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Can MaaS change users' travel behaviour to deliver commercial and societal outcomes?

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Abstract

Mobility as a Service, or MaaS, is a relatively new business model that aims to disrupt the passenger transport industry by integrating existing mobility services into an intuitive smartphone app that allows everyday travellers to search, book, use, and pay for all their transport needs. In a fully integrated ecosystem, MaaS is envisaged to integrate not only travel information and payment, but also mobility services and societal goals to obtain the so-called four levels of MaaS integration. This paper describes the strategies used in the Sydney MaaS trial to obtain all four levels of integration and empirically assess the prospects of having a commercially viable and environmentally sustainable MaaS. Leveraging empirical data collected by GPS-tracking technology, ticketing management systems, and survey questionnaires over the five-month in-field trial of MaaS in Sydney, this paper develops a discrete-continuous modelling system to quantify, for the first time, the impacts of MaaS on users' travel behaviour and extra volume/revenue for shared modes. Based on the quantitative evidence obtained, the paper suggests a new commercial model for MaaS and identifies the likely opportunities and challenges faced by MaaS integrators.

1. Introduction

Mobility as a Service, or MaaS, is an emerging concept that aims to bring together every kind of transport service into a single intuitive mobile app, enabling its users to plan, book, use, and pay for multiple mobility services seamlessly. Simply put, MaaS handles everyday travel needs in the smartest way possible, and users can use MaaS under a pay-as-you-go (PAYG) option; however, what make MaaS truly special is the monthly subscriptions, and hence the term "Netflix of Transport".

MaaS is perceived as the next transport 'revolution' because it represents a value-adding proposition for every stakeholder involved. For users, MaaS represents the best value proposition by helping them meet their mobility needs. For service providers, MaaS promises increasing profits through additional volume. For society, cities, and governments, MaaS promises higher customer satisfaction, lower emissions, and less traffic congestion. For app developers, MaaS represents new challenges and business opportunities. Finally, for investors such as MaaS brokers or integrators, MaaS promises new business models and markets, estimated to be worth hundreds of billions of dollars (Baltic et al., 2020).

With these promising potentials, MaaS is seen as an ecosystem that can offer a way forward for government and other interested parties to achieve a wide range of sustainability objectives such as reducing transport-related emissions and traffic congestion by promoting sustainable travel choices (e.g., reducing private car use and car ownership and increasing active travel and/or use of shared modes). The question is, can MaaS realise its potential in the current market to deliver its promises to the end-users, transport providers and society? Put differently, what is the likelihood of MaaS to change users' travel behaviour towards more sustainable choices while delivering the promised benefit to transport providers involved, and how exactly can this be achieved?

The extent to which MaaS changes users' travel behaviour and delivers commercial value represents a largely unknown area with much speculation and little substantial insight. This is mainly because of the lack of transparency and empirical data, particularly revealed preference (RP) data that can be used to quantify the impact of MaaS on travel behaviour and sustainability goals. With few exceptions (see review below), early studies investigated how MaaS may change travel behaviour based on stated preference (SP) data (Matyas and Kamargianni, 2019), self-reported data (Sochor et al., 2015, Strömberg et al., 2018, Storme et al., 2020, Fioreze et al., 2019), and qualitative data (Smith et al, 2021). While these studies undoubtedly offer useful evidence for evaluating the potential of MaaS to change travel behaviour and promote green(er) travel choices, the evidence should be taken with caution due to the nature of the underlying data based on which the analysis was conducted.

Specifically, SP data may suffer from a well-known hypothetical bias (see Hensher et al 2015), especially when the respondents have no prior experience with the product (i.e., MaaS) that they were asked to express their preferences (either by ranking all products or selecting the most preferred option, or a variant thereof). By contrast, while self-reported data such as travel diaries are regarded as a standard way to collect RP data for estimating travel demand, these data sources are known to have many limitations in estimating travel behaviour changes because people tend to under-report short trips while exaggerating certain aspects such as the time spent walking, driving or using public transport (PT) due to rounding effects (Gerike et al., 2015). Similarly, while qualitative data are undoubtedly useful for identifying themes or topics that are worth further analysis, qualitative analysis cannot estimate the magnitude of change, which is required to establish the case for MaaS, either as a new business model (Polydoropoulou et al., 2020) or a mobility management tool (Mulley, 2017) to achieve societal outcomes. This prompted us to undertake an in-field trial of MaaS in the Sydney Greater Metropolitan Area (SGMA) to verify MaaS potentials, including societal outcomes and commercial prospects.

This work aims to quantify the impacts of MaaS on travel behaviour and volume for shared modes by analysing the usage data collected by the Sydney MaaS trial which offers the highest integrated MaaS product with monthly subscription bundles along with PAYG option. During the five-month in-field trial, 93 customers used MaaS for their everyday travel and undertook more than 15,000 trips by almost all transport services found in SGMA. This unique dataset allows us to verify the impact of MaaS uptake on not only private car use but also other shared modes including PT, ride-hailing, car-sharing and car-rental such that the net impact on car-based and shared modes can be quantified. Obtaining quantitative evidence is important for many reasons, ranging from pricing MaaS subscription bundles to assessing MaaS commercial prospects and sustainability outcomes.

The remainder of this paper is structured as follows. The next section briefly describes the Sydney MaaS trial, followed by a description of the methodology, including datasets and analysing techniques. Modelling results are then presented, followed by an assessment of commercial prospects where the developed models are applied to predict the impact of MaaS subscription bundles on demand for shared modes and the private car as well as all car-based modes. The paper ends with key conclusions and discussion on the pathway to commercialise MaaS.

2. The Sydney MaaS trial

2.1. The system architecture

The trial was an R&D project financially funded by iMOVE Corporate Research Counsel. The trial was set up with a tripartite structure in which SkedGo acted as the MaaS app developer, leveraging their existing white-label TripGo app and adding extra features to create a Tripi app for the participants to use during the in-field trial period. The University of Sydney's Institute of Transport and Logistics Studies (ITLS) took the project management role, leading the study design and working closely with the IAG MaaS team to conduct pre-trial surveys, qualitative interviews, design of subscription bundles and app feature, data management, integration, processing, analysis, and reporting to iMOVE as a co-sponsor. Finally, IAG was the industrial leader and a mobility broker, procuring and offering MaaS products to the end users with support from both ITLS and SkedGo.

The trial placed the customers at the centre of the MaaS offering with five objectives. First, to explore the mixes of transport services desired by the users. Second, to design and assess mobility subscription bundles in terms of their potential to promote sustainable choices. Third, to verify potential uptake and willingness to pay (WTP) for MaaS bundles in the real world setting of the Sydney transport networks. Fourth, to assess MaaS potential in achieving societal goals through

promoting greener travel choices. Fifth, to assess the prospects for commercialisation of MaaS post-trial. A detailed exploration and evaluation of the first objective is reported in Ho, Hensher, Reck, Lorimer, & Lu (2021b) while Hensher, Ho, & Reck (2021a) evaluates the second objective using car usage data from a subset of the trial participants. This paper mainly focuses on the last two objectives with the aim to quantitively assess the extent to which MaaS could live up to its promises. To this end, the paper measures the impacts of MaaS on travel behavioural changes and discusses various ways in which MaaS could proceed to the commercial phase.
The Sydney MaaS trial is a world-first study that is able to obtain the top level of MaaS by integrating not only information (Level 1), booking and payment (Level 2), services (Level 3) but also societal goals (Level 4) as summarised in Figure 1. The readers are referred to the work of Sochor, Arby, Karlsson, & Sarasini (2018), Lyons, Hammond, & Mackay (2019) and Ho, Hensher, Reck, et al. (2021b) for an in-depth discussion of MaaS integration levels and example products of each in the current mobility market.

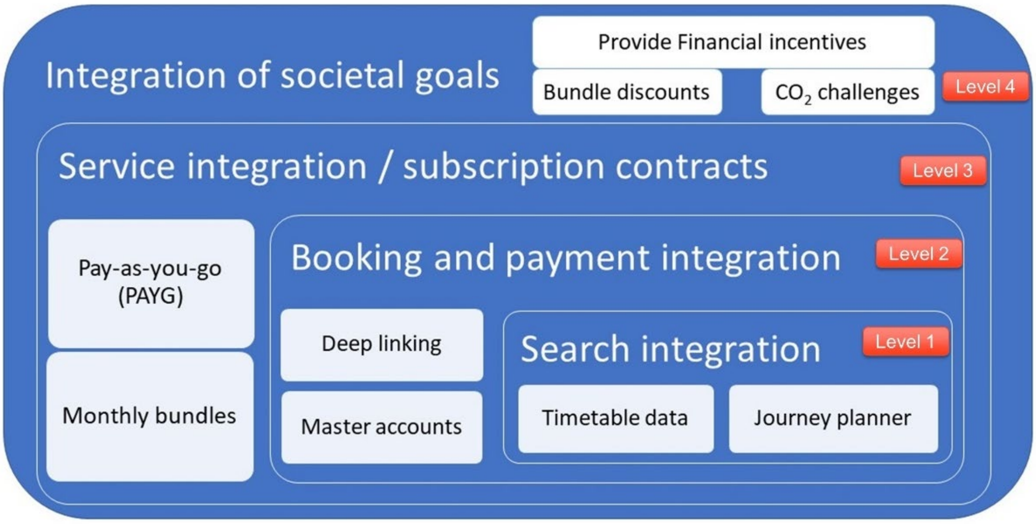

Figure 1. The Sydney MaaS Trial: System Architecture

Briefly, the Sydney MaaS trial obtained an integration of information through the Tripi app which offered a multi-modal journey planner function for its users to search for available mobility services when they needed to travel from A to B. Booking and payment integration (Level 2) was achieved by using a deep-linking method and a master account built into the Tripi app. The former allowed Tripi users to book mobility services from within the app while the latter allowed all payments to be made whenever they were due (i.e., some were in real-time while some were in a periodical manner). An integration of services (Level 3) was obtained by offering the users not only a PAYG option but also monthly subscription bundles that included multiple services, ranging from all public transport modes to car-based shared modes and covering almost all types of mobility found in Sydney, except for bike-sharing (see Ho et al., 2021b). Finally, the trial integrated societal goals (Level 4) by incentivising MaaS users for using (or continuing to use) sustainable travel modes. Incentives were provided regularly through subscription bundles with built-in discounts, but also through ad-hoc green travel initiatives such as emissions buster. The latter is, in essence, a CO_2 challenge formulated as a gamification or 'nudging' feature whereby all participants would receive $1 for every 1% reduction in the group CO_2 emission. That is, a gamification was designed as a group challenge with equal personal rewards. We hope to report on the assessment of using gamification in MaaS design in future work.

2.2. The customer journeys

The trial was scheduled as a six-month in-field experiment of mobility services where users used the customised smartphone app (*Tripi*) to plan, book, use, and pay for all transport services included in the trial, either as a PAYG user or a monthly subscriber. Figure 2 summarises the Sydney MaaS trial journey from the customer perspective. The graph on the bottom left of Figure 2 shows the progress of on-boarding the participants to the in-field trial, while the graph on the bottom right shows the distribution of incentive cost per subscriber per month. Most subscribers saved about $20 to $30 per month while PAYG users saved $0 (due to no discount and no subscription fee).

As bundle design and individual bundle choices have been analysed in previous work (Ho et al., 2021a, Ho et al., 2021b), it is sufficient to mention that the trial successfully segmented the market with each bundle targeting one market segment. The SuperSaver25 bundle, which replaced its predecessor – the Saver25 – targeted infrequent public transport users with one or two Uber/Taxi trips per fortnight. The Fifty50 bundle was aimed at frequent public transport users with an odd Uber/Taxi trip whilst the GreenPass bundle targeted heavy public transport users. Since introduced, each subscription bundle successfully segmented the market by attracting PAYG users instead of existing bundle subscribers. Consequently, the percentage of subscribers increased substantially as more bundles were added, and by March 2020, the final month of the subscription period, 57% participants used MaaS as monthly subscribers, with the balance being on PAYG. The GreenPass bundle saw the most growth and was also the one promoting the most sustainable travel ($125 for unlimited use of public transport).

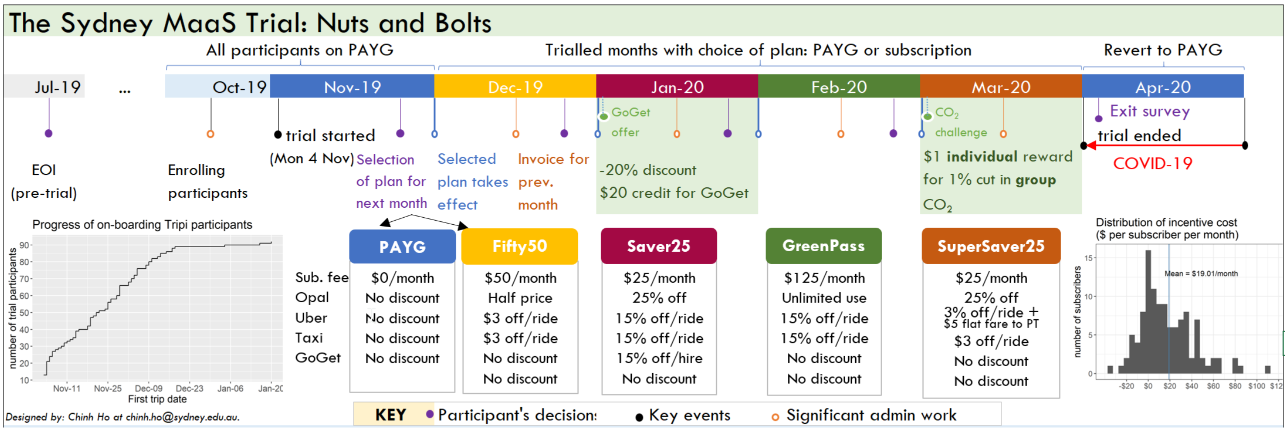

Figure 2. The Sydney MaaS trial: Customer journey

While promising, it is not clear from the descriptive statistics as to whether higher bundle uptake translates to more sustainable choices. Put differently, whether the benefits of achieving travel behaviour changes through the provision of financial incentives built-in to subscription bundles is worth the incentive costs. This work aims to answer this question using quantitative analysis of the data collected throughout the 5-month in-field trial period. The methodology is described below.

3. Methodology

3.1. Data processing and descriptive statistics

The Sydney MaaS trial collected many datasets using tracking methods and conventional survey questionnaires, both qualitatively and quantitatively. The work used three main datasets, namely usage dataset, subscription dataset, and the pre-trial survey dataset. This sub-section describes these datasets and provides some descriptive analysis.

The *usage dataset* is a tracking/booking data at the trip level, recording all trips that each trialled participant made on all transport modes included in Tripi for five months. This dataset was enriched by the GPS-tracking data for the private car usage for a subset of the participants who were also the users of *Safer Journeys* app, a complementary program independently implemented and managed by IAG before the MaaS trial (see Hensher et al., 2021 for more details). The usage dataset had a total of 15,615 trips, with 9,599 trips made by the participants using the mobility services provided by the MaaS trial (the balance was by the private car). As a booking dataset, the usage dataset included fields that represent customer ID, transport mode, departure time, arrival time, cost to MaaS provider (i.e., non-discounted cost) and cost to user (discounted cost), trip origin, destination, and trip distance for some of the car-based modes (private car, car-sharing, car-rental).

The usage data were processed to add fields on trip distance (for all modes, including PT) and CO_2 emissions. To this end, the origin and destination of each trip were geocoded to obtain the locations in latitude and longitude, which were then used as an input into a routing algorithm developed by the author and realised via ESRI's ArcMap v10.8 for PT modes and Google Map for taxi and Uber to obtain travel distance and travel time. As for GoGet car-sharing and Thrifty car-rental trips, odometer readings before and after each hire were used to compute the total kms for each trip. CO_2 emissions for every trip was then computed as the product of distance travelled and the emission rate for the corresponding mode, using the same emission rate (grams of CO_2 per passenger km or per vehicle) that the *Tripi* app used internally to compute and show the CO_2 emissions for each transport option (see SkedGo, 2019).

The *subscription dataset* registered the monthly bundles, including PAYG, each participant subscribed to for each month. Data fields included participant ID, month, and the mobility bundle each participant subscribed to. Combined with the usage dataset described above using participant ID as the key, the subscription bundle information allowed Tripi to apply correct discounts for difference services (i.e., trips) the participant entitled to via their selected bundle. This dataset was used to model user's choice of monthly bundles in Ho, Hensher, & Reck (2021a).

The *pre-trial survey dataset* included, among other things, socio-demographics, residential and work locations, and household structure of 238 respondents who expressed their interest in participating in the in-field trial, from which 100 participants were invited to join and assigned a unique participant ID. The data were collected using a self-administered online survey method which took approximately five minutes to complete. This dataset was enriched by the NSW public transport accessibility level (PTAL) by geo-coding the respondent's residential location and spatially intersecting this with mesh-block (MB) polygons in the PTAL dataset. This spatial analysis resulted in an addition of 24 sets of indices, known as *PTAI,* that measured how well the place is connected to PT services by every hour of the day. PTAL and PTAI are well documented and have been used in various planning projects for many years (see Transport for London, , 2016 for details). This work uses the minimum, maximum, mean, and median of PTAI for modelling analysis. Looking ahead, the median PTAI was adopted in modelling as there are strong correlations amongst the four PTAI metrics and the median PTAI results in the best models, according to model goodness of fit statistics.

The enriched pre-trial survey data was integrated with the usage and subscription datasets into a format ready for modelling of bundle choices and monthly counts. Table 1 shows descriptive statistics of the sample. The variables *mkm_pt* to *m_trpcb* are the dependent variables of the count models. The variables *ppayg* to *ps25* are the outcomes of the choice model for monthly bundle subscription, with the remaining variables being potential explanatory variables for both discrete choice and count models. The following sub-section describes the modelling method.

Table 1: Sample profile

Variable	description	Mean	Std. Dev.	N
mkm_pt	monthly kms by PT	403.839	360.045	397
mkm_tx	monthly kms by taxi and Uber	17.378	38.894	397
mkm_gg	monthly kms by car-sharing GoGet	8.456	68.79	397
mkm_cr	monthly kms by car-rental	12.526	114.296	397
mkm_ca	monthly kms by private car	150.582	411.332	397
mtrp_pt	monthly trips by PT	26.403	17.338	397
mtrp_tx	monthly trips by taxi and Uber	2.244	4.242	397
mtrp_gg	monthly trips by car-sharing GoGet	0.312	1.873	397
mtrp_cr	monthly trips by car-rental	0.033	0.228	397
mtrp_ca	monthly trips by private car	12.582	24.916	397

mtrp_cb	monthly trips by car-based modes	15.171	24.653	397
mkm_cb	monthly kms by car-based modes	188.942	426.72	397
ppayg	probability of choosing PAYG	0.704	0.32	397
p50	probability of choosing Fifty50 bundle	0.136	0.152	397
pgp	probability of choosing GreenPass bundle	0.056	0.106	397
p25	proability of choosing Saver25 bundle	0.075	0.182	397
ps25	proability of choosing SuperSaver25 bundle	0.029	0.088	397
adults	#adults in household	2.196	0.83	397
kids	#kids under 18 in household	0.816	0.929	397
caracc	has daily access to private car dummy	0.776		397
hhdriv	#drivers in household	1.947	0.778	397
hhcar	#cars in household	1.249	0.785	397
haslic	has a valid driving licence dummy	0.899		397
age24	age <= 24 years dummy	0.043		397
age34	age 25-34 years dummy	0.335		397
age44	age 35-44 years dummy	0.38		397
age54	age 45-54 years dummy	0		397
age64	age 55-64 years dummy	0.053		397
male	male participant dummy	0.479		397
nwdays	#weekdays in month	17.171	6.126	397
nwends	#weekends in month	6.887	2.425	397
Nov	November dummy	0.166		397
Dec	December dummy	0.224		397
Jan	Janurary dummy	0.217		397
Feb	February dummy	0.202		397
Mar	March dummy	0.191		397
ptai_max	Best PTAI of the day in the mesh block (MB)	33.78	29.022	388
ptai_med	Median PTAI of the day in the MB	23.93	21.929	388
ptai_min	Worst PTAI of the day in the MB	3.099	2.803	388
ptai_ave	Average PTAI of the day in the MB	21.08	17.96	388
sj_user	*Safer Journey* user dummy	0.375		397

3.2. Modelling approach

To address the research questions, we need to quantity the impact of individual choices of monthly mobility bundles on their monthly consumption of various transport modes, controlling for potential confounding factors, such as socio-demographics and public transport supply or level of service, that may impact individual travel demand, or more precisely trip generation. The requirement to control for confounding factors dictated a multivariate analysis that this work follows. The adopted modelling approach involves a system of two models: (i) a discrete choice model describing individual choices of monthly bundle and (ii) a count model describing the number of monthly trips (or kms) by each mobility service. The method used herein extends previous work by Hensher, Ho, and Reck (2021) in three ways. First, the discrete choice model represents each mobility bundle as a separate arrangement (or alternative), allowing us to verify whether different subscription bundles impact travel behaviour differently. This extension is important because the mobility bundles, by design, target different segments of the population, and some bundles may have been more successful than others in altering travel behaviour towards more sustainable choices. Second, the count model extends the regressors to include public transport supply measures and spatial variables so that the spatial effect on mobility consumption can be quantified. This extension is important to evidence the speculation that MaaS may benefit inner city residents, with the benefits fading away as we move further to the outer areas where parking is abundant and public transport level of service is lower. Finally, this work assesses the impact of MaaS on the demand for all mobility services included in the trial using two different metrics for demand (monthly kms and trips) instead of limiting to the private car kms as in Hensher et al (2021). The aim is to paint a big picture as to how MaaS may benefit different mobility providers differently. The discrete choice model is described in detail in Ho, Hensher, and Reck (2021a). Once this model is estimated, the predicted probabilities that an individual chooses different mobility bundles, including PAYG, are fed into the count model as instrumental variables so that the impact of monthly bundle subscription that is purged of the self-selection attitudinal/preference component on monthly trips and monthly kms by transport mode can be quantified (see Mokhtarian and Cao, 2008). The count model is specified either as a basic Poisson, a Negative Binominal (NegBin) or a Zero-inflated negative binominal (Zinb). That is, for a discrete random variable, Y, observed over a period of length T_i, and observed frequencies, y_i for an individual i =1,…,n, where y_i is a non-negative integer count, and regressors $\mathbf{x}_i$ (including the choice probabilities), the three models are (see Cameron and Trivedi, 1986 and Greene, 2011 for more details):

Poisson: $$Prob(Y = y_i|\mathbf{x}_i) = \frac{exp(T_i\lambda_i)(T_i\lambda_i)^{y_i}}{y_i!}, y_i = 0,1,\ldots;\ log(\lambda_i) = \boldsymbol{\beta}'\mathbf{x}_i. \quad (1)$$

NegBin $$Prob(Y = y_i|\mathbf{x}_i, \varepsilon_i) = \frac{\theta^{\theta}\lambda_i^{y_i}}{\Gamma(\theta)y_i!}.\frac{\Gamma(y_i+\theta)}{(\lambda_i+\theta)^{y_i+\theta}}, y_i = 0,1,\ldots;\ log\lambda_i = \boldsymbol{\beta}'\mathbf{x}_i; \quad (2)$$
$$log\mu_i = log\lambda_i + \varepsilon_i.$$

Zinb: $$Prob(Y_i = 0) = q_i + (1 - q_i)\,R_i(0) \quad (3)$$
$$Prob(Y_i = y > 0) = (1 - q_i)\,R_i(y)$$

where λ_i is the variance of y_i *per unit of time* T_i; μ_i is the conditional mean, ε_i is the heterogeneity, $\theta = 1/\alpha$ is the over-dispersion parameter, $\Gamma(\cdot)$ is the gamma function, and q_i is the ancillary probability, described by a binary logit $q_i = \Lambda(\gamma'\mathbf{z}_i) = \frac{\exp(\gamma'\mathbf{z}_i)}{1+\exp(\gamma'\mathbf{z}_i)}$, or binary probit model $q_i = \Phi(\gamma'\mathbf{z}_i) = \int_{-\infty}^{\gamma'\mathbf{z}_i}\frac{\exp(\frac{-t^2}{2})}{\sqrt{2\pi}}dt$ with γ being a vector of parameters to be estimated for a set of variables $\mathbf{z}_i$ which may or may not share with $\mathbf{x}_i$.
All three variants of the Poisson models for count data described above were tested with the empirical data. The estimation results and statistical tests are presented below.

3.3. Estimation results

The estimation results of the discrete choice model for monthly bundle subscription are reported in Ho et al (2021). Therefore, this paper reports the estimation results of the count models as specified in Eq. (1), (2), and (3). Both *Nlogit* and *R* (packages ***pscl, MASS***, and ***margins***) were used for model estimation to enjoy the best of both worlds. Specifically, we used *Nlogit* to explore many variants of model for count data, including models for under-dispersion such as the Gamma model (Winkelmann, 1995) that are not described herein. Once the best model formulation was found, *R* programming language was used for bulk estimation and visualisation. A total of 30 models were estimated, covering three variants of count model (Poisson, NB, and ZINB), five transport modes (PT combined, Taxi/Uber, private car, GoGet, and car-based) and two metrics of monthly statistics (trips and kms).
Figure 3 compares the performance of different model specifications for counts of monthly trips by transport service included in the empirical data. All PT services (bus, train, ferry, light rail, BRIDJ on-demand bus) were combined into one group while the ride-hailing group included taxi and Uber. The private car and GoGet car sharing had its own group, which are combined with the Thrifty car-rental mode to form all car-based modes. Car-rental by itself does not have enough non-negative observations to estimate a separate model. Figure 3 shows that the negative binomial (NegBin) and the zero inflated negative binomial (Zinb) models approximate the empirical data quite well, with

their predicted probabilities almost overlapping with the observed probabilities for monthly count of trips by mode. The same patterns are observed for the counts of monthly kms by mode.

The estimation results of the preferred models for counts of trips and kms by mode are not presented herein for space limitation (available on request). In short, where a Zinb model can be estimated, a Vuong test statistic for non-nested models (Vuong, 1989) conclusively rejects the Poisson and NegBin specifications (*p-value* <0.001); however, for GoGet car-sharing, we failed to fit a Zinb model, presumably due to a small number of observations with a positive count of monthly GoGet trips/kms. Thus, a NegBin model was adopted for monthly count of GoGet trips and kms, which rejects the Poisson model at 99% level of confidence using a log-likelihood ratio test for nested models.

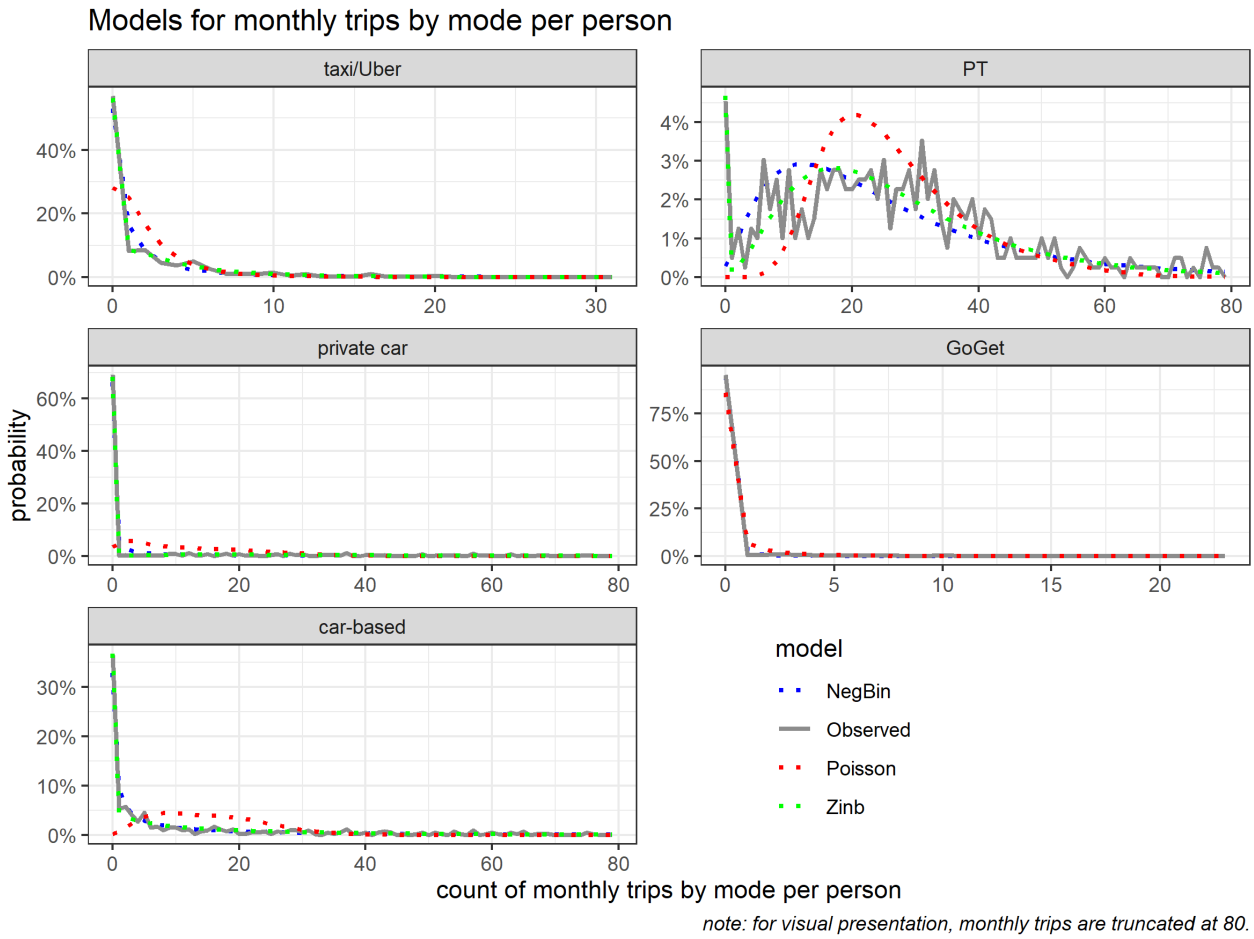

Figure 3. Model performance: comparing predictive power of different model specifications for monthly trips

As non-linear model parameters are not very meaningful, this paper does not provide an interpretation of coefficient estimates. Instead, the magnitude of the impact is interpreted through a concept known as *marginal effect* or *partial effect,* defined as the partial derivative of the conditional mean function with respect to the variable of interest. For the highly non-linear ZINB model with a log link splitting function (i.e., the zero-inflated model is specified as a binary logistic), the marginal effects are computed as follows (see Greene, 2017) using the command **partials** in *Nlogit* or **margins** in *Stata/R*:

$$\frac{\partial E[y_i|\mathbf{x}_i, \mathbf{z}_i]}{\partial \mathbf{x}_i} = (1 - q_i)\lambda_i \boldsymbol{\beta} - \lambda_i \frac{\partial q_i}{\partial \mathbf{x}_i} = (1 - \Lambda(\gamma' \boldsymbol{z}_i))\lambda_i \boldsymbol{\beta} - \lambda_i \Lambda(\gamma' \boldsymbol{z}_i)[1 - \Lambda(\gamma' \boldsymbol{z}_i)]\gamma \quad (4)$$

where $\Lambda(\gamma' \boldsymbol{z}_i)$ is defined under Eq. (3).

For complicity, the marginal effects of the NegBin and Poisson models are:

$$\frac{\partial E[y_i|\mathbf{x}_i]}{\partial \mathbf{x}_i} = \lambda_i \boldsymbol{\beta} = exp(\boldsymbol{\beta}'\mathbf{x}_i)\boldsymbol{\beta} \tag{5}$$

Table 2 presents the AME of each regressor on the monthly count of trips and kms by mode for all models shown in Table 1. For continuous variables, the marginal effects represent the change in the expected count of trips/kms for one unit change in the value of the regressor. For dummy variables, the marginal effects represent the change in the expected counts when the corresponding dummy switches on and off (AME = E[y|x,d=1] - E[y|x,d=0]). Of most interest are the AMEs of the probability of subscribing to a monthly bundle (*p50, p25, pgp, ps25*) on monthly trips/kms. As an example, the significant AME of the *p50* variable (in the first row) on monthly count of PT trips (in the fourth column) indicates that *on average*, monthly PT trips per participant will increase by 7.65 trips if the probability of choosing the Fifty50 bundle increases by 0.10 (or 10% probability points, from for example .1 to .2 or from .3 to .4). For the same change in the choice probability of the Fifty50 bundle, the effects on monthly PT kms and private car kms are +106 km and −70 km, respectively. Across the four subscription bundles offered, it appears that the GreenPass and SuperSaver25 bundles increased taxi/Uber use, while the Fifty50 and Saver25 bundles increased PT usage. All bundles appeared to reduce private car use, except for the SuperSaver25 whose effects are small and not significant. Interestingly, the GreenPass bundle that offered unlimited PT use did not increase PT usage, neither did the SuperSaver25 that offered a $5 flat fare for the subscribers to use Uber to connect to/from PT services. Indeed, their effects are negative but insignificant. Respondents having daily access to a private car (*caracc*), on average, used taxi/Uber about 7 km less and the private car 42 km more than those who did not have private car access. The variation in PT accessibility level (*ptai_med*) across the participants' residential locations did not appear to influence monthly count of trips and kms the participant undertook, except for taxi/Uber kms where the impact is significant but negligible. One possible explanation is that the variation in PTAL across the sample is small, which would require a much larger sample size to deliver significant estimates.

Table 2. Estimated Average Marginal Effects (AME) on monthly counts of trips and kms by mode (significant AMEs are in **bold**)

	Taxi/Uber		PT		Private car		Car-sharing		Car-based modes	
factor	**trips**	**kms**	**trips**	**kms**	**trips**	**kms**	**trips**	**kms**	**trips**	**kms**
p50	0.77	12.8	**76.53**	**1059.8**	**-40.11**	**-699.69**			**-26.29**	**-499.93**
pgp	**11.87**	**89.56**	-15.64	-1020.8	**-51.8**	**-910.36**	0.03	-282.9	11.14	185.45
p25	0.19	-10.77	**30.37**	**476.5**	**-28.34**	**-564.79**	0.03	-282.9	**-10.73**	**-315.94**
ps25	**12.27**	**70.26**	-7.17	-459.9	6.91	35.4			28.96	345.68
nwdays	-0.19	-2.09	0.49	35.8	-0.59	9.48			0.36	20.2
nwends	**0.26**	2.82	-1.35	-88.8	4.88	28.53			1.4	-8.82
Dec#	0.14	2.78	-13.88	-150.7	4.02	92.47			3.82	75.27
Jan#	-1.4	-7.62	**-12.78**	**-156.1**	7.47	65.51	0.13	289.5	-0.42	-56.34
Feb#	-2.85	-21.15	-15.91	-57.3	12.12	223.9			3.7	52.46
Mar#	-4.58	-33.39	**-15.41**	**-39.7**	18.73	300.86			5.39	74.65
age34#	1.03	5.98	**-4.08**	**8.3**	-0.11	-4.5			3.97	86.9
age44#	0.77	2.96	-3.95	77.7	6.28	135.61			**7.82**	**144.45**
age64#	1.3	9.37	-10.52	-13.5	-0.91	63.95			1.41	81.75
ptai_med	0.03	**0.19**	-0.01	-5.1	-0.18	-4.39			-0.02	-0.71
male#	0.21	0.17	2.88	-104.0	-3.95	-92.65	0.08	-75.5	1.15	-30.63
kids	-0.65	-3.29	-2.72	-6.9	0.05	12.42	-0.09	-145.6	-1.77	11.28
caracc#	-0.82	**-6.96**	-11.82	-229.2	**10.31**	**41.96**	-1.38	-738.8	7.99	-2.79
sj_user#									**46.72**	**149.42**

Note: # indicate dummy variables.

4. Discussion and conclusions

Despite the fast-growing literature, MaaS is still a relatively new business with very few trials and commercial products. To date, several MaaS pilots and commercial operations have been commenced or initiated in various places (see Hensher et al., 2020 Chapter 4); however, UbiGo and Tripi are the only two trials of MaaS that have been transparently documented and independently evaluated to help advance our understanding of the challenges associated with MaaS and its future, including the potential to alter travel behaviour towards more sustainable choices. On this topic, most previous work focuses on changes to the private car use and/or car ownership. This is comprehendible because MaaS was initially conceptualised as an alternative to the private car. However, the impacts of MaaS on travel behaviour are expected to be much wider as MaaS also promises higher volume for shared modes. From the conceptual perspective, MaaS combining services across multiple modes in the most effective way possible can affect mode choice but also trip generation. Put differently, MaaS may help users meet the so-called *induced demand* which is, in essence, the travel demand that is unmet in the current market where different transport services are operated and priced in silo. Using the tracking and booking data from the Sydney MaaS trial, this work has shown, for the first time, that MaaS with subscription bundles can generate extra volume, and hence revenue, for shared modes. Also, this impact varies significantly across the subscription bundles and the shared modes.

Within the limit of the trial which designed and procured four monthly subscription bundles, this study found that the two bundles aimed at promoting PT use among the heavy and the infrequent PT users (i.e., the GreenPass and SuperSaver25 bundles, respectively) benefited Uber and taxi providers more than PT providers. The GreenPass bundle, which charged subscribers \$125 subscription fee per month for unlimited use of PT (cost ~\$200 to provide), plus a \$3 discount for every taxi/Uber trip, is estimated to have brought an extra 90 kms (average marginal effect = 89.56) for taxi and Uber per subscriber per month while the impacts on PT trips and kms were not statistically significant. The SuperSaver25 bundle (which charged a subscription fee of \$25 per month and offered affordable and convenient first/last mile service with unlimited \$5 Uber flat fare trips to connect to PT services whose fares are discounted by 25%) delivered a similar benefit for taxi and Uber services (an extra 70 kms per subscriber per month) while the SuperSaver25 subscribers' use of PT did not statistically differ from that of PAYG users (who paid per ride with no discounts and no subscription fee). Conversely, the remaining two bundles, Fifty50 and Saver25, were found to increase PT use significantly, with an average marginal effect of 76.5 trips (1,060 km) and 30 trips (477 km) per subscriber per month, respectively. Their impacts on taxi, Uber, and car-sharing volume, however, were negligible and insignificant.

These findings suggest that a commercially viable business model for MaaS should carefully develop a cross-subsidy strategy in that the benefits gained from one or multiple services are used to support the loss-making service(s) to create attractive mobility bundles. Taking the GreenPass bundle as an example, it costs the MaaS operator a maximum of \$200 per month to provide unlimited use of PT to each subscriber in Sydney in the current fare system (capped at \$50 per week). Charging a subscription fee of \$125 per month means that providing PT services to subscribers would see the MaaS operator makes a maximum loss of \$75 and an average loss of \$30 per subscriber per month. The extra patronage/revenue for PT, however, is effectively zero (i.e., statistically insignificant) while the extra revenue for taxi/Uber is significant (average of 89.56 kms / 11.87 trips per subscriber per month, see Table 2). This translates to an extra revenue for taxi/Uber services of around \$225 per subscriber per month after discounts, using a regression formular (\$3 + \$2.5 per km) estimated from the booking data to calculate taxi/Uber fare (i.e., 11.87 trips *(3+2.5*7.5 km) – 11.87 *\$3 discount = \$225 where the average trip distance is 89.56/11.87 = 7.5 km/trip). If 20% to 40% of this extra revenue could be used to build financial incentives into monthly bundle offers, MaaS operators would make an *operational* profit, even before the benefit of reduction in CO_2 emission is priced in. The challenge is how to build trust and collaborations with transport providers so that profits and losses can be mobilised across services to obtain MaaS products that are commercially viable and scalable. This is a big question and with the evidence produced herein, we hope to initiate the discussion and contribute to the debate.

When it comes to achieving societal goals, such as reducing traffic congestion and CO_2 emission, it is the net impact of MaaS on car-based modes that matters because any reduction in the private car use may be offset by an increasing use of other car-based shared modes such as car-sharing, car-rental, uber and taxi. This offset effect is possible as Strömberg et al (2018) and Smith et al (2021) find qualitative evidence from the UbiGo and EB2C MaaS trials, respectively that indicates participants replace not only private car trips but also PT trips with car-sharing and bike-sharing services. To this effect, this work has found quantitative evidence of this offset effect, but the net impact of MaaS subscription bundles on the use of car-based modes is still negative (i.e., reducing car-based kms). This is a very promising and important finding, as it shows for the first time and with empirical evidence, that MaaS bundles can reduce car-based kms travelled.

Another potential benefit of MaaS that can be associated with societal goals relates to reducing CO_2 emission. To this end, a before and after analysis (not presented herein due to space limitation) has shown that for every dollar spent on incentivising subscribers, the society obtains an environmental benefit of 3 kg reduction in CO_2 emission. While this represents a significant environmental benefit, the incentivise cost is still much higher than the carbon tax in Australia ($23 per cubic tonnes) and other OECD countries (ranging from $4 to $140 per cubic tonnes) (OECD, 2019). Thus, environmental benefits of MaaS alone would not be enough to justify the cost of incentivising MaaS users, not to mention the operational costs of running the service at scale in terms of customer service, supplier relationship and integrations, and improving the app along the way. Thus, finding ways to capitalise on the extra revenue/volume that MaaS brings about for shared modes and the environmental benefits are critical to fund MaaS commercialisation. A potential commercial model is the Public Private Partnership (PPP) where the public sector funds societal objectives and the private sector commercialises MaaS. Within the scope of this trial, it is evidenced that MaaS could be profitable if sustainability improvements (e.g., CO_2 reductions) are priced in, together with extra volume/revenue for transport service providers involved.

Without public funding and cross-subsidy, MaaS might still be commercially viable if it is carefully designed to target the segments that have the highest potential to deliver commercial outcomes. For example, if the objective is to increase the fare box revenue for PT, MaaS operators should identify the population segments that are more likely to take up the Fifty50 and Saver25 bundles (frequent PT users with some odd taxi/Uber trips and infrequent PT users with one or two taxi/Uber trips per fortnight (see Ho, Hensher, & Reck (2021a)) and design attractive bundles that maximise uptake (see Ho, Hensher, Reck, et al. (2021b)) by minimising financial incentive. This is because subscribers to these two bundles are least sensitive to financial incentive while most likely to increase PT trips once subscribed (see Table 2). Admittedly, MaaS that targets a particular travelling segment is likely to be a niche product instead of a mainstream one. Thus, we argue that profitability should go hand-in-hand with scalability and sustainability. Without any of these, MaaS is unlikely to take off. However, we also recognise that the development of MaaS is still in its very early phase. Indeed, MaaS in its full definition has not yet been made available to the travelling public anywhere. Thus, it is difficult to speculate on how disruptive transport technologies and advancements in personalised marketing may make something currently unprofitable, profitable in the future.

While this work has provided encouraging evidence on the prospect of MaaS obtaining societal and commercial goals, we must recognise that we assess these goals using tracking/booking data from a relatively small trial that tests specific mobility bundles on a limited number of customers who are all employees of a very large firm based in Sydney. Within the context of a MaaS trial, however, the sample size of nearly 400 subscription months (93 participants over 5 months in-field operation) and over 15,000 trips is not small by any standard. Nevertheless, one must be careful in generalising the evidence reported herein to the wider population and/or different places. We encourage further research on assessing the potential of MaaS in changing travel behaviour and quantifying the benefits and costs that accrue to different services included in the MaaS offerings. To this end, having accurate usage data is critical as without such data, one can only speculate (at worst) or speak to the qualitative evidence (at best) on MaaS potentials.

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