Combining samples to offset nonresponse and respondent biases

Abstract
What if probabilistic-based sampling does not result in a representative sample? How can researchers overcome low respondent engagement and hypothetical choices that are perceived as being socially desirable? These questions are relevant regardless of the way primary data collection is conducted.

A statistically sound sampling strategy still depends on individuals volunteering their participation. Even with extrinsic rewards, there is no guarantee the respondent will contribute an honest effort. This research reports on the data collection for a study investigating the acceptance of electric vehicles (EV) in Australia. Complementing the Western Australian Electric Vehicle Trial, this research focuses on household preferences and attitudes towards EV. The data set represents the last stage of data collection with four surveys (initially delivered to trial participants and later aimed at the broader community).

An initial sample showed high interest in EV and environmentally friendly technologies, but higher education levels and higher socioeconomic status households were overrepresented. To compensate for the bias, a second sample was collected from an online panel (PureProfile). Although neither sample is representative of the population, the results from the pooled data are deemed more appropriate for understanding drivers of EV uptake in Western Australia and informing policy making accordingly.

1 Introduction
1.1 Background
Increased cost of non-renewable fuel sources (Lidicker *et al*., 2010; Lieven *et al*., 2011; Ziegler, 2010) and higher levels of pollution due to increased traffic and congestion (Mierlo *et al*., 2006) provide the motivation for exploring alternative energy sources for transport. However, the market penetration of alternative fuel vehicles for personal travel remains low: In Australia, less than 5% of vehicles on the road use fuel technologies other than petrol or diesel (Australian Bureau of Statistics [ABS], 2013). Whilst the electric vehicle (EV) driving experience is similar to that of an internal combustion vehicle (Jabeen *et al*., 2012), recharging the battery is different from refuelling at the pump. The electric vehicle offers lower operating costs, lower emissions and the opportunity to recharge overnight at home. However, higher purchase price, lower driving range and a finite battery life have proved to be barriers to EV uptake (Hess *et al*., 2006).

1.2 Aim
The Western Australian Electric Vehicle Trial (http://www.therevproject.com/waevtrial/) was implemented to investigate driving and charging behaviours of EV owners (Jabeen *et al*., 2012); the relative trade-offs between charging at home, work or a (currently non-existent) fast charging station (Jabeen *et al*., 2012); and the factors and attitudes affecting EV uptake. This research involved a stated preference inquiry of the factors and attitudes affecting EV uptake. The responses from a mail-out survey (sent to a representative segment of the population) overrepresented men and people with higher-than-average levels of income and

education. In addition, the results indicated a very high concern for the environment and a high perception of usefulness of new technology coupled with a strong preference for EV over other fuel technologies. We believe that the response bias was due to the respondents having high engagement with environmental and fossil fuel depletion issues, in the same way that surveys about "socially and morally charged" topics may lead to response bias in attitudes and behaviours and a lower response rate from those uninterested in the matter (Bonsall 2009: 59). Therefore, we administered a second quota-based survey to an online panel (PureProfile) to help balance the initial respondent and response bias. The online panel respondents were also self-selected, but with regard to their engagement in EV technology. The current study reports the differences in attitudes and responses in the stated choice instrument and investigates whether a pooled sample could be considered a second-best option to a representative sample when a segment of a population exhibits overenthusiasm for a given topic.

1.3 Outline of the paper

We organise the remainder of the paper as follows: Section 2 presents a short literature review on factors affecting EV uptake and research methodologies applied to understanding these factors. Section 3 presents the methodology used in this research, describes the samples and offers an overview of the survey instrument used. In Section 4, we compare the samples in terms of demographics, stated attitudes and choice results. Section 5 concludes with a discussion of the results.

2 Literature Review

2.1 Factors affecting adoption of electric vehicles

Commonly acknowledged benefits associated with EV include energy conservation, zero tailpipe emissions, reduced noise (Mierlo *et al.,* 2006), home charging (Kurani *et al*., 1996) and low running costs (iMiEV, 2012; Lidicker *et al*., 2010), and major automobile manufacturers have announced plans to bring EV technology into the mainstream. Lieven *et al*. (2011) find price ranked as top priority for both conventional and EV cars, with range ranked second. Of 1,152 buyers, 4.2% chose EV as the "first vehicle for all uses". These buyers rated price and range as a lower priority than potential non-EV buyers.

Golob and Gloud (1998) suggested that EV is likely to be competitive with petrol only if the household vehicle's average mileage is less than 45 kilometres per day. This requirement would be met in most cities; for example, in Perth, the average daily driving distance is 30 kilometres per day, well within the limit. Although EVs are technically competitive at low driving ranges, it appears that consumers are less accepting: Hess *et al*. (2006) reported an acceptable range for EV adoption as being closer to 460 kilometres (Hess *et al*., 2006), equivalent to one recharge every week using Perth's average daily travel.

The time it takes to recharge an electric vehicle represents a substantial change in the way drivers would repower their cars. Home charging may be an attractive alternative (Kurani *et al*., 1996) to those with private garages, and EV charging at the workplace would be popular for those who have the option open to them (Jabeen *et al*., 2012). However, even with fast charging stations, an owner cannot pull over, refuel and go as they do with petrol or diesel.

From an environmental perspective, the use of conventional vehicle technologies in Australia remains a major source of carbon dioxide (CO_2-e) and noxious pollutant emissions. Mierlo *et al*. (2006) suggested that EV is an optimum solution for urban mobility with no exhaust fumes. A study of the full lifecycle of vehicle and fuel greenhouse gas emissions shows that

EVs have a positive balance when compared with internal combustion vehicles or hybrid EVs (Ma *et al*., 2012). Ziegler (2010) also found that younger men favour environmentally friendly products, showing a preference for hydrogen vehicles or EVs over petrol-fuelled vehicles.

Finally, a current challenge for EV uptake is their high purchase price, which is largely determined by the battery cost (mainly the cost of lithium). To address this concern, Ritchie (2004) discussed improvements in the characteristics of lithium-ion batteries that would reduce cost and increase safety. These advancements could decrease the cost of battery packs gradually in the future, which would make an EV a cost-efficient vehicle, especially in the long run. Even at current prices, Mullan *et al*.'s (2011) cost analysis of EV batteries indicated that over a period of eight years, the reduction in travel cost offsets the added battery cost. While range anxiety, charging time and high purchase price remain consumers' main concerns, Hidrue (2010) noted that a reduction in the cost of the EV battery would appreciably increase EV acceptance.

2.2 Methodological approaches applied in examining EV uptake

Although various methodologies have been applied in investigating EV uptake, we can broadly categorise them into three classes:

- Adoption and multivariate models (Ahn *et al*., 2008; Egbue & Long, 2012; Schuitema *et al*., 2012);
- Discrete choice models (Axsen *et al*., 2009; Bolduc *et al*., 2008; Brownstone *et al*., 2000; Dagsvik *et al*., 2002; Ewing & Sarigollu, 2000; Hidrue, 2010 Jensen *et al*., 2013; Lieven *et al*., 2011; Ziegler, 2010);
- Other approaches (e.g., agent-based modelling [Zhang *et al*., 2011]; decision trees [Moura *et al*., 2012]).

Many consumer behaviour models for technology adoption incorporate psychological and marketing factors that influence purchase decisions (Son & Han, 2011; Yang, 2012). However, this practice is not common in models that address adoption of new fuel and vehicle technologies (Egbue & Long, 2012; Kuwano *et al*., 2012; Schuitema *et al*., 2012). Kurani *et al*. (1996) were among the first scholars to incorporate attitudinal data in their research. Their findings indicated that environmental concerns may not have had much influence on the market initially, though they are a motivating feature for choosing EV. Heffner *et al*. (2007) used semiotics as a basis to explore consumers' preferences. Less than half the buyers in their study indicated that the vehicle they purchased *"makes a statement about who they are"*. Their interview results showed that current hybrid EV owners were influenced to purchase their vehicles by such factors as *"preserving environment, opposing war, saving money, reducing support for oil producers, and owning the latest technology"* (ibid: 411–412). Schuitema *et al*. (2012) tested the relationship between perceived instrumental attributes and intention to adopt EVs and found that EV attributes are significant, even though the amount of variance explained by their regression model was only 27%.

3 Methodology and Data Collection

3.1 Stated Choice Experiments

Many Australian households use more than one car (ABS, 2013) so that the range limitation of EVs may not be considered an issue when there is a second car available for long distance trips. The low travel cost means EVs can be used for all short trips within the city, but the charging requires considered trip planning. The location of charging stations is therefore crucial to ensure that the destination is reached, when unexpected detours become necessary. These elements were investigated through stated choice experiments where drivers and households were asked to compare a set of optimally designed scenarios with various vehicle and fuel alternatives (including the EVs) and choose the preferred alternative.

We presented respondents with four vehicle alternatives—petrol, diesel, plug-in-hybrid (PIH) and EV—from which to choose their most and least preferred options. We chose the nine attributes that had emerged as most relevant in previous scholarly work (and were validated in the Australian context using focus groups) for use in the experimental designs: purchase price, running cost, engine size, driving range, emissions, noise, battery charging time, the availability of charging infrastructure and the battery capacity after 10 years of use. The design was D-p optimised using genetic algorithms (Olaru *et al.,* 2011), and we obtained the prior parameters from a pilot study with 22 respondents. The pilot study also tested for the optimal number of choice experiments (6, 8, 10 or 12) and their effect on response rate and time; as a result, in the final surveys, each respondent evaluated 6–8 scenarios.

3.2 Survey Instrument

The survey instrument collected information about household location and structure, travel patterns, vehicles in use and future purchase decisions, as well as attitudes towards the environment, renewable energy and new technologies. These constructs represented the covariates used in the utility functions for discrete choice analysis. As mentioned previously, the survey concluded with 6–8 choice sets (For an example of the experiments, see Figure A1).

3.3 Data Collection

The data collection for the entire research program involved focus groups comprising EV drivers in Western Australia and two online driver surveys, followed by stated preference household surveys aimed at determining likely EV acceptance in Australia. The study reported here refers to the household surveys, which were the last stage of the research (Jabeen *et al*., 2012). No incentives were offered for participation. The focus groups and the driver surveys informed the household surveys in terms of the main attributes relevant for EV purchase and use.

The initial household survey used a sampling frame from a Perth utility company with spatial and socio-demographic strata. However, respondents were more likely to live in the southern suburbs and to have higher-than-average incomes and educational attainment. In addition to the nonresponse bias concerns, the respondents also exhibited social desirability bias, given their high interest in environmentally friendly technologies as reflected in responses to the stated preference questions; respondents tended to choose EVs in most scenarios. Along with the overrepresentation of certain socio-demographic groups, the link between engagement and returning a completed survey meant that any inference at the general population level was invalid. Therefore, we recruited a second quota sample from an online panel with participants from Perth (PureProfile). However, this sample is not representative of the general population, either.

Thus, we explore the discrepancies between each sample and reported census data and compare the choice functions between the samples. The results are examined in terms of the sampling strategy used in topics of high interest to a small section of the population and whether the response bias is critical in that the respondents are possibly early adopters of green technologies.

3.3 Samples and survey instrument

Between September and November 2012, we mailed 6,000 invitations to households asking them to participate in the EV study. The households were given the option to receive a mail-back paper survey or to respond online (https://www.surveymonkey.com/s/EV_households). Of the 390 complete responses received, 98 were completed online and 292 opted for the paper survey. The analysis of the data revealed that most respondents were from the southern suburbs of Perth and a large number of return-to-sender envelopes came from the northern suburbs (510 survey packs). To provide more equitable coverage of the population in the sample, we sent another round of distribution (2,000) in February–March 2013 to cover the underrepresented areas. In this distribution, we received 73 responses, 13 online and 60 paper-and-pencil surveys. In total, we obtained 463 responses, 111 web-based and 352 paper-and-pencil responses. After data cleaning, we had a total of 450 complete responses to use for further analysis. As Section 4.3 details, the discrete choice analysis using this sample indicated a negative sign for range, contrary to the well-documented finding that driving range is a main perceived barrier for EV uptake (Bolduc *et al.,* 2008; Dagsvik *et al*., 2002; Hess *et al.,* 2006; Hidrue, 2010; Lieven *et al.,* 2011). Although the survey design may have added to this effect (the scenarios had ranges for petrol and diesel vehicles together with EV; because they vary substantially, a petrol or diesel car buyer would scarcely give it a thought, but an EV buyer would pay attention to it), the main explanation is that the limited range appeared irrelevant for the EV-enthusiastic respondents.

To clarify the findings, in October 2013, we arranged a commercial survey using an online panel data. We obtained a second sample of 305 respondents from PureProfile (http://www.pureprofile.com/au). We compared the samples against each other and with census population information. For simplicity of presentation, we refer to the pencil-and-paper and online household sample as the "mail-out" sample, and the online panel sample as "PureProfile".

The mail-out and PureProfile surveys used the same questionnaire with a few changes, as Table 1 shows. We reduced the request for detailed socio-demographic information and used fewer items for the attitudinal constructs collected in the PureProfile survey. Specifically, we did not include 12 attitudinal items deemed weak in the analysis of the mail-out sample in the PureProfile survey. There were also changes in the experimental design, aimed to shed more light on the sign reversals obtained in the discrete choice models for the mail-out sample.

Table 1: Instrument changes

Changes in the instruments		Mail-Out	Pure-Profile
Items included in the latent constructs			
Number and type of items in the survey	Four attitudinal constructs: environmental concerns, perceived usefulness of technology, awareness and excitement for new technologies and social influence/norms	30 questions	18 questions
	Socio-demographics: gender, age and education	✓	
	Purchasing an EV and its use	3 questions	2 questions
	Solar panels		✓
Experimental designs	Number of scenarios	6	8
	Alternatives: EV, petrol, PIH and diesel	✓	✓ + two EV
	Order of presentation: randomised		✓

Although not recorded in the PureProfile survey, gender, age and education of respondents were representative for the population as a result of PureProfile's recruitment process. That is, PureProfile filtered the participants on the basis of these characteristics to ensure consistency between the sample and the population proportions.

Changes in the SP experiments involved the *range* variable, which we removed for petrol and diesel cars, along with the introduction of stimuli with two EVs and randomised presentation of the alternatives. Figure A2 provides an example of scenario applied in the PureProfile survey (with two EVs compared in a scenario).

3.4 Sample Comparison

Table 2 summarises the differences between the survey administration conditions and the number of responses elicited in the two surveys. Although the data collection period for the PureProfile commercial survey was short compared with the mail-out, we obtained a comparable number of responses and a more even geographical distribution of respondents, covering northern and southern suburbs equally, as per Moran's I indicator. Figure A3 presents the geographical coverage in the two surveys. As expected, the cost per respondent in the mail-out survey was much higher, considering its low response rate (<4.5%).

Table 2: Sample comparison

Characteristic		Mail-Out	PureProfile
Data collection period		7.5 months [Sep-2012 to Mar-2013]	2 weeks [7-Oct-2013 to 21-Oct-2013]
Deployment		Pencil-and-paper and Surveymonkey	PureProfile online survey
Sample size		450	305
Spatial dependence (Moran's I)		0.3697 (significant spatial clustering)	0.0069 (even geographical spread)
Total number of observations	**Without Explosion**	2,700 (450*6)	2,440 (305*8)
	Exploded Logit	8,100 (450*18)	7,320 (305*24)
Non-trading and Lexicographic Behaviour		100 (58 EV, 13 Petrol, 13 PIH, 11 Diesel, 5 Lowest Price)	7 (3 EV, 4 Lowest Price)

4 RESULTS

4.1 Samples Versus Population

Table 3 profiles the two samples and compares them with the households of Perth to ascertain their representativeness of the population.

Table 3: Comparison of the samples with the population

Variable	Mail-out	PureProfile	Pooled data	Census 2011

Gender (% male)	59.7	49.8	55.7	49.6
Average age (years)	51.45	42.55	47.85	36.91
Education (% with min year 12)	93.8	41.5	69.6	38.4
Household size	3.08	N/A	N/A	2.62
Car ownership	1.86	1.75	1.81	1.73
Driving licences/individual	1.05	N/A	N/A	1.07
Household income (in $AU 1,000s)	112.10	N/A	N/A	87.29

Note: Census statistics include the whole population, not only individuals over 20 years of age interviewed in the EV surveys.

The mail-out survey had a higher representation of male participants (59.7%), compared with the population. Census data from 2011 (http://www.abs.gov.au/websitedbs/censushome.nsf/home/data?opendocument&navpos=200) indicates that Perth's male population is 49.6% of the total and Australia's is 49.4%. The higher percentage of men in our sample is likely caused by men's greater preference/interest in car purchase decisions than women. Although consumer behaviour studies such as Belch & Willis (2002) showed that wives are increasingly gaining influence in the decision-making process regarding vehicle make, model and colour, husbands still have more influence on the initiation of the household decision to buy a vehicle. Kirchler *et al*. (2008) also found that decisions related to car buying are more controlled by male partners, while women appear to be more concerned about their preferences for kitchen appliances and number of bedrooms in a house.

The age comparison reveals a higher average for the participants in the mail-out survey due to underrepresentation of younger groups (18–29 years) and the higher participation rate in groups 50 years and older. This self-selection bias may be indicative of financial constraints that people younger than 30 years typically experience (thus, they may exhibit a reduced interest in expressing their views on an issue with little relevance to them) and of the fewer budgetary limitations of respondents over 50 years, as well as their greater interest in investing more money and time into car-buying decisions. The higher proportion of people 50 years and older might also be the reason that in this sample, 72% of the respondents had some postsecondary education, and approximately 23% had a university degree (bachelor's/master's/doctorate). Finally, the average annual household income for the mail-out sample was AU$112,000, much higher than the population average (AU$87,000). This sample had low representation in low-income groups and a high representation in high-income groups (greater than AU$100,000).

On average, the mail-out survey's respondents had approximately 3.08 persons in a household, well above the Perth average (2.6 persons per household). All households owned a car (average of 1.86 vehicles per household), and there were 1.97 licences per household. The PureProfile sample provided respondents more closely matching Perth's population in terms of age, gender, education and car ownership, which made the pooled sample more representative in those characteristics.

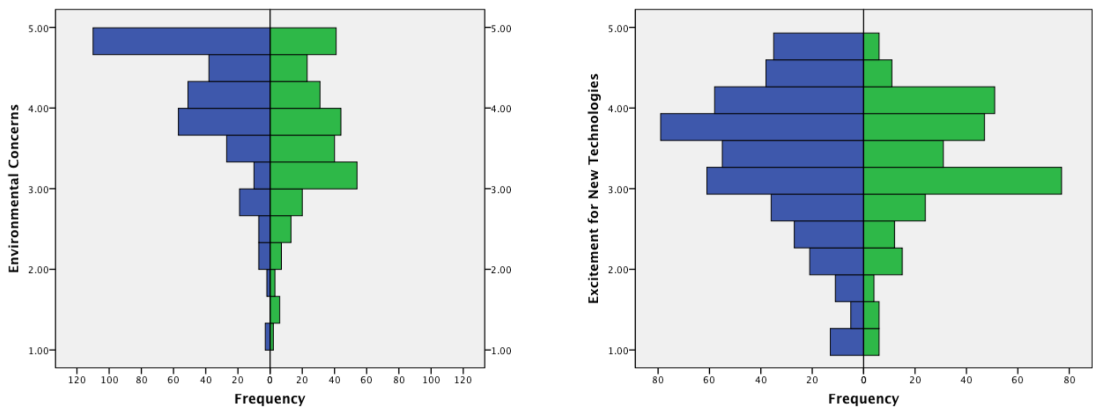
The mail-out survey also collected detailed responses on the vehicle characteristics. The results indicated a large variety of car brands; however, the most common was Toyota (18%), followed by Holden (11%), comparable to the population of Australian cars, in which Toyota and Holden remain the top registered vehicles in 2012 (ABS, 2013). Petrol dominated as a fuel (84% of vehicles), followed by diesel (12%). Only 1% of households owned EV/hybrid vehicles, also consistent with the Australia-wide data, which show that petrol-powered cars constitute 79.9% of the total vehicle fleet, diesel (including heavy vehicles) make up 17.2% and the rest represent liquefied petroleum gas (LPG), hybrid and EVs.

In both surveys, approximately one-third of the respondents indicated that they would likely purchase an EV in the next three years. When requested to indicate the amount that they were willing to spend to purchase their next car, mail-out sample respondents reported an average of AU$30,200 (with 35% willing to spend more than AU$35,000), much higher than the average for the PureProfile sample (AU$26,600, with only 15% willing to spend more than AU$35,000). This result is consistent with the socio-demographic profile of the mail-out sample: higher socioeconomic status, higher education level and, as Section 4.2 details, vested interest in green technologies.

4.2 Results: Confirmatory Factor Analysis

Table A2 presents the results of confirmatory factor analysis conducted in MPLUS7. The four identified constructs—environmental concerns (EC), perceived usefulness of technology (PU), awareness/excitement for new technologies (ET) and social influence/norms (N)—explained more than 50% of the variance of constructs (two exceptions for the mail-out sample) and had strong loadings (47 loadings of 54 above 0.6). Items in both data sets were the same, so we pooled the data sets to test a combined model. The models with constrained loadings for mail-out and PureProfile data had better model fits compared with the free models, even if not significantly different. We further applied the constrained models for deriving the latent scores included in the discrete choice analysis.

With one exception (awareness and excitement for new technologies, ET), the analysis of the factor scores showed statistically significant differences between respondents' attitudes towards environment and new technologies (Figure 1). The mail-out respondents displayed a significantly higher level of environmental concerns, EC (4.29 compared with 3.65 for the PureProfile sample) and of perceived usefulness, PU (3.78 versus 2.18 for the PureProfile sample). Yet the PureProfile sample scored significantly higher in social norms, SN (3.62 versus 2.19 for the mail-out sample). These distinctions indicate that the mail-out sample has a clear preference for environmentally friendly technologies and EV and suggests an elaborate decision process in purchasing a new vehicle that is not influenced by others but primarily by respondents' own assessment of the technology's merits.



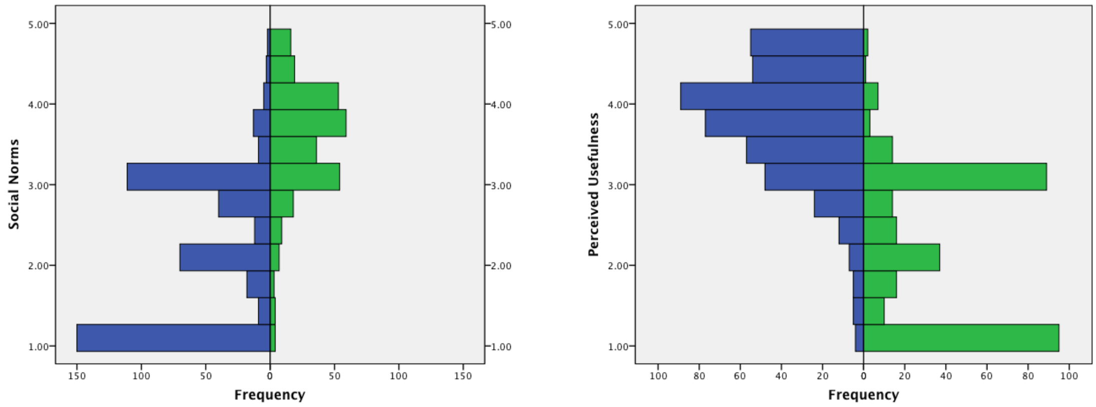


Figure 1: Attitudinal constructs across samples (*blue – mail-out; green – PureProfile)*

4.3 Results: Discrete Choice Models

This section presents the results of the multinomial logit (MNL) analysis with attitudinal covariates, taking advantage of the best-worst specification[1]. Although many more complex models have been tested, our objective here is to show the bias that affected the mail-out sample and alert on the danger of drawing inferences from such samples, thus the simplest models are deemed sufficient.

Given the unconcealed predilection for green technologies and EV, we analysed respondents' potential non-compensatory and lexicographic behaviour (Table 2) before estimating the discrete choice models. "Lexicographic behaviour" refers to when a respondent's choice, regardless of experiment, is based on a particular set of attributes. Respondents might choose one alternative as a best case in all given choice sets, also known as nontrading behaviour, which may particularly occur in labelled choice experiments (Hess *et al*., 2010). Hess *et al*. (2010) identify three potential reasons for this behaviour: utility maximisation (strong preference for an alternative as compared to other alternatives), heuristics (misunderstanding/boredom) and policy-response bias.

In this study, we identified both non-trading and lexicographic situations: several respondents had a strong preference for low-running-cost, zero-emissions, low-noise cars and selected EV in all choice tasks; other respondents selected diesel in all instances, possibly because of their preference for maximum range. For the mail-out sample, 58 respondents selected EV, 13 selected petrol, 13 chose PIH and 11 indicated diesel as their most preferred choice in all given choice tasks. Only 5 respondents chose the low-price vehicle as their best choice in all given scenarios. In contrast, for the PureProfile sample, non-trading and lexicographic behaviour was low, with only 3 respondents of 305 choosing EV in all choice tasks and 4 respondents considering a low-price vehicle as their best option in all given experiments (Table 2).

When heuristics and biases affect the response—which seems to be the case with the mail-out sample—it is prudent to carry out the analysis without non-trading observations. Given their substantial proportion in the mail-out sample (22%), and because it was not possible to probe their reason for the choice, we estimated the MNL models with reduced sample sizes (Table 4). However, we kept the lexicographic behaviour responses to account for individual preferences and avoid statistical inefficiency (Lancsar & Louviere, 2006).

[1] Table A1 provides the attributes and the levels used in the experiments for the two samples.

Mail-out respondents had a strong negative preference for purchase price, noise, running cost and charging time and a strong positive preference for a large engine, all significant at the 1% level (Table 4). As indicated previously, the parameter estimate for range was opposite to that obtained in past studies, suggesting that respondents had a negative preference for EV driving range. We initially tested the range for all vehicles together, judging that their range could be compared (e.g., PIH can be switched from electric mode to petrol at any time, thus eliminating range anxiety). However, we acknowledge that doing so may have confused the respondents, given the difference of an order of magnitude between range for petrol, diesel, and EV. Environmental concerns (EC) and willingness to purchase an EV were also significant for this sample.

Table 4: Hybrid MNL model for the two samples and pooled data

Attributes	**Mail-Out Traders Exploded Logit**		**Pure-Web-Based [a] Exploded Logit Traders**		**Pooled Data Exploded Logit**	
	Par.	**t**	**Par.**	**t**	**Par.**	**t**
Purchase Price	–0.0298	–7.40	–0.0478	–18.7	–0.0338	–17.05
Emissions$_{Generic}$	–0.0077	–1.05	0.0128	2.01	0.0080	1.85
Noise$_{Generic}$	–0.1840	–6.67	–0.3065	–9.66	–0.2330	–11.89
Running Cost$_{Generic}$	–0.1220	–8.25	–0.0199	–1.49	–0.0699	–7.96
Engine Size (Petrol, Diesel)	0.4770	4.60	0.0174	0.23	0.0989	2.00
Charging Time EV	–0.0029	–6.82	–0.0308	–2.24	–0.0012	–3.76
Battery Life (EV)	–0.5690	–0.68	0.1087	0.65	0.4310	2.19
Range $_{EV}$	–0.0048	–2.28	0.0034	5.05	–0.0001	–0.16
Range $_{(PIH, Petrol, Diesel)}$			0.0007	1.73	–0.0003	–1.28
Number of Charging Stations (EV)	0.0004	1.65	0.0002	2.98	0.00002	0.43
Environmental Concerns $_{(EV, PIH)}$	0.6480	10.15	0.4390	7.37	0.4640	11.74
Social Norms $_{(EV, PIH)}$	0.0113	0.42	0.1990	7.23	0.1170	6.50
Perceived Usefulness $_{(EV, PIH)}$	–0.1093	–1.98	0.2730	4.61	0.0429	1.13
Excitement for New Technologies $_{(EV, PIH)}$	0.0362	0.74	–0.2470	–4.43	–0.0847	–2.47
EV_Buy $_{(EV, PIH)}$	0.2170	7.79	0.3290	10.45	0.2730	13.97
EV_Use $_{(EV, PIH)}$	0.0435	1.49				
Solar panels at home $_{(EV, PIH)}$			-0.1830	-2.67		
Without_ICE $_{(EV, PIH)}$	0.1250	5.89	0.2270	8.80	0.1810	11.10
ASC$_{EV}$	0.883	0.64	-0.154	-0.64	-0.799	-3.38
ASC$_{Diesel}$	1.38	4.30	2.87	7.90	2.13	9.81
ASC$_{Petrol}$	1.672	3.88	3.22	8.65	2.35	10.47
Number of estimated parameters	19		20		19	
Number of observations	6,548		7,320		8,378	
Log-likelihood	-5,606.38		-6,175.24		-12,648.49	
Akaike Information Criterion (AIC)/N	1.72		1.69		1.70	
Pseudo-R^2	0.053		0.076		0.059	

For the PureProfile sample, the sign of parameter range changed, consistent with the a priori expectation that the autonomy of driving is important (for other vehicles, the parameter was also positive, but insignificant). Other important findings involve the presence of charging infrastructure and the positive role of social norms (SN) for this group and the negative associations of excitement for new technologies (ET) and solar panels with the purchase of EV, which suggest that other decision mechanisms may intervene in the vehicle selection, driven perhaps by price.

When we combined the two samples, we found that purchase price, running costs, charging time, and engine size were statistically significant. Whereas EC, SN, willingness to buy an EV and stated ability to manage travel without an internal combustion engine (ICE) were positively associated with the utility functions, ET detracted from the utility. Overall, more parameters were significant and consistent with the a priori expectations in the PureProfile sample, which partially mitigated the effect of the biased mail-out sample.

5 Discussion

We present results from two surveys that were joined in an attempt to minimise the effect of sample selectivity bias (self-selection and social desirability bias). Despite using a multistage stochastic sampling process, we found that our mail-out sample was non-representative in spatial and socio-demographic characteristics (including more male, older, highly educated, with higher-income and car ownership and who were unevenly distributed across the city). This sample displayed a high predilection towards EV, as demonstrated by their attitudes, their non-trading and lexicographic behaviour and the modelling results. Thus, we collected a second PureProfile sample to 'correct' for the bias. This sample's characteristics were closer to the general population and had significantly different attitudes.

Researchers have widely recognised the effects of self-selection, starting with Heckman's (1979) pioneering work. In transport, Bonsall (2009) reviews the challenges posed by collecting information on "socially and morally charged" issues: systematic biased reporting of attitudes and behaviours and lack of participation from those disengaged in the topic. In our case, self-selection meant that respondents with higher environmental values and commitment (including members of the WA Electric Vehicle Association), who subscribed to the prevailing norm, were overrepresented in the sample. In addition, given the social desirability of environmentally responsible technologies, it is possible that our sample over-reported their agreement with the attitudinal statements, reflecting "political correctness" and a desire to maintain consistency with their credo (e.g., 43 EV trial respondents were engaged in green actions).

Although we are not suggesting intentional misrepresentation, we conclude that the overoptimistic reaction of those who responded and the lack of response from those less motivated contaminated our results. Moreover, even though the mail-out survey is the least susceptible deployment technique to such biases, the degree of positive EC and PU responses called our attention to the combined demand effects and self-selection. However, caution should be exercised when reporting these results and, as shown in this paper, for new technologies it may be worth validating or triangulating survey results using different samples and different methods. As noted in Jabeen *et al*. (2012), when asked directly, drivers expressed concern about technical aspects of EVs, primarily limited driving range, charging infrastructure and charging time. This should have been reflected in the discrete choice results. The expected sign for range was obtained only for the PureProfile sample, indicating that increasing driving range and providing ample opportunities for charging may alleviate worries about trip planning, which many drivers hold. This is especially important for cities that are characterised by suburban sprawl, such as Perth.

Our findings are crucial for policy considerations, because formulation of effective interventions requires valid data from all households or individuals and accounting for populations underrepresented in our samples. Conclusions based on the mail-out sample would have shown greater environmental values than the general population and thus would be incorrect. Egbue & Long (2012) recognise this effect in their study of a sample of "technological minded group towards EV", which provides insights on early adopters' decisions. At the time of this study, EV adoption in Western Australia was limited to a few enthusiasts, who in many cases had retrofitted a petrol-driven vehicle and a limited number of early adopters. However, the share of EV's in the fleet is expected to rise substantially over the next ten years and the need to survey a representative sample of the driving public on their EV ownership intentions and anticipated driving and charging habits is increasingly important to support future infrastructure needs.

We deemed the PureProfile sample more immune to these biases, having a better spatial representation and coverage of socio-demographic groups[2]. The PureProfile sample did not exhibit lexicographic responses, and the models did not have sign reversals (i.e., respondents seemed to have traded off more of the attributes in the vehicle technology bundles). Finally, the analysis shows that the aggregated sample became more representative of the population in terms of household size, income and number of owned vehicles, and covered the whole metro area.

Our results suggest that mixed data collection may address the sample selection and response biases (Bonnel *et al*., 2009) and reduce the halo effect associated with socially desirable topics. Furthermore, they show that more effort should be made to systematically assess and correct bias effects, when possible, especially if the results inform practice. As the *"adoption of more environmentally sustainable lifestyles and travel patterns, whether in response to deliberate policy initiatives by public authorities, in response to social pressures, or as a result of personal motivation, is becoming an increasing phenomenon among certain groups"* (Bonsall, 2009: 50), we contend this issue is a top-agenda item for emerging research.

6 Acknowledgements

This research has received funding from the Australian Research Council LP100100436.

7 References

- ABS (2013) *Motor Vehicle Census*, 9309.0, ISSN 0728-2923, available at http://www.ausstats.abs.gov.au/ausstats/subscriber.nsf/0/268932501A477446CA257BB00011A2FF/$File/93090_31%20jan%202013.pdf.
- Ahn J., Jeong G. and Kim Y. (2008) A forecast of household ownership and use of alternative fuel vehicles: A multiple discrete-continuous choice approach, *Energy Economics* 30, 2091–2104.
- Axsen, J., Mountain, D. and Jaccard, M. (2009) Combining stated and revealed choice research to simulate the neighbor effect: The case of hybrid electric vehicles, *Resource and Energy Economics* 31(3), 221–238.
- Belch, M. A. and Willis, L. A. (2002) Family decision at the turn of the century: Has the changing structure of households impacted the family decision-making process? *Journal of Consumer Behaviour* 2(2), 111–124.
- Bolduc, D., Boucher, N. and Alvarez-Daziano, R. (2008) Hybrid choice modeling of new technologies for car choice in Canada, *Transportation Research Record,* 2082, 63–71.
- Bonnel, P., Lee-Gosselin, M., Madre, J.-L., and Zmud, J. (2009) Keeping up with a changing world: Challenges in the design of transport survey methods, in: P. Bonnel, M. E. H. Lee-Gosselin, J. Zmud and J.-L. Madre (Eds.) *Transport Survey Methods: Keeping Up with a Changing World*, 3–14 (Bingley, UK: Emerald).
- Bonsall, P. (2009) What is so special about surveys designed to investigate the environmental sustainability of travel behaviour? in: P. Bonnel, M. E. H. Lee-Gosselin, J. Zmud and J.-L. Madre (Eds.) *Transport Survey Methods: Keeping Up with a Changing World*, 49–69 (Bingley, UK: Emerald).
- Brownstone, D., Bunch, D. S. and Train, K. (2000) Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles, *Transportation Research* B 34, 315–338.
- Dagsvik, J. K., Wennemo, T., Wetterwald, D. G. and Aaberge, R. (2002) Potential demand for alternative fuel vehicles, *Transportation Research B* 36, 361–384.

[2] Because we did not apply a formal procedure to assess the non-participants bias (they could not be located or refused), we used census data to compare the socioeconomic profile of the samples with the population.

- Egbue, O. and Long, S. (2012) Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions, *Energy Policy* 48, 717–729.
- Ewing, G. and Sarigollu, E. (2000) Assessing consumer preferences for clean-fuel vehicles: A discrete choice experiment, *Journal of Public Policy & Marketing* 19, 106–118.
- Golob, T.F. and Gould, J. (1998) Projecting use of electric vehicles from household vehicle trials, *Transportation Research* B, 32, 441-454.
- Granovskii, M., Dincer, I. and Rosen, M.A. (2006) Economic and environmental comparison of conventional, hybrid, electric and hydrogen fuel cell vehicles, *Journal of Power Sources* 159, 1186–119.
- Heckman, J. (1979) Sample selection bias as a specification error, *Econometrica* 47(1), 153–161.
- Heffner, R., Kurani, K. and Turrentine, T. (2007) Symbolism in California's early market for hybrid electric vehicles, *Transportation Research D* 12, 396–413.
- Hess, S., Rose, J. M. and Polak, J. (2010) Non-trading, lexicographic and inconsistent behaviour in stated choice data, *Transportation Research D 15*(7), 405–417.
- Hess, S., Train, K. E. and Polak, J. W. (2006) On the use of a modified Latin hypercube sampling (MLHS) method in the estimation of a mixed logit model for vehicle choice, *Transportation Research* B 40, 147–163.
- Hidrue, M.K. (2010) The demand for conventional and vehicle-to-grid electric vehicles: A latent class random utility model, doctoral dissertation UMI Number: 3440476.
- iMiEV (2012) Mitsubishi iMiEV, http://i.mitsubishicars.com/faq.
- Jabeen, F., Olaru, D., Smith, B., Speidel, S. and Bräunl, T. (2012) Acceptability of electric vehicles: Findings from a driver survey, paper presented at the 35th Australasian Transport Research Forum, September 26–28, Perth, Australia.
- Jensen, A. F., Cherchi, E. and Mabit, S. L. (2013) On the stability of preferences and attitudes before and after experiencing an electric vehicle, *Transportation Research D* 25, 24–32.
- Kirchler, E., Hoelzl, E. and Kamleitner, B. (2008) Spending and credit use in the private household, *Journal of Socio-Economics* 37(2), 519–532.
- Kurani, K. S., Turrentine, T. S. and Sperling, D. (1996) Testing electric vehicle demand in hybrid households' using a reflexive survey, *Transportation Research D* 1, 131–150.
- Kuwano, M., Tsukai, M. and Matsubara, T. (2012) Analysis on promoting factors of electric vehicles with social conformity, paper presented at the *13th International Conference on Travel Behaviour Research*, Toronto, Canada, 15–20 July.
- Lancsar, E. and Louviere, J. (2006) Deleting 'irrational' responses from discrete choice experiments: A case of investigating or imposing preferences? *Health Economics* 15(8), 797–811.
- Lidicker, J. R., Lipman, T. E. and Shaheen, S. A. (2010) *Economic assessment of electric-drive vehicle operation in California and the United States*, UC Davis Institute of Transportation Studies research report, available at http://76.12.4.249/artman2/uploads/1/EAEVO.pdf.
- Lieven, T., Muhlmeier, S., Henkel, S. and Waller, J.F. (2011) Who will buy electric cars? An empirical study in Germany, *Transportation Research D* 16, 236–243.
- Ma, H., Felix, B., Tait, N., Xavier, R. P., and Andrew, H. (2012) A new comparison between the life cycle greenhouse gas emissions of battery electric vehicles and internal combustion vehicles, *Energy Policy* 44, 160–173.
- Mierlo, V. J., Maggetto, G. and Lataire, P. (2006) Which energy source for road transport in the future? A comparison of battery, hybrid and fuel cell vehicles, *Energy Conversion and Management* 47, 2748–2760.
- Moura, F., Lopes, M. M., Costa, P. C. and Silva, M. (2012) Electric vehicle diffusion in the Lisbon metropolitan area: Major constraints and possible market shares in the medium and long term, paper presented at European Transport Conference, Glasgow, October 8-10, available at http://abstracts.aetransport.org/paper/index/id/3992/confid/18.
- Mullan, J., Harries, D., Braunl, T. and Whitely, S. (2011) Modelling the impacts of electric vehicle recharging on the Western Australian electricity supply system, *Energy Policy*, 39(7), 4349–4359.

- National Research Council (2013) *Transitions to Alternative Vehicles and Fuels* (Washington, DC: The National Academies Press).
- Olaru, D., Smith, B. and Wang, J. (2011) Optimal discrete choice experimental designs using genetic algorithms, paper presented at the International Choice Modelling Conference, July 4–6, Oulton Hall, UK.
- Ritchie, A. G. (2004) Recent developments and likely advances in lithium rechargeable batteries, *Journal of Power Sources* 136, 285–289.
- Schuitema, G., Anable, J., Skippon, S. and Kinnear, N. (2013) The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles, *Transportation Research A* 48(2), 39–49.
- Son, M. and Han, K (2011) Beyond the technology adoption: Technology readiness effects on post-adoption behaviour, *Journal of Business Research* 64(11), 1178–1182.
- Yang, K. (2012) Consumer technology traits in determining mobile shopping adoption: An application of the extended theory of planned behaviour, *Journal of Retailing and Consumer Services* 19, 484–491.
- Zhang, T., Gensler, S. and Garcia, R. (2011) A study of the diffusion of alternative fuel vehicles: An agent-based modelling approach, *Journal of Product Innovation Management* 28, 152–168.
- Ziegler, A. (2010) Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis, Economics Working Paper 10/125, available at http://www.cer.ethz.ch/research/WP-10-125.pdf.

8 Appendix

1. **Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:**

	Electric car	**Petrol car**	**Plug-in hybrid car**	**Diesel car**
Price	$50,000	$36,000	$53,000	$46,000
Driving range	140km	800km	400km (including 30km electric)	800km
Charging time	Fastest charging available - 1.5h*	n/a	n/a	n/a
No of charging stations	500 public stations available	n/a	Charging at home (30 min)	n/a
Running cost	$1.4/100km	$7.5/100km	$6.0/100km	$7.5/100km
Engine size	Equiv. 2.4L	2.4L	Equiv. 1.6L	2.0L
Life cycle Emissions	11kg/100km	21kg/100km	17kg/100km	23.5kg/100km
Battery capacity after 10 years	85%	n/a	85%	n/a
Engine noise	No engine noise	Medium engine noise	Medium engine noise	High engine noise
Most preferred	○	○	○	○
Least preferred	○	○	○	○

Figure A1: An example of a stated choice experiment in the mail-out survey

4. **Please indicate which one of the following options is the Most Preferred and which one the Least Preferred:**

	Electric car 1	**Petrol car**	**Electric car 2**	**Diesel car**
Price	$34,000	$28,000	$42,000	$38,000
Driving range	160km	n/a	80km	n/a
Charging time	Fastest charging available - 0.2h*	n/a	4 hours	n/a
No of charging stations	1000 public stations available	n/a	500 public stations available	n/a
Running cost	$2.0/100km	$7.5/100km	$2.0/100km	$9.0/100km
Engine size	Equiv. 1.6L	1.6L	Equiv. 2.4L	1.6L
GHG Emissions	13kg/100km	31kg/100km	11kg/100km	23.5kg/100km
Battery capacity after 10 years	65%	n/a	95%	n/a
Engine noise	n/a	High engine noise	n/a	Medium engine noise
Most preferred	○	○	○	○
Least preferred	○	○	○	○

Figure A2: An example of a stated choice experiment in the PureProfile survey

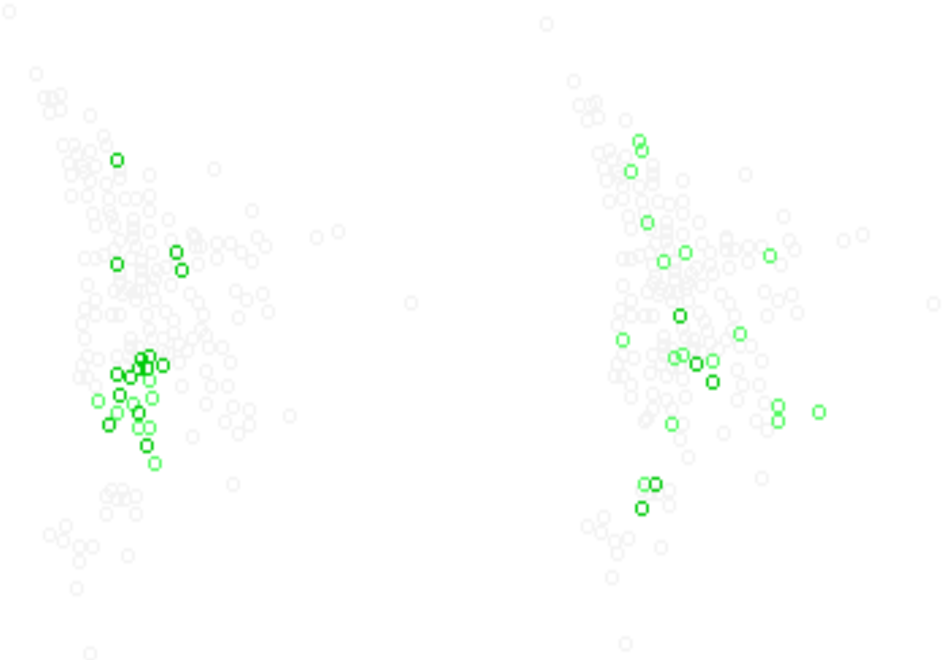


Fig.A3a) mail-out Fig.A3b) PureProfile

Figure A3: Spatial distribution of the surveyed households

Note: Greener dots represent more respondents.

Table A1: Attributes and levels used in the experiments

Attribute	**Levels**
Engine size (L)	1.6; 2.0; 2.4
Range (km)	EV: 100; 120; 140 (mail-out) and 80; 120; 160 (PureProfile) PIH: 400; 500; 600 (both samples) Petrol: 600; 700; 800 (mail-out only) Diesel: 800; 900; 1000 (mail-out only)
Running cost (AU$/100km)	EV: $1.40; $1.70; $2.00 PIH: $4; $5; $6 Petrol: $7.50; $10.70; $12.50 Diesel: $6.00; $7.50; $9.00
Purchase price (in AU$1,000s)	EV: 34; 42; 50 PIH: 37; 45; 53 Petrol: 28; 36; 44 Diesel: 30; 38; 46
GHG emissions (kg/100km)	Between 11 to 31kg/100km depending on the fuel
Noise	No engine noise (EV); Low; Medium; High engine noise (PIH, petrol, Diesel)
Charging time (min)	12; 30 (public); 90; 240 (home)
Battery capacity after 10 years	0.85; 0.90; 0.95 (Mail-Out) and 0.65; 0.80; 0.95 (PureProfile)
Number of charging stations	500; 1,000; 1,500

Table A2: Results: CFA for the two samples and for the pooled data

Construct	Items	Loadings		
		Mail-out	**PureProfile**	**Pooled data**
Environmental Concerns (EC)	Saving the environment requires our immediate efforts.	0.668	0.781	0.742
	I am concerned that future generations may not be able to enjoy the world as we know it currently.	0.727	0.835	0.791
	I am willing to pay more for products or services to save the environment.	0.570	0.650	0.644
	Now is high time to worry about the effects of air pollution.	0.745	0.776	0.773
	Climate change is a myth.	–0.647	–0.849	–0.733
	Goodness-of-fit measures X^2 (df); p CFI/TLI RMSEA; SRMR	 *2.182* (4); 0.702 1.000/1.011 <0.001; 0.008	 *8.696* (4); 0.069 0.991/0.977 0.062; 0.016	 *1.089* (4); 0.896 1.000/1.009 <0.001; 0.003
	Variance, r_c	48%	59%	55%
Perceived Usefulness of Technology (PU)	I love gadgets.	0.608	0.759	0.657
	Using new technologies makes life easier.	0.564	0.581	0.571
	I use online maps to plan my travel when I need to visit a new place.	0.768	0.723	0.757
	Exploring new technologies enables me to take benefit from latest developments.	0.766	0.810	0.778
	X^2 (df); p CFI/TLI RMSEA; SRMR	*0.979* (1); 0.322 1.000/1.001 <0.001; 0.009	*0.653* (1); 0.419 1.000/1.008 <0.001; 0.008	*0.389* (1); 0.533 1.000/1.008 <0.001; 0.004
	Variance, r_c	42%	54%	51%
Awareness & Excitement for New Technologies (ET)	Keeping my knowledge up to date about technology is necessary.	0.686	0.681	0.686
	I enjoy the challenge of figuring out high-tech gadgets.	1.022	0.963	0.996
	I prefer to use the most advanced technology available.	0.926	0.795	0.876
	I am excited to learn new technologies.	0.869	0.788	0.840
	New technologies enable me to resolve my daily tasks.	0.684	0.724	0.692
	X^2 (df); p CFI/TLI RMSEA; SRMR	*5.952* (3); 0.114 0.995/0.985 0.047; 0.016	*6.934* (3); 0.074 0.993/0.978 0.066; 0.020	*9.747* (3); 0.021 0.994/0.981 0.055; 0.016
	Variance, r_c	61%	67%	63%
Social Influence/ Norms (SN)	People who are important to me think that I should buy an EV.	0.979	0.998	0.995
	I would buy an EV if many of my friends would use an EV.	0.780	0.800	0.786
	Being fashionable means having up to date knowledge of this techno-world.	0.549	0.471	0.510
	People who influence my behaviour think I should buy an EV.	0.920	1.000	0.994
	X^2 (df); p CFI/TLI RMSEA; SRMR	*0.429* (1); 0.512 1.000/1.009 <0.001; 0.003	*1.410* (1); 0.235 0.999/0.994 0.037; 0.003	*0.555* (1); 0.456 1.000/1.004 <0.001; 0.002
	Variance, r_c	56%	65%	60%

Notes: CFI = confirmatory fit index; TLI = Tucker–Lewis Index; RMSEA = root mean square error of approximation; SRMR = standardised root mean square residual.