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How the longer term success of a social marketing program is influenced by socio-demographics and the built environment

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Abstract Urban sprawl is pervasive in Australian cities arising from the low density development of dwellings with the consequence that private vehicle use dominates daily travel in Australia. This paper examines a community based social marketing program, *TravelSmart*, which targeted reducing vehicle kilometres travelled as part of a transport demand management strategy. This paper uses 3-year panel data collected by GPS tracking and a conventional survey methodology in northern Adelaide, South Australia, to examine whether *TravelSmart* had a sustained impact and whether this was impacted by socio-economic and built-environment factors. A latent growth model is employed and demonstrates *TravelSmart* led to a declining trend in private car driving over the 3 years at both individual and household levels with effects being sustained beyond 1 year and up to 2 years. There is some evidence of compensatory behaviour between household members. Socio-demographic factors are significant with males decreasing their driving times faster than females. Built environment impacts were also significant with different levels of walkability showing different trajectories in the reduction of car trips after the implementation of *TravelSmart*, suggesting social marketing interventions work better when supported by hard policies such as a supportive built environment.

Keywords Social marketing · TravelSmart · Latent growth model · Built environment impacts · Travel demand management interventions · Travel behaviour change

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Introduction

Urban sprawl is pervasive in Australian cities arising from the low density development of dwellings. One of the consequences of this is that private vehicle use dominates daily travel in Australia as demonstrated by recent statistics (BITRE 2014) which identify private road vehicles accounting for approximately 86% of the aggregate passenger activity within the Australian capital cities. Overall, the transport sector accounts for 16% of Australia's greenhouse gas emissions, and within this light vehicles contribute 57%. As importantly, car use is also associated with series of negative personal effects, such as obesity and other health problems related to sedentary lifestyles (Bassett et al. 2008; Ding et al. 2014). Reducing car travel by reducing VKT is a target of many transport demand management policies of which community based social marketing programs are proving increasingly popular and effective.

The approach of community-based social marketing programs was originally developed by a social psychologist (McKenzie-Mohr 2000), and used by planners to promote sustainable environmental and travel behaviour. Whilst conventional planning tools focus on changing the land use by planning regulations, social marketing programs aim to change behaviour primarily through affecting intra-personal factors such as attitudes, perceptions and norms (Bamberg et al. 2011; Dill and Mohr 2010). These social marketing programs are thus designed to influence travel behaviour by encouraging participants to change their mobility options in undertaking their daily life which in turn is likely to involve trade-offs between mode of travel, time spent travelling and the activities undertaken. Social marketing programs typically use voluntary action and incentive approaches to change behaviour by providing personalized information on alternative travel options to private cars (Friman et al. 2013). In policy terms, social marketing programs are regarded as 'soft' measures and have been extensively used to influence travel demand in many cities worldwide.

Reported empirical studies evaluating the effects of social marketing programs on travel behaviour change are limited and have provided mixed results, in particular on the long-term effects of social marketing programs (Brög 1998; Brög et al. 2009; Cooper 2007; Dill and Mohr 2010; Möser and Bamberg 2008; Rose and Ampt 2001; Rose and Marfurt 2007; Taniguchi et al. 2003). However, most of the previous studies have relied on pre- and post-surveys using self-reported measures without any objective measures of travel behaviour change being included. In particular, none of the previous studies have looked at the individual variations in travel behaviour change in response to the social marketing program. Specifically whether an individuals' social-demographic characteristics and their living environment influences the changes of travel behaviour is a gap in the literature. Understanding the factors that influence the effects of a social marketing program is important for future program design and policy implications and this paper contributes by using objective measures of travel over much longer periods than previous studies as well as taking into account built environment structural features such as walkability.

This paper aims to fill the research gaps identified by the literature though answering the following three questions: (1) Does *TravelSmart* reduce car travel in the long-term? This is a complicated question and this paper looks at individuals and household responses to the *TravelSmart* program to see whether there is compensatory behaviour intra-household. (2) Does an individual's socio-demographic characteristics influence the effects on the social marketing program on travel behaviour change? (3) Does the built environment make a difference in the effects of the social marketing program on travel behaviour change?

By answering these questions, this study aims to contribute to the previous literature on travel behaviour in three ways. First, this study employs a natural experiment design which is able to rigorously to quantify the causal effects of social marketing program on travel behaviour change. Second, this study uses a relatively new survey methodology of GPS tracking to measure the travel behaviour change: this is a significant contribution to the previous studies that have primarily relied on self-reported survey data. GPS tracking also generates a considerable quantity of data of the order of magnitude commensurate with Big Data. Finally, this study examines the different effects of social marketing programs on different people and at different locations.

This paper relies on 3-year panel data collected in Australia using both GPS and a normal travel survey in northern Adelaide, South Australia. This is a new methodological approach to the collection of data to evaluate social marketing programs and provides passively collected objective data for review. The social marketing program introduced to participants was called *TravelSmart* and was a voluntary program introduced in many of the Australian states (and is further described below). Such programs are often referred to as voluntary travel behavior change programs as the individual voluntarily makes changes to their behavior without financial (dis)incentives.

The paper is organized as follows. The next section provides the "Literature review" section on the effects of social marketing programs on travel behaviour change. This is followed by a description of the data and the methodology used in the paper. Finally, the paper summarizes the key findings and limitations, as well as provides policy implications on travel behaviour change.

Literature review

Social marketing programs have been well recognized and implemented in many cities around the world as a travel demand management measure. These social marketing programs aim to change travel behaviour by providing individuals with information on using alternative transport to the car and helping participants to realise the consequences of different travel modes on their health and the environment.

The literature identifies two possible theories to explain the mechanism of how a social marketing program changes travel behaviour. One is based on the traditional random utility theory (McFadden 1986), which assumes that individuals have perfect knowledge and information and their travel decision follows a utility maximising strategy. However, in the real world, people may behave "irrationally" because they rarely have full information and/or the capacity to solve complex problems to make a perfect decision. As Simon (1957) argues, people only have bounded rationality as a result of limited and fragmented information and time constraints. A social marketing program, provides additional information to add to the information that individuals already know so that individuals can reassess the travel information they received and make a new decision on fuller information with perhaps some change in travel behaviour. Under the typologies of travel information as defined by Ben-Elia and Avineri (2015), social marketing programs primarily offer "prescriptive information", which provides suggestions and recommendations on travel choices based on the personal characteristics. In other words, this theory argues that social marketing programs influence people's travel decision by providing them with additional information and suggestions on travel options so as to change the outcome of maximising their utility function.

A second theory explaining how social marketing can change travel behaviour is based on socio-psychology theory. Social marketing programs are generally deemed a 'soft' measure of the travel demand management tool-box since social marketing focusses on influencing individual psychological factors, such as attitudes and perceptions, through information and information campaigns and education. The theory of planned behaviour (TPB) (Ajzen 1991), widely used theory in social psychology, has been employed as a theoretical framework to explain the mechanism of intervention effects of social marketing programs on changing travel behaviour (Bamberg et al. 2011; Dill and Mohr 2010). Based on TPB, social marketing influences people's travel decisions by altering their attitudes towards different travel modes, by influencing their opinions on the travel choices of their family members, friends and others who are important to them, and by empowering them to choose alternative travel options. In addition to TPB, another popular socio-psychology theory that is widely used to predict pro-environmental behaviour, including travel behaviour, is value-belief-norm (VBN) theory (Stern 2000; Stern et al. 1999). While the TPB focuses on the importance of attitudinal components, the VBN emphasizes the role of values and moral norms on behaviour change. By educating people on the positive and negative consequences of the car use, social marketing programs help people to become aware and perceive it as a social obligation to reduce their car travel which is causing harm to others. Previous studies have applied VBN in analysing the effects of social marketing programs on travel behaviours and psychological factors (Bamberg et al. 2011; Taniguchi et al. 2003). In contrast to the theory that assumes all individuals are rational utility maximisers, socio-psychology theory stresses the way in which social marketing programs affect travel behaviour by influencing the perceptual state of individuals. This is also the case with the transtheoretical model (TTM) (Prochaska and Velicer 1997) which, in contrast to TPB and VBN, stresses that behaviour change should be considered as a stepwise process. Under the TTM, the behaviour change is a process involving progress through six stages and ten processes. TTM has been widely used to design interventions that help to reduce car use and improve active travel (Bamberg et al. 2007; Cooper 2007). Bamberg (2013) has been able to integrate the constructs from TPB and VBN into a TTM framework, and proposed the self-regulation theory. One application of this theory in travel behaviour study is the Max Self-regulation Model (MaxSEM) framework, which was applied in European Platform on Mobility Management (EPOMM) project to theorize, monitor and measure travel behaviour change after the introduction of mobility management measures (Bamberg 2013; Van Acker et al. 2012).

A growing number of studies have evaluated the effect of social marketing on reducing the car travel and most of these have confirmed the effectiveness of social marketing program in travel demand management. For example, from the early 1990s, Brög (1998) undertook a series of experimental projects to examine the effectiveness of an individualised marketing program approach on public transport use in 13 European countries: he found the use of public transport increased quickly in nearly all projects after the individualized marketing program and without making any system improvements to the public transport itself. Rose and Ampt (2001) evaluated two early trial projects known as *Travel Blending* conducted in Australia, one in Sydney and the other in Adelaide. Their qualitative analysis of the 50 participants in Sydney found an increased awareness of the environmental consequences of using private cars with good intentions displayed by participants to reduce their car travel. The quantitative analysis of the 100 households in Adelaide found about a 10% reduction in vehicle kilometres travelled. Rose and Marfurt (2007) quantitatively assessed the impact of a "Ride to Work Day" event on travel behaviour change using a follow up survey carried out 5 months after the event. Their results showed about

27% of participants riding to work for the first time were still riding to work 5 months after the event with over 80% of the first time participants indicating that the event had a positive impact on their willingness to ride to work. All of these social marketing programs aim to identify people who are open to change their travel behaviour rather than trying to influence the population at large. This group of people are usually those in "contemplation" and "preparation" stages based on transtheoretical model of behaviour change (Prochaska and Velicer 1997).

In the United States, Cooper (2007) evaluated the Washington State's King County Metro Transit's *In Motion* program, a community-based social marketing approach, and found a 24–50% decrease in single occupancy driving and a 20–50% increase in public transport use. Although the results show promising results for the *In Motion* program, there is no evidence to identify whether these changes in travel mode share are sustained in the longer term. Dill and Mohr (2010) examined the effects of City of Portland's *SmartTrips* program in three different neighbourhoods of Portland, Oregon (US): they found the effects of *SmartTrips* did last beyond 1 year and up to a least 2 years but the effects were not significant in one suburban neighbourhood which had less good walkability than the two neighbourhoods where positive effects were achieved. However, there are several studies which have less positive outcomes from a social marketing intervention. James et al. (1999) evaluated the effects of the *IndiMark* program implemented in Perth, Australia finding the initial changes were not sustained after 12 months. In Taylor's review (2007) of soft transport policy measures implemented in Nottingham (UK), Leeds (UK) and Santiago (Chile), he also concluded that the trials of Voluntary Travel Behaviour Change Programs (VTBC) which showed short-term benefits did not show lasting changes in the travel behaviour of participants. All these studies used self-reported measures.

A review of social marketing programs and their effects on travel behaviour change over the three continents of Europe, Australia, and North America by Brög et al. (2009) found only two studies monitoring the long-term effects of behaviour change with most evaluation studies undertaking only pre- and post-surveys with the post-surveys being conducted immediately following the project. A more recent review by Richter et al. (2011) concluded that more panel studies are needed to investigate the long-term effects of social marketing programs so as to enable valid conclusions to be drawn and address the contradictory findings reported in previous studies. This review also identified, as a priority for future research, the need to investigate how hard transport policy measures might increase the effectiveness of soft transport policy measures. In the context of social marketing programs this means investigating whether there are different impacts on different target groups in different locations since existing research already shows that soft transport policy measures have different impacts on different target groups. This paper considers both these aspects: the way in which social marketing impacts may be differentiated by different socioeconomic groups and the impact of different built environments.

The most recent review specifically looks at the Swedish experience (Friman et al. 2013) and found that 32 out of 50 programs discovered had enough information to examine their outcomes. However, the review identified none of these programs met the basic method requirements for evaluation without systematic randomised design with only one program having used a comparison group. Well-designed interventions and their evaluation are under-represented in the literature particularly in the identification of whether social marketing interventions have long-lasting results.

In summary, the literature identifies two possible theoretical frameworks for explaining how social marketing can deliver travel behaviour change. This study however is more focussed on the outcome of a social marketing intervention and does not claim to unravel the theoretical foundations or point to one theory's dominance over another. This paper adds to the literature through providing a rigorous method for evaluation through the use of objective data collection using GPS tracking of participants. The opportunity offered by this approach allows clear evidence on whether the impact of a social marketing intervention is short or long lasting. This paper also adds to the literature through a consideration of whether the effects social marketing varies between individuals with differing social demographics and between different built environment configurations. This study addresses these issues through the use of a natural experiment design and longitudinal statistical models.

Data and methods

Data

TravelSmart, a voluntary travel behaviour change initiatives was introduced as a social marketing program by a number of localities around Australia from 2000 onwards. The program provided information to participant households about their travel options: the intention was that households would voluntarily reduce their car use, either by ride sharing, or by using public transport, bicycling, or walking. The details of the specific *TravelSmart* approach of South Australia can be found in Government of South Australia (2009).

As part of evaluating this program, daily travel data were collected using GPS in suburbs of inner northern Adelaide (Fig. 1), by the Institute of Transport and Logistics Studies (ITLS) of the University of Sydney (Stopher et al. 2009, 2013) between 2012 and 2014. GPS records were collected for all individuals aged over 14 in the household through their carrying of a portable GPS device for a period of 15 days during March–May for each year of the 3 years. This provides three waves of GPS panel data which is enhanced by the information provided in a paper based questionnaire, completed as part of the study.

The first wave of data collection commenced in March 2012 from a random sampling of the driver license listings, and randomly generated telephone numbers. The first wave of data were collected just before the implementation of TravelSmart program and is the before 'treatment' observation. The final eligible sample comprised 332 households that were successfully recruited, <19 households that subsequently dropped out, leaving a final total of 313 households. The second wave of data were collected immediately after the implementation of the TravelSmart instruments and the third and final wave approximately 1 year later. Table 1 gives a summary of the recruitment process and shows details of the panel data for this study, showing the levels of attrition over the 3 years. In summary, the panel consists of 144 households with valid data for each of the three waves of data collection. Among those 144 households, 104 provide continuous 15 days' GPS data.

Measures

Outcome variable

The GPS data have been processed by using software called G-TO-MAP, developed by the ITLS. G-TO-MAP has been shown to be reliable in detecting travel modes (Shen and Stopher 2014). G-TO-MAP, pre-processes the data before splitting the data into a number of trips, identifying the mode travelled by reference to the speed of travel and rules relating

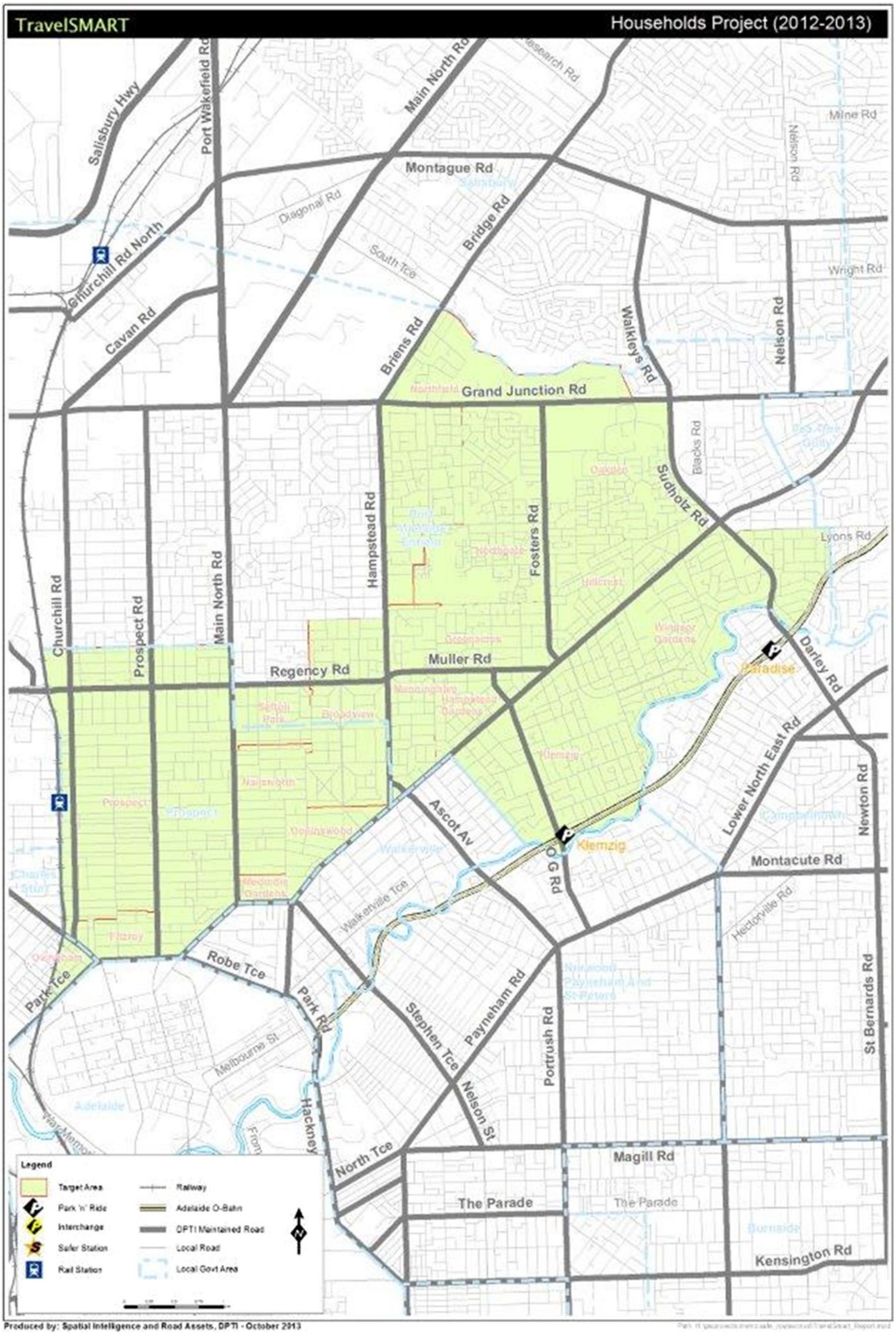

Fig. 1 Study area

Table 1 Summary of recruitment process

	First wave	Second wave	Third wave
Recruitment time	March–June, 2012	April–May, 2013	April–May, 2014
Number of households recruited	332	213	149
Number of recruited households with valid data	313	201	144
Number of recruited households with 15 days' valid GPS data	192	184	104

to the road network to detecting the car share and the likely purpose of travel. The five primary modes detected by G-TO MAP in this study include walk, bicycle, car, bus and rail. It should be noted that the detection of a car trip cannot distinguish between a car trip as a driver or as a passenger: not being able to distinguish between these is a common limitation of GPS based data collection. Following the mode detection, the time and distance by each mode were calculated for each person and by each wave to provide the panel data. The principle objective of TravelSmart is to reduce the car travel, thus this study uses as the outcome variables the trip time and trip distance by car. Only those with valid 15 days of GPS data were included in the analysis. The trip time and trip distance are the average driving time and driving distance per day by each individual or household over the 15 days. We estimated separate sets of models using driving time and driving distance as the outcome variables respectively, however, the model results are very similar in terms of making the conclusion. To avoid unnecessary duplication, in the following "Results and discussion" section, we only report the model results from using the driving time as the outcome variable. The model results for driving distance are available upon request.

Socio-demographic variables

The paper questionnaire completed by each participant provides the source of the socio demographic characteristics. Table 2 provides the basic description of the participants who were recruited and provided valid data over the three waves. The sample is not truly representative since it was drawn predominantly on listed telephone numbers and driving licence listings. For these reasons it is important to be cautious in transferring the findings of this study to other areas. Further, as shown by the *p* values, no significant differences were detected in terms of socio-demographics between the samples from the three waves,

Table 2 Characteristics of sampled participants from Wave 1 to Wave 3

	Wave 1 (n = 341)	Wave 2 (n = 309)	Wave 3 (n = 179)	*p* values
Age	50.11	51.07	49.63	0.66
% Female	54%	55%	58%	0.72
Household size	2.84	2.77	2.84	0.81
#Vehicles	2.07	2.03	2.08	0.78
#Bikes	1.77	1.65	1.73	0.71
Walk Score	54.15	53.97	53.33	0.87

Table 3 Characteristics of treatment and control group at Wave 1

	Non-*TravelSmart* (n = 96)	*TravelSmart* (n = 245)	*p* values
Age	48.96	50.57	0.47
% Female	53%	55%	0.78
Household size	2.88	2.82	0.77
#Vehicles	2.01	2.10	0.46
#Bikes	1.93	1.71	0.38
Walk Score	55.06	53.79	0.53

indicating that sample attrition over time is not systematic, and should not cause serious attrition bias.

Among the 341 individuals (belonging to 192 households) were recruited at Wave 1, 245 (belonging to 139 households) participated in TravelSmart after the recruitment and are the 'treatment' group. The 96 participants (belonging to 53 households) who did not participate in *TravelSmart* are the 'control' group. There were no statistically significant differences between the two groups before 'treatment' at Wave 1 (Table 3).

Walkability

The built environment around each participant's home was measured using Walk Score® (www.walkscore.com). The Walk Score® is a publicly available website that provides walkability score for any addresses. The score is calculated primarily based on a location's accessibility to commonly used commercial and civic services taking account of the built environment through recognising the level of intersection density. The Walk Score® has been previously demonstrated as a valid and reliable measure of neighbourhood walkability (Carr et al. 2010; Duncan et al. 2011; Manaugh and El-Geneidy 2011) and has been used in Australian context (Cole et al. 2015). Each participant was assigned a walkability score based on their home address. The resulting walkability score, ranging from 9 (car-dependent neighbourhood) to 88 (very walkable neighbourhood), suggested significant variations of the built environment among the households in the sample. The walkability score was then dichotomized into two groups using a median split of 56 to give individuals in more walkable and less walkable neighbourhoods.

Modelling methods

The methodology involves the estimation of a latent growth model (LGM) first to investigate whether travel behaviour changed after the intervention of TravelSmart. LGM is a flexible latent variable technique that allows for the estimation of inter-individual variability in intra-individual patterns of change over time (Chan 2003; Curran et al. 2010). LGM also allows an exploration of the factors contributing to any identified patterns of change through the estimation of the association between these patterns and time-invariant or time varying variables (Chan 2003). LGM has been widely used in the analysis of longitudinal data in social and behavioural research (Laird and Ware 1982; McArdle and Nesselroade 2003; Zhang 2013). There are several advantages to model behavioural change over time using LGM. First, compared with conventional longitudinal models, such as repeated measures analysis of variance and multivariate analysis of variance, LGM is very flexible in terms of its ability to include a variety of complexities including partially missing data, non-normal distributed measures, complex nonlinear trajectories (Curran et al. 2010) with high levels of statistical power (Muthén and Curran 1997). Second, the LGM resembles the classic confirmatory factors analysis, where observed repeated measures are incorporated as multiple indicators on one or more latent factors to characterize the unobserved growth trajectories (Curran et al. 2010; Duncan and Duncan 2004). By using the latent variables in structural equation model (SEM), LGM can relax the assumption of equal variances over time as required in the traditional repeated measures analysis. Despite the above advantages, as LGM is carried out using SEM methodology, one well know limitation of SEM is the assumption of multinormally distributed variables (Duncan and Duncan 2004), although this drawback could be addressed by bootstrapping estimation which would require a relatively large sample.

The model depicted in Fig. 2a represents the basic form of a LGM in which two parameters, the intercept (representing initial status) and slope (representing rate of change) together describe a linear pattern of intra-individual change over the three time periods, T1 to T3. T1 to T3 are the observations of the response variables which in this paper are the different travel behaviours measured at the three points of time. The intercept is constant over time, modelled by constraining the loadings of all time points on the intercept factor to be equal to one. The latent slope factor is the slope of a linear curve, modelled by constraining the loadings of the three time points to be equal to 0, 1, and 2 respectively. The successive loadings for the slope factor define the slope as the linear trend over time (Hox et al. 2010).

The basic LGM model can be expanded to include one or more predictors of growth. The LGM with covariates is often called a conditional growth model because the growth trajectories are now conditioned on the predictors (Curran et al. 2010). In this study, for example, the socio-demographic characteristics of the participants could influence both the initial status of travel behaviour (shown by the intercept) and rate of changes in travel behaviour (shown by the slope). The socio-demographic variables are, therefore, incorporated as covariates in the LGM model to predict intercept and slope factors (Fig. 2b). The conditional LGM specified as Fig. 2b aims to test whether the rate of change in travel behaviour (slope) and initial level of travel behaviour is attributable to participants' social-demographic characteristics.

To explore whether *TravelSmart* influenced travel behaviour through its intervention, and the synergistic effects of social marketing and the built environment on travel

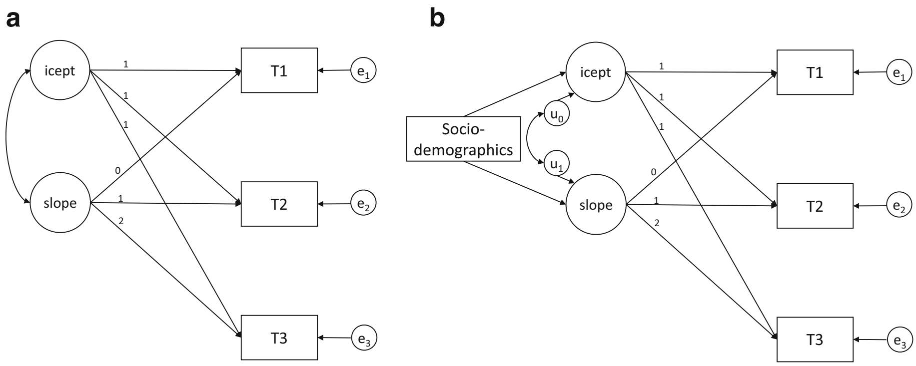

Fig. 2 Modelling frameworks with two parameters, intercept and slope (**a**) and a conditional growth model with covariates (**b**)

behaviour change, multiple-group LGM models were estimated. For this first question, the dummy variable, TravelSmart, is used as the grouping variable to see if the trend in travel behaviour change is different for TravelSmart participants (TS group) and non-TravelSmart participants (Non-TS group). For the second question, walkability (1 = more walkable, 0 = less walkable) is used as the grouping variable to see if the trend in travel behaviour change is different for high-walkable neighbourhoods compared to low-walkable neighbourhoods. The underlying hypothesis is that residents in high-walkable neighbourhoods are more likely to switch their travel modes from cars to alternative modes after the TravelSmart intervention and therefore more likely to reduce car travel than those living in low-walkable neighbourhoods. Moreover, it is expected that high-walkable neighbourhoods will give rise to a steeper trajectory of change than residents located in low walkable neighbourhoods. With this modelling approach, the multiple-group latent growth model simultaneously fits latent growth models to high-walkable and low-walkable groups.

All the analysis were conducted at both individual and household level. This was to explore the hypothesis as to whether there is compensatory behaviour being undertaken within a household with the reduction of car trips of one member of the household perhaps leading to more trip chaining or activities being undertaken by different members of the household whose car travel may increase. Identifying whether household behaviour change may be different from the travel behaviour change of the individual is important for a wider exploration of the possible synergistic effects of social marketing programs and the built environment.

Results and discussion

In total, six models were estimated using Mplus 7.4 which is convenient software for estimating SEM models with latent variables, developed by Muthén and Muthén (2010). The first two models are basic LGM models estimated at both individual and household level, aiming to investigate how the travel behaviour changed after the TravelSmart, the second two models are conditioned LGM models with socio-demographic covariates estimated at both individual and household level, aiming to answer whether socio-

Table 4 Model fit indices

	χ^2	*df*	*p* value	CFI*	SRMR*	No. obs.
Model 1: Multi-group (TS vs. Non TS) LGM (Individual level)	9.044	2	0.011	0.949	0.057	179
Model 2: Multi-group (TS vs. Non TS) LGM (Household level)	8.831	2	0.012	0.961	0.092	104
Model 3: Conditioned LGM (Individual level)	8.884	3	0.031	0.952	0.033	128
Model 4: Conditioned LGM (Household level)	3.206	3	0.361	0.998	0.021	64
Model 5: Multi-group (Walkable vs. Non walkable) LGM (Individual level)	5.206	2	0.074	0.968	0.044	131
Model 6: Multi-group (Walkable vs. Non walkable) LGM (Household level)	3.769	2	0.152	0.986	0.036	77

* CFI is comparative fit index. SRMR is standardized root mean square residual

demographic characteristics influence travel behaviour change. The final two models are multi-group LGM models using walkability as the grouping variable, again estimated at both individual and household levels, aiming to explore whether the travel behaviour change is different in more walkable neighbourhoods as compared to less walkable neighbourhoods. All the six models fit the data well (Table 4): this is measured by two goodness of fit indices Comparative Fit Index (CFI) and Standardized Root Mean Square Residual (SRMR). Based on Hu and Bentler (1999), who suggest a cut-off value close to 0.95 for CFI and a cut-off value close to 0.08 for SRMR, Table 4 shows a relatively good fit between the hypothesized model and the observed data. Table 4 also reports a χ^2 value since in these type of analyses it is typically reported but it is not really an appropriate measure of model fit as it is sensitive to sample size and several other conditions.

The effects of the TravelSmart on travel behaviour change

To investigate effect of the TravelSmart on travel behaviour change, multi-group latent growth curve models were tested at both individual (Model 1) and household level (Model 2). The model results are reported in Table 5. In terms of interpretation, in each of Tables 5, 6 and 7, *p* values refer to intra-model comparison, and therefore a significant (Mean) intercept for Non-TS group suggests the intercept is significantly different from zero for Non-TS group. It is not used to compare between the groups. The means of growth factors (intercept and slope) suggest the intra-individual growth patterns. The variances capture the inter-individual differences in growth factors. A significant slope mean indicates that it is significantly different from zero which means that there is development over

Table 5 Multi-group (TS vs. Non-TS) LGM model results for driving time at both individual and household level

	Non-TravelSmart			TravelSmart		
	Effect	SE	*p* value	Effect	SE	*p* value
Individual Level (n = 179) (Model 1)						
Means						
Intercept	26.742	2.299	0.000	31.524	1.834	0.000
Slope	−1.002	1.346	0.457	−3.027	0.935	0.001
Variance						
Intercept	266.944	88.888	0.003	277.550	60.256	0.000
Slope	70.770	32.686	0.030	22.781	25.774	0.377
Covariance	−102.260	46.577	0.028	−49.330	32.246	0.126
Household Level (n = 104) (Model 2)						
Means						
Intercept	41.311	6.222	0.000	53.095	4.311	0.000
Slope	−0.783	2.440	0.748	−6.504	1.734	0.000
Variance						
Intercept	2222.288	708.830	0.002	1082.102	233.176	0.000
Slope	470.094	181.061	0.009	57.136	75.030	0.446
Covariance	−869.438	320.393	0.007	−185.790	100.534	0.065

Table 6 Conditioned LGM model results for driving time at both individual and household level

	Individual level (n = 128) (Model 3)			Household level (n = 64) (Model 4)		
	Effect	SE	*p* value	Effect	SE	*p* value
Direct paths from socio-demographics to intercept and slope						
Female (male is base) → Intercept (β_1)	−7.993	3.647	0.028	–	–	–
Female (male is base) → Slope (β_2)	3.734	1.888	0.048	–	–	–
#Vehicles → Intercept (β_3)	3.480	1.653	0.035	13.027	4.545	0.004
#Vehicles → Slope (β_4)	−0.325	0.856	0.704	0.397	2.038	0.845
#Bicycles s → Intercept (β_5)	–	–	–	5.573	2.772	0.044
#Bicycles → Slope (β_6)	–	–	–	−2.106	1.243	0.090
Means						
Intercept (α_0)	37.064	7.305	0.000	22.519	8.359	0.007
Slope (α_1)	−8.370	3.781	0.027	−5.561	3.748	0.138
Variance						
Intercept (ψ_{00})	263.706	58.877	0.000	641.070	181.460	0.000
Slope (ψ_{11})	24.834	25.420	0.329	54.698	67.692	0.419
Covariance (ψ_{01})	−49.895	31.940	0.118	−109.359	85.208	0.199

Table 7 Multi-group (Walkable vs. Non-walkable) LGM model results for driving time at both individual and household level

	Non-walkable			Walkable		
	Effect	SE	*p* value	Effect	SE	*p* value
Individual Level (n = 131) (Model 5)						
Means						
Intercept (α_0)	30.370	2.010	0.000	32.808	3.052	0.000
Slope (α_1)	−2.117	1.161	0.068	−3.992	1.464	0.006
Variance						
Intercept (ψ_{00})	157.022	60.264	0.009	398.036	109.164	0.000
Slope (ψ_{11})	29.335	25.689	0.253	13.869	46.067	0.763
Covariance (ψ_{01})	−52.350	33.995	0.124	−42.619	55.944	0.446
Household Level (n = 77) (Model 6)						
Means						
Intercept (α_0)	51.628	6.483	0.000	54.489	5.704	0.000
Slope (α_1)	−4.938	2.313	0.033	−8.010	2.547	0.002
Variance						
Intercept (ψ_{00})	1178.874	365.529	0.001	982.296	294.148	0.001
Slope (ψ_{11})	−6.137	115.666	0.958	114.311	97.611	0.242
Covariance (ψ_{01})	−160.825	152.233	0.291	−205.176	131.171	0.118

time on average. A significant slope variance means that not all individuals grow at the same rate.

The average baseline driving time for TS group was slightly higher than that for Non-TS group at both individual (32 vs. 26 min per day) and household level (53 vs. 41 min per day). For both groups, there were significant variability in these driving times shown by the variances across individuals (Non-TS: $\psi_{00} = 266.944$, $p < .005$; TS: $\psi_{00} = 277.550$, $p < .005$) and across households (Non-TS: $\psi_{00} = 2222.288$, $p < .005$; TS: $\psi_{00} = 1082.102$, $p < .005$) at the baseline. Furthermore, the model shows an average decrease of 1 min for individuals and almost 1 min for households, but these are not statistically significantly different from zero.

On average, for TS group, the daily driving time declined by 3 min for individuals and 7 min for households each year shown by the means, and this decrease is statistically significant for both the individual level (unstandardized $\alpha_1 = -3.027$, $p < .005$) and the household level (unstandardized $\alpha_1 = -6.504$, $p < .005$). For Non-TS group, however, the decrease of the driving time was not statistically significant for both the individual level (unstandardized $\alpha_1 = -1.002$, $p =$ ns) and the household level (unstandardized $\alpha_1 = -0.783$, $p =$ ns).

For TS group, slopes did not significantly vary at both individual ($\psi_{11} = 22.781$, $p =$ ns) and household level ($\psi_{11} = 57.136$, $p =$ ns), suggesting that all individuals and households changed over time at approximately the same rate. For Non-TS group, however, slopes vary significantly at both individual ($\psi_{11} = 70.770$, $p < .05$) and household level ($\psi_{11} = 470.094$, $p < .05$), suggesting that all individuals and households changed over time at different rate.

For TS group, the correlation between intercept and slope at individual level was not significant ($\psi_{01} = -49.330$, $p =$ ns), however, there was a marginally significant negative correlation between baseline scores and slopes at the household level ($\psi_{01} = -185.790$, $p < .1$), indicating that households with higher driving time at the beginning of the study were more likely to experience decline in driving time over time. For Non-TS group, there was a significant negative correlation between baseline scores and slopes at both individual ($\psi_{01} = -102.260$, $p < .05$) and household level ($\psi_{01} = -869.438$, $p < .05$), indicating that individuals and households with higher driving time at the beginning of the study were more likely to experience decline in driving time over time.

The way in which there are similar results from individual and household level estimations and different trajectories of driving behaviour change between TS and Non-TS groups confirm that driving time decreased after the TravelSmart intervention. Further, it is also worth noting that the average rate of decreasing in driving time for each individual calculated based on household level estimation (by dividing the slope of household by the average household number ($-6.504/2.8 = -2.32$)) is lower than that estimated from the individual level model (-3.03), suggesting that there is compensatory behaviour being undertaken within a household with the reduction of car trips perhaps leading to more trip chaining or activities being undertaken by different members of the household.

Role of socio-demographics on travel behaviour change after the TravelSmart

To investigate whether decreases in driving time observed above are moderated by socio-demographic characteristics, conditioned latent growth curve models are tested at both individual (Model 3) and household levels (Model 4). Only those who participated in TravelSmart program were included in this analysis. The model results are reported in Table 6. The interpretation is as identified above for Table 5.

The socio-demographic variables tested included age, gender, household size, number of vehicles in the household, and the number of bicycles in the household. In the reported model estimation, only the variables that are significant in at least one path estimation are presented: this allowed the models to be parsimonious which in turn improved model fit. The individual-level model results for gender at the mean show females, on average, driving approximately 8 min less than males at the baseline ($\beta_1 = -7.993$, $p < .05$), with decreases in driving time for females over the 3 years being significantly smaller than the decrease in driving time for males, as shown by the positive association with slope ($\beta_2 = 3.734$, $p < .05$) and thereby a flatter slope for females. Also, as expected, individuals having more vehicles had higher driving times than others at the baseline ($\beta_3 = 3.480$, $p < .05$), however, the number of vehicles have an insignificant impact on the decreasing trend over the 3 years ($\beta_4 = -0.325$, $p = 0.70$). The model results at the household level indicated that the households with more vehicles drove more at the baseline than other households ($\beta_3 = 13.027$, $p < .005$), but their changes in driving time over the 3 years were not significantly different from others ($\beta_4 = 0.397$, $p = 0.85$). It is interesting to note that the households with more bicycles also had higher car driving times at the baseline ($\beta_5 = 5.573$, $p < .05$), but they exhibited a quicker decline to their driving time than households with fewer bikes ($\beta_6 = -2.106$, $p < .1$). Of course, households having more bicycles might be related to financial capacity with bicycle ownership representing greater mobility options for lower income households in their replacement of car trips.

The effects of walkability on travel behaviour change after the TravelSmart

To investigate whether there are differences in the decrease trajectory of driving times between the walkability of neighbourhoods, a multi-group LGM models is estimated at both individual (Model 5) and household levels (Model 6). Only those who participated in TravelSmart program were included in this analysis. The model results are reported in Table 7 and again the interpretation is as identified above for Table 5.

Model results at the individual level show the average baseline driving time was slightly higher in high-walkable neighbourhoods ($\alpha_0 = 32.808$) than in low-walkable neighbourhoods ($\alpha_0 = 30.370$), and there was significant variability in these driving times across individuals in both types of neighbourhoods as shown by the significant variances in intercept (non-walkable: $\psi_{00} = 157.022$, $p < 0.01$; walkable: $\psi_{00} = 398.036$, $p < 0.01$). On average, the driving time declined by nearly 4 min each year in high-walkable neighbourhoods, and this decrease was statistically significant (unstandardized $\alpha_1 = -3.992$, $p < .05$). In contrast, for low-walkable neighbourhoods the decline was just over 2 min, and this decrease was only significant at the 10% level of significance (unstandardized $\alpha_1 = -2.117$, $p < .1$). This suggests that the walkability of the neighbourhood moderates the effects of TravelSmart on travel behaviour change, with faster decreases in driving time over the 3 years observed in high-walkable neighbourhoods than in low-walkable neighbourhoods. The model results at the household level are very similar to results at the individual level and provide further confirmation of these findings.

Conclusions and policy implications

Soft policies such as the social marketing program investigated in this paper aim to reduce driving and promote walking, bicycling and public transport use. These programs are increasingly being proposed and implemented across the world to address the challenges of climate change. Increasingly these programs are being delivered using non-traditional methods that rely on ICT through information delivered by smart phones, for example.

This study differs from evidence otherwise in the literature by its use of objective data collected through GPS tracking of the cohort under investigation. This was possible because of the G-TO MAP program allows the GPS data to be transferred to trips and identify mode use so that the evaluation is not dependent on self-reported data. In addition, this paper provides evidence on the longer term effects which in other studies has not been possible because of lack of data or an absence of a longitudinal experimental design or limited by not taking account of individual differences in response to the social marketing program and the interactive effects of hard and soft policies. This paper uses unique 3-year panel data together with latent growth curve models to evaluate the long-term effects of the social marketing program *TravelSmart*, implemented in Adelaide, South Australia, to explore whether travel behaviour change varies among individuals with different socio-demographic characteristics and among individuals living in different types of neighbourhood.

The latent growth models at both individual and household levels show that both driving time and the driving distances of *TravelSmart* participants have a declining trend over the 3 years, indicating that *TravelSmart* had a significant effect on reducing car travel with effects being sustained beyond 1 year and up to 2 years. This finding is consistent with the few studies that have demonstrated the long-term effects of the social marketing program. However, by comparing the effects of *TravelSmart* at the individual level and household level, there is some evidence of compensatory behaviour between household members, with the reduction of car trips of one member of the household leading to more car trips being undertaken by different members of the household. This may dilute the effects of *TravelSmart* but not to the extent of making the overall effects on reducing driving time and driving distance at the household level insignificant.

Together, these findings build on studies such as Dill and Mohr (2010) to provide further evidence to support using social marketing programs as a soft measure to intervene travel behaviour change. In addition, this paper shows the effects of *TravelSmart* on reducing the amount of driving varies among individuals with different socio-demographic characteristics. In particular, males decrease their driving time or distance faster than females after the intervention of *TravelSmart*, in other words, females are less responsive to the *TravelSmart* program than males. This is somewhat at variance with the convergence of male and female travel the aggregate level but is likely to be due to the way in which females continue to have specific travel needs and patterns (Rosenbloom 2004). For example, women already do more trip chaining than men as they tend to take more household chores than men, such as grocery shopping and taking their children to school, and thus have less room to change their travel behaviour. Furthermore, women drive less than men at the baseline and thus reducing their driving by similar absolute numbers to men would be a higher percentage and perhaps more difficult to achieve. Interestingly, households with more bicycles showed a quicker decline to their driving time than households with fewer bikes. However, the panel data only allows for limited socio-demographic variables to be included in the analysis. The results in this paper thus provides some preliminary evidence showing how individual differences in response to the social marketing program are important. This suggests that the design of future social marketing programs must pay special attention to specific groups of people in the preparation of material, distinguishing between information given to males and females, for example.

Finally, this study found that people living in neighbourhoods with different levels of walkability show different travel behaviour change trajectories after the intervention of *TravelSmart*. In particular, those living in high-walkable neighbourhoods have a steeper decrease in total driving time and distance than those living in low-walkable neighbourhoods. A future research area with a larger sample size could consider modelling the interaction effects of walkability with the social marketing program. This paper's results points to a soft policy of social marketing to reduce VKT working better when it has the support of hard policies such as a supportive built environment. Without a neighbourhood environment that provides the opportunity for alternative travel, the effects of social marketing programs of reducing car travel are more limited. This suggests that the design of future social marketing program must pay attention to the location and built environment of the study area in the promotion of a social marketing program.

This paper has several limitations. First, the relatively small sample size limits the robustness of statistical models and maybe there are other variables that would be significant in a larger panel that would allow confirmation and generalisation of the findings from this study. Second, this analysis could only include the very limited number of social demographic variables collected by *TravelSmart* and more studies are needed to explore the moderation effects of other socio-demographic characteristics on travel behaviour change using social marketing programs. This also limits the possible segmentation of the sample that might give more detailed insights. Third, like other natural experimental studies in social science may face, we could not account for other unobserved changes, such as different changes in the built environment between treatment and control group, during the study period, and this may confound our model results. Finally, as children under 14 were not included in the data collection and analysis, changes in travel behaviour of children over time might influence the changes of travel behaviour of parents in the household and this is not captured in this evaluation.

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