and work trips respectively.

Second, this study makes a methodological contribution to understanding MaaS use. While several studies have explained what might affect MaaS use under various situations, this research is the very first study that adopts ANN for investigating the predictors of MaaS use. Such a study can serve as a good reference for future research where predictive models are needed for understanding technology adoption.

In addition to its contribution to theory, the findings of this research provide important insights to transport policy makers and commercial MaaS operators. This study suggests that early adopters of MaaS tend to be young adults, college educated, employed and middle income. These early adopters should be the target market segment for the early release of the product. To increase the adoption rate, MaaS suppliers may need to focus on product rather than pricing strategies. They may support these early adopters with additional product information to encourage them to use it and then to share their experience with their friends and families.

Another important finding of this study is that the market segments for MaaS use for social, general and work trips are slightly different. This finding also has significant implications for policy and practice. In addition to the different marketing strategies to target the different segments effectively, policy makers may also wish to consider the effect on the transportation system in general. Since work trips occur mainly during peak hours while social and general trips occur more during off-peak hours, any policies or practice to promote the use of MaaS in different segments may also have an impact on the challenge to optimise the transport capacity and utilisation rate to meet peak demand, as well as the corresponding peak-load pricing or price discrimination strategy.

6. Conclusion

Despite the growing policy, market prediction and research interest in MaaS, there are very few successful MaaS business models in the market, the most notable being Whim. Results from experiment indicate that most participants would have purchased the trialled offering if it became available after the trial (Hensher et al., 2021). However, whether users are likely to use MaaS remains an open question.

In this paper, three predictive models with 33 input variables are developed and tested. Of these 33 predictors, only 11 variables related to socio-economic and personal travel factors can predict consumers decision to use MaaS. Overall, consistent with other studies (e.g Alonso-González et al., 2020), individuals who are young, highly educated, having no children, employed and earning middle to high income are more likely to adopt MaaS.

This study has produced predictive models using a machine learning technique to identify the factors that contribute to MaaS use for work, social and general trips. The models show a consistent result across the three trip purposes with more than two-third predictive accuracy. However, several theoretically drawn variables have been found to be not important in predicting MaaS use. While this result could be attributed to the difference between methodologies used, it is too early to preclude the importance of these and other variables that may predict MaaS use.

The implications of the current research for transport policy makers and commercial MaaS operators are that, since socio-economic and personal travel related factors emerged as more important than other factors, marketing and awareness raising campaigns targeting different segments of the population are likely to be effective. Also, while similar sets of predictors are identified for different types of trips, their relative rankings are slightly different for social trips, general trips and works trips. Policies aiming to increase MaaS uptake may have a knock-on effect on the challenges to optimise the network to meet peak and off-peak demands in the various parts of the transportation system.

The study has limitations. Survey participants were given a description of MaaS and a figure that explains it. The purpose of the study is to predict the three scenarios of MaaS. Therefore, future research can spur from this study to compare the performance of ANN with other statistical analyses such as ordered and unordered regression analyses, and structural equation modelling, as well as other machine learning methods such as bagged or boosted decision trees, and random forest. Also, the study could be replicated in the future using a more international sample or samples from other countries to enable comparisons across countries to determine transferability of the model and generalisability of the findings. Furthermore, future research may utilise an existing commercial MaaS instead of a hypothetical service which will increase the validity of the study since respondents will have more accurate and realistic responses based on their personal experience. In addition, further research should consider the inclusion of other variables to produce more accurate and stronger predictive models.

CRediT authorship contribution statement

Sophia Xiaoxia Duan: Conceptualization, Methodology, Data curation, Investigation, Writing – original draft, Writing – review & editing. **Richard Tay:** Conceptualization, Writing – original draft, Writing – review & editing, Supervision. **Alemayehu Molla:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing. **Hepu Deng:** Conceptualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

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

Appendix

See Table A.

Table A
Sample comparison with ABS.

Measure	Item	Frequency	Percentage	ABS Statistics (%)	*p*-value
Gender	Male	136	41.1	49.6	0.2312
	Female	195	58.9	50.4	
Age	18–24	17	5.1	9.2	0.4281
	25–29	42	12.7	10.0	
	30–34	39	11.8	9.9	
	35–39	40	12.1	9.3	
	40–44	43	13.0	8.3	
	45–49	29	8.8	8.8	
	50–54	23	6.9	8.0	
	55–59	13	3.9	8.1	
	60–64	24	7.3	7.3	
	65+	61	18.4	21.1	
Education	Primary	4	1.2	32.4	<0.0001
	Secondary	82	24.8	16.1	
	Certificate/Diploma	112	33.8	21.0	
	Bachelor degree	96	29.0	11.6	
	Postgraduate degree	37	11.2	6.0	
Weekly income	$3,000 or more	29	8.8	3.1	<0.0001
	$2,000 - $2,999	46	13.9	5.1	
	$1,000 - $1,999	101	30.5	22.3	
	Below $1000	155	46.8	60.6	
Car ownership	Yes	279	84.3	76.8*	0.0756

*Based on number of registered passenger cars divided by population who are 20 years and older.

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