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Using Facebook to Recruit Urban Participants for Smartphone-Based Travel Surveys

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ABSTRACT

Social media has become an integral part of everyday life for many individuals, serving as a platform to express opinions, share memories and lifestyles, follow news, and adapt to social trends and norms. The wealth of user information and analytics on these platforms has facilitated the development and sale of tailored products and services, benefiting advertisers and researchers seeking survey participants. Social media advertising has demonstrated its effectiveness in reaching hard-to-reach populations. However, transport researchers have yet to capitalise on this potential fully. This paper presents our experience using social media to recruit participants for two smartphone travel surveys conducted in Australia. We demonstrate that social media recruitment and smartphone-based travel surveys are highly effective, adaptable, and can be rapidly deployed in response to research opportunities, such as during the early phase of the COVID-19 pandemic when traditional methods may be less suitable. This approach also holds great potential for travel surveys targeting the general population. This paper shares several lessons from this experiment, including our administrative approach and detailed technical instructions to utilise open-source software tools for conducting smartphone travel surveys like ours. This approach significantly reduces study costs compared to most commercial solutions.

1. Motivation and background

Following the global COVID-19 pandemic, travel behaviour has significant changed due to mobility restrictions and public health directives. Many routine activities, including meetings and classes, have shifted to virtual platforms, public transport usage has declined due to contagion fears, and social distancing is widely practised in public spaces (Chinazzi et al., 2020). Traditional travel surveys, which typically capture data annually, fail to reflect these rapid behavioural shifts. Conventional methods such as telephone, face-to-face interviews, mail-back surveys, and online surveys are costly, time-consuming and unsuitable for tracking the swift changes in travel patterns during the pandemic (Itsubo and Hato, 2006; Nitsche et al., 2014). For example, the UK's Department for Transport suspended face-to-face National Travel Survey fieldwork at the pandemic's onset, resuming in May 2020 with a new 'push-to-telephone' method (Cornick et al., 2020).

This paper discusses our experience using Facebook advertisements to recruit participants for two smartphone-based travel surveys in Australia during the pandemic. While social media has been effectively used for participant recruitment across various research disciplines, its adoption in transport research, particularly for smartphone-based travel surveys, remains limited.

1.1. Smartphone travel survey platforms

GPS-equipped devices in travel surveys have proven to be a game changer for collecting individuals' travel diaries (Yue et al., 2014). It fills several shortcomings of the traditional data collection methods such as the trip under-reporting issue and the low spatio-temporal detail of the surveyed data (Bricka and Bhat, 2006). The strengths and weaknesses of GPS and smartphone-based travel surveys have been discussed extensively in research (Wolf, 2000; Stopher et al., 2008; Shen and Stopher, 2014; Gadziński, 2018; Harrison et al., 2020).

Within the last decade, many studies (Cottrill et al., 2013; Greaves et al., 2015; Zhao et al., 2015) rely on the GPS-equipped devices that can be found in most people's pockets today, smartphones, rather than a single-purpose GPS device that participants are asked to carry during

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daily travel (e.g., Murakami and Wagner (1999) and Wolf (2000)). Hence, participants must only install an app on their smartphones from the official app stores (i.e., Apple App Store and Google Play Store) and keep it running for several days. Such apps are designed to utilise internal sensors (e.g., GPS and accelerometer) to collect GPS trajectories and infer transport modes. In addition, data collection through a mobile application allows for user inputs (e.g., response to a trip end prompt) and off-load complex computing tasks and data from the device, hence consuming less battery, which is one of the participants' main concerns.

Many platforms have been developed to collect individuals' travel diaries as an alternative to traditional methods. Their mobile apps can be classified into two types: those that are an all-in-one travel diary app where confirming the accuracy of recorded trips can be done within the app (e.g., Shankari et al. (2018) and Patterson et al. (2019)) and the other type is those that use an app for travel logging and a web-based form to validate the collected trips (e.g., Greaves et al. (2015) and Geurs et al. (2015)). Which one is more convenient for users remains to be explored.

Apart from the classification mentioned above, they may have other differences in how they work. Different platforms may use various models and algorithms for trip segmentation and activity classification. Some only work on a specific mobile operating system, which limits the number of potential participants; some are not available from the official app stores, which means they may require special installation procedures unfamiliar to most people. Some cost a lot of money to deploy, and some are open-source and free to use but require a full-stack developer to set up.

Existing platforms are available as open-source (Patterson et al., 2019; Prelipcean et al., 2018), open-source and community-maintained (Shankari et al., 2018), closed-source (Safi et al., 2015; Berger and Platzer, 2015), closed-source and commercialised (Greene et al., 2016; Cottrill et al., 2013). Advancement in these platforms means that end users can expect to see their trip data after the raw data have undergone some level of processing to remove errors or inconsistencies, unlike in the early days of GPS data where significant pre-processing was needed before they could be used, see Stopher et al. (2008). Despite these efforts in application development, there is still a lack of low-cost travel survey platforms to deploy and capable of collecting high-quality travel data suitable for travel surveys. Moreover, a total cost comparison study of smartphone travel surveys to help researchers evaluate their options does not exist to the best of our knowledge.

Furthermore, there is a lack of discussion on challenges related to administering a smartphone travel survey. Changes in mobile operating systems always create new challenges when administrating a smartphone travel survey. If these challenges are not identified and dealt with appropriately, they can significantly impact the participation rate of the survey and could mislead the interpretation of data obtained from the app, see Cottrill et al. (2013).

1.2. Travel survey recruitment

Travel survey recruitments have been conducted using various tactics. These recruitment methods range from mailing surveys, setting up booths at public places with high foot traffic, advertising on the traditional media (e.g., television, radio, flyers, newspapers), e-mails, blogs, and social media advertisement. Some unorthodox approaches can also be practical, Maruyama et al. (2015) claim that using of a famous mascot in the local area, Kumamon (Wikipedia, 2021), may also be attributed to their successful travel survey recruitment. However, most smartphone-based travel surveys have been conducted on small scales; hence, the effectiveness of different recruitment methods has not been thoroughly explored. Patterson and Fitzsimmons (2016) suspect that it could be because most studies are experimental and aimed at testing their applications or models. Some large-scale smartphone travel surveys exist (Zhao et al., 2015; Faghih Imani et al., 2020; Tchervenkov et al., 2020). One of the most well-advertised studies is the "City Logger" project conducted in Toronto, Canada, by Faghih Imani et al. (2020). They advertised their smartphone-based travel survey on various local traditional media channels, the university's webpage, social media platforms and YouTube. As shown by Maruyama et al. (2015), people from different generations came to know of their study from different mediums, and their posters and flyers were most effective among people aged between 40 to 59. Hence, Using multiple mediums can reduce the chance that the sample is compromised by the biases inherited in such medium.

1.3. Social media recruitment in survey research

Social media plays a significant role in modern communication, providing a robust platform for targeted advertising. Advertisers leverage detailed user data—demographics, interests, and behaviours to deliver tailored ads, enhancing profitability. Studies like Faghih Imani et al. (2020) and Silvano et al. (2020a) have utilised social media for survey recruitment, though it remains unclear whether these were paid campaigns or organic posts. The effectiveness of such approaches can vary widely based on page popularity and audience demographics.

King et al. (2014) highlight that combining online data collection with social media recruitment can efficiently target specific populations at reduced costs. Topolovec-Vranic and Natarajan (2016) suggest evidence supporting social media as an effective recruitment method for hard-to-reach populations. This method simplifies survey processes and potentially engages underrepresented demographic groups in travel surveys, a topic not extensively covered in the literature.

Social media allows advertisers to monitor real-time ad performance time through metrics like views, clicks, and shares, enabling iterative improvements through A/B testing (Scheinbaum, 2016). Despite its promise, social media recruitment can induce biases by attracting distinct population segments, as discussed in previous studies (Inbakaran and Kroen, 2011; Ramo and Prochaska, 2012; Frandsen et al., 2014, 2016). Social media users generally skew younger and more tech-savvy, which can influence survey results, especially in smartphone-based travel surveys (Astroza et al., 2017; Dal Fiore et al., 2014).

Assemi et al. (2018) found that a survey app's ease of use and perceived usefulness significantly impact completion rates, with privacy concerns playing a minimal role. However, their study focused only on university students without incentives, limiting the applicability of findings to a broader population. Understanding what drives survey participation is crucial for improving engagement and ensuring representative results.

1.4. Contributions

As pointed out by Gadziński (2018), using smartphones in travel data collection is 'flexible' in terms of how data should be collected by the sensors, 'straightforward' as any additional questionnaires can be integrated within the app, 'scalable' as the direct contact with any participant is not required. Combined it with social media recruitment, similar research can be deployed almost anywhere in a short time instead of the traditional recruitment methods.

This study presents our experience in administrating two smartphone travel surveys during the COVID-19 pandemic in Australia, prompting us to use Facebook ads to recruit all our participants. We showed that Facebook can be used to recruit a specific group of the population and the broad population of a particular region for a smartphone travel survey. We also provide several survey resources in the supplementary document to help researchers or agencies quickly kick-start low-cost smartphone travel surveys. Section 2 presents the results of our recruitment and smartphone travel survey. We discuss the challenges and remedies of this study to increase the number of recruited participants, the socio-demographic characteristics of our participants and their attitudes before and after the data collection, an analysis of three incentive schemes, and a cost comparison between outsourced and insourced smartphone travel surveys. Finally, the last section concludes the main lessons learned from this study.

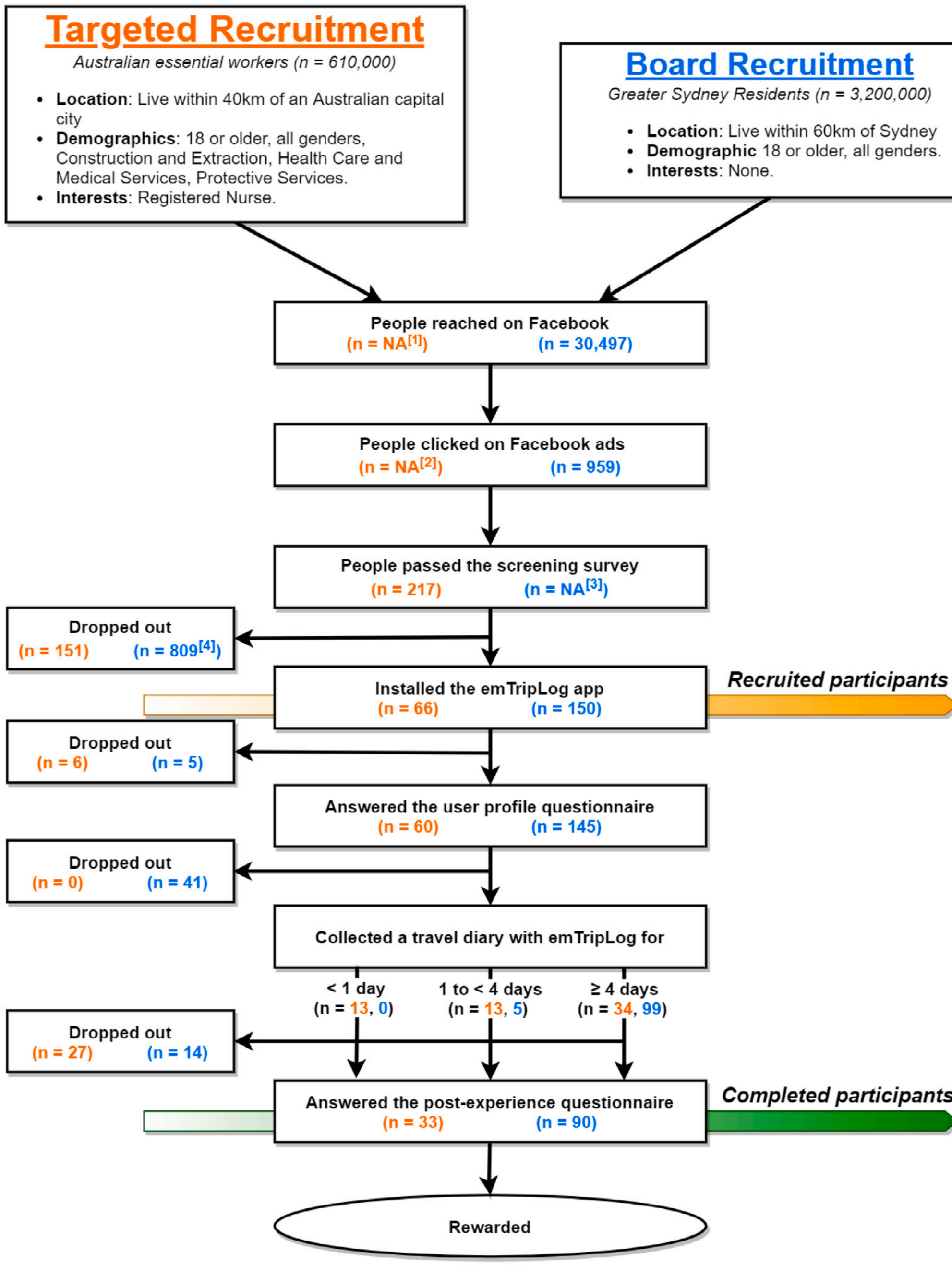


Fig. 1. Participant flow diagram of the two smartphone travel surveys. [1] and [2]: Facebook ad performance data of the targeted advertisements were not fully available. [3]: There was no screening survey for the broad recruitment. [4]: This is the number of people who clicked on our Facebook ads but did not proceed to install the app. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

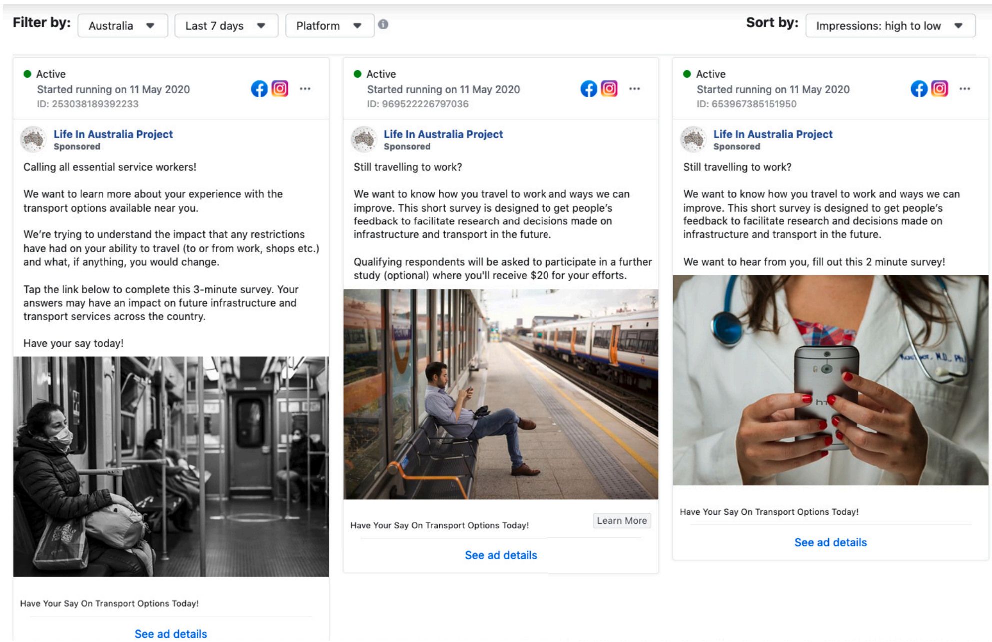
2. The study

This study presents findings from two smartphone travel surveys conducted in Australia during the COVID-19 lockdowns. The surveys were conducted approximately one year apart, and advertised only on Facebook. Section 2.1 details our initial survey, which explored targeted recruitment via Facebook's advertising platform, while Section 2.2 focuses on recruiting the general population of Greater Sydney. The administrative approach minimises interaction between administrators and participants and can be scaled according to budget.

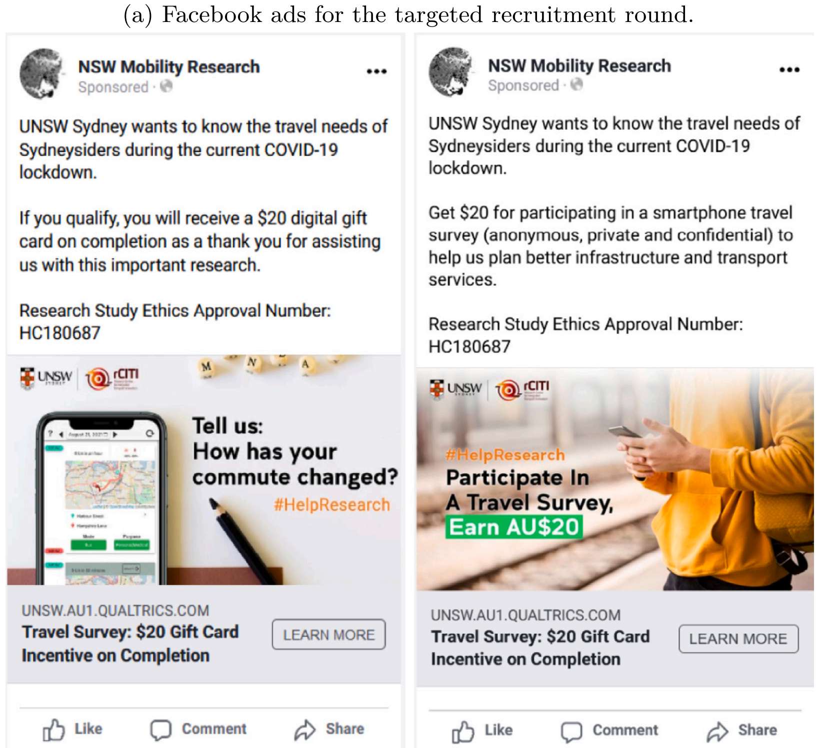
Facebook, a leader in the social media industry with the highest active user base in 2021, reaches approximately 17 million Australians aged 18 and older, nearly 86% of the adult population (Statista, 2021). This extensive reach and deep user insights informed our choice to use Facebook over other platforms like Twitter or LinkedIn.

Participants clicking our ad were redirected to a webpage detailing the onboarding process for the emTripLog app, where they could opt to participate. Those who consented were asked to record their travel diary for four days, with incentives of up to AUD$20. Eligible participants received an electronic gift card upon completing or dropping out of data collection.

Fig. 1 illustrates the participant flow for both surveys. In the diagram, *n* indicates the number of participants at each stage; orange numbers represent targeted recruitment, and blue numbers indicate



(a) Facebook ads for the targeted recruitment round.



(b) Facebook ads for the broad recruitment round.

Fig. 2. Examples of the Facebook advertisements used in this study.

broad recruitment. The following subsections discuss the findings and any discrepancies in the advertising materials and boarding procedures. The results are believed to be comparable and meet the study's objectives. *Recruited participants* refer to those who joined the survey and installed the app, while *completed participants* include those who completed the survey. This distinction helps clarify the dropout rates during onboarding and data collection.

2.1. Targeted recruitment

2.1.1. Participants

The first travel survey was conducted in mid-May 2020, targeting specific groups of COVID-19 essential workers in metropolitan areas of Australia. Using Facebook's advertising tools, we defined our audience as individuals aged 18 or older living within a 40 km radius of any Australian capital city and working in specific sectors. The targeted sectors included Construction and Extraction (67,000 people), Health Care and Medical Services (89,000 people), Protective Services (21,000 people), and those with an interest in 'Registered Nurse' related Facebook pages (460,000 people). Facebook's data suggested a match of 610,000 users, approximately 32% of the relevant population, according to the 2016 Australian census. The survey recruitment continued without demographic quotas until the advertising budget was depleted.

2.1.2. Ads

We selected one of four bidding strategies to manage our advertising budget on Facebook. We opted for the 'lowest cost' strategy, which aims to achieve the lowest cost per ad exposure while fully utilising the daily budget (Facebook, 2021). While cost control strategies such as cost cap, bid cap, and target cost are better suited for campaigns with a fixed recruitment budget per result, these could extend the recruitment duration, especially if other advertisers highly sought after the target audience.

During our recruitment phases, we closely monitored metrics like the clicks-per-recruited-participant ratio to enhance the cost-effectiveness of our recruitment efforts. It is important to note that our advertising firm managed our campaign, which limited our direct access to detailed campaign results; we received only partial data from the firm.

2.1.3. Onboarding procedure

Despite Facebook's extensive user data, the accuracy of user-provided information such as demographics and employment history cannot be guaranteed. To address this, we implemented a screening survey to filter out respondents who did not meet our criteria. However, exceptions were made for individuals who, despite not working in our targeted industries, commuted to work more than three days per week.

After passing the screening survey and consenting to participate, individuals were directed to a landing page with instructions for installing the app and guidelines for the four-day survey period. Participants were required to keep the app running in the background for location tracking, log trip details daily (including mode and purpose) and complete an in-app survey at the end of the participation period or upon choosing to discontinue.

Log in to the app required a Gmail account, which may have deterred some potential participants who did not have or wish to use their Gmail for authentication. At the time, this was the only secure authentication method available on the *e-mission* platform.

Recruitment occurred in three phases between 12 May and 4 June 2020, with a total budget of AUD$5000. Fig. 3(a) illustrates this process. Subsequent subsections detail the adjustments made to enhance recruitment effectiveness based on emerging insights.

2.1.4. Phase 1

The first phase of the recruitment was aimed at measuring the effectiveness of our advertising posts which contained different images, headlines, and amounts of incentives. Three different tiers of incentives were advertised: a '*please do it for a good cause*' tier or $0 tier, an AU$ 5 per day tier, and an AU$ 20 per completion tier. Each tier has three different advertising posts, with various images and messages, as shown in Fig. 2(a). In this phase, AU$ 500 was allocated to the ads. Once the phase's ad budget had been exhausted, we stopped all the running ads to evaluate each campaign's initial engagement and participation rates.

Several insights were generated from this initial exercise. All the posts reached 18,022 people across Australia within 24 h. We found where people had dropped out in the recruitment process, which versions of our advertisements worked best, which incentives were the most effective, and how many interested participants installed the app on their smartphones.

2.1.5. Phase 2

Four major changes were implemented based on initial findings to increase app installations.

1. The survey landing page was simplified by replacing detailed written instructions with an instructional video, effectively guiding participants on setting up and using the app.
2. Information on expected engagement time and minimum duration of use was removed to prevent discouraging potential participants, following insights from Keusch (2015) that initial time investment tends to increase continuation likelihood.
3. We initiated follow-up emails for participants who had not installed the app, leading to increased installation rates. This approach was adopted for all new participants, with a reminder email sent to each to respect privacy.
4. The number of questions and steps was reduced to decrease the dropout rate in the screening survey.

Following these adjustments, ads were relaunched on 15 May with a budget of AU$1000, allowing us to evaluate the effectiveness of these changes. This phase recruited an additional 84 participants, reducing the cost per recruited participant from an average of AU$20.83 to AU$11.9. The ads ran over a weekend, capitalising on higher user activity, with Saturday recording the highest recruitment.

Based on these outcomes, the AU$5 per day incentive scheme was identified as the most effective, likely due to the perceived flexibility it offered participants. Consequently, we decided to allocate the remaining budget to this scheme in subsequent phases, focusing exclusively on the AU$5 per day ad.

2.1.6. Phase 3

In this final phase, we focused exclusively on our most successful incentive scheme, AU$ 5 per day, and our most effective advertisement. Despite utilising all remaining funds, this phase recruited 92 participants over nine days, significantly fewer than anticipated and at a cost that was 3.2 times higher per participant than the previous phase. Given that data-driven insights informed all our modifications, the likely cause for this reduced efficiency was increased competition for the same audience by other advertisers on Facebook during this period.

Our social media campaign spanned 16 days across three phases, each with varying budgets and incremental strategic adjustments to optimise recruitment outcomes. In total, 200 individuals agreed to participate in our study and visited the survey's landing page. However, the cost-effectiveness of recruitment diminished in the last phase, particularly for the AU$ 5 per day incentive. Concurrently, the Australian Government's promotion of the COVIDSafe app might have heightened privacy concerns related to location-aware apps, potentially impacting participation in our study (Taylor, 2020).

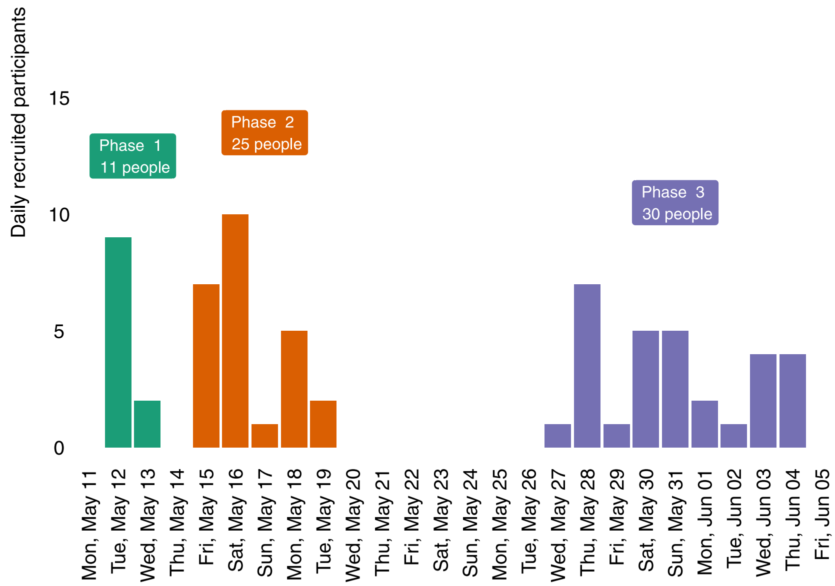
2.2. Broad recruitment

2.2.1. Participants

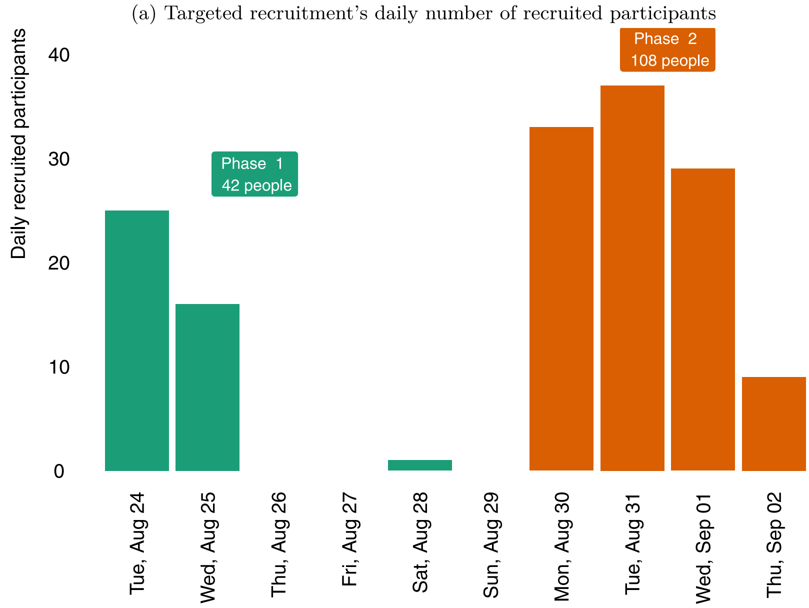
Our second travel survey was conducted in late August 2021. This time, we aimed to examine the effectiveness of the recruitment method on the general population of a specific urban region in Australia. Our advertisements for the travel survey were targeted at people aged 18 or more **AND** who live within a 60 km radius of Greater Sydney, Australia. Facebook estimated that 3,200,000 users matched all our criteria. This covered around 60%[1] of the region's estimated resident population.

Knowing that a representative sample cannot be easily achieved on a natural fallout basis, demographic quotas aimed at recruiting 100 participants that rendered the age and sex distribution of 2016 Greater Sydney residents aged 18 or more were used. The quotas were

[1] https://profile.id.com.au/australia/population-estimate?WebID=250.



(a) Targeted recruitment's daily number of recruited participants



(b) Broad recruitment's daily number of recruited participants.

Fig. 3. The timelines of the two smartphone travel survey recruitment campaigns.

implemented in the survey landing page. More details on this are provided later; for example, once a quota had been met for females aged 18–24, the landing page would be closed for people that belonged to that demographic group from joining our travel survey. However, this does not mean that those completing the onboarding procedure before a quota was reached would be denied from participating in the travel survey. For this reason, the quotas could be exceeded.

2.2.2. Ads

In this recruitment, we fully controlled our advertising campaign on Facebook. The same cost control strategy as the previous recruitment, *lowest cost*, was used to gain an understanding of the cost per link click for this broad audience. This later allowed us to decide whether a cost control strategy should be used to prevent the mistake we made concerning the cost of recruitment in the previous round. Fig. 2(b) shows the two versions of the advertisements used. The main difference between both versions was their message. We intended was to examine participants' effects (e.g., the cost per recruitment and the participation rate) based on their initial motive to participate. The result of this can be found in Section 3.1. The decision of how often the images of each version were shown, and to whom, was left to Facebook's algorithm. It is generally advised that a few advertisement creatives should be used to compare their effectiveness on different people.[2] It should also be noted that, our Facebook page was 'engineered' for this study, hence the people that liked our page were mostly friends and family of the authors. Therefore, we had to exclude those who liked our Facebook page from seeing our ads to ensure that no participants were associated with the authors.

2.2.3. Onboarding procedure

Learning from the targeted recruitment, many things were done differently this time. First, the screening survey was no longer required since we were recruiting a region's general population. This also made the onboarding procedure significantly shorter than before.

[2] https://www.facebook.com/business/m/facebook-dynamic-creative-ads.

Assuming a longer procedure had some impact on the decision to participate, this shorter procedure should positively affect the participation rate compared to the previous procedure. Second, the landing page was completely overhauled. Interactive guided instructions that walk through each step and have the participant confirm that they are on the right track in every step of the procedure were added. The landing page was the first thing people saw if they clicked on one of our advertisements. Lastly, participants were given a unique token that they could use to log in to the app, meaning they were no longer required to have a Gmail account to participate.

2.2.4. Phase 1

Fig. 3(b) shows the number of participants who installed the app during the recruitment phases. We started off by running both versions of the advertisements with a small budget to test the recruitment and onboarding system we had established, which allowed us to observe any potential problems that might affect the recruitment. We stopped the advertisements after two days and evaluated the initial recruitment results. Some differences between the two versions were observed. It was apparent from the result that some demographic groups were targeted more often than others. With this information, we prepared for the next phase, in which changes would be implemented. We also found that the research version cost 46% more per link click than the reward version.

2.2.5. Phase 2

Instead of letting Facebook decide which categories of people in the target audience, categorised by age and gender, get to see our ads more often, we started by allocating the same amount of daily advertising budget to each audience segment. In total, there were 12 categories made up of six age groups and two genders. Despite using the same images and headlines as the other ones, some of the advertisements that targeted certain categories did not get approved by Facebook. Although we tried to appeal against Facebook's decision and submitted several revisions, those were never approved. This meant that not all the 12 categories had two versions of the advertisements.

3. Findings

This section highlights the findings of the targeted recruitment (TR) and the broad recruitment (BR) described for a smartphone travel survey described in the previous section. These findings should be a comparison between the two travel surveys, and when possible, we combine the answers to form a single analysis.

3.1. Advertising results

Our Facebook advertising campaign's effectiveness can be assessed through various metrics including reach, demographic breakdown of viewers, frequency, click-throughs, and advertising spend. These metrics allow us to compare the performance of different ad creatives. Unfortunately, complete ad results from the Targeted Recruitment (TR) phase are unavailable, so this analysis focuses solely on the Broad Recruitment (BR) results.

During BR, our ads reached 30,497 users over seven days, averaging 1.11 impressions per user, resulting in 959 clicks. The detailed breakdown by phase is shown in Table 1. Fig. 4 displays key metrics across different age groups and genders, focusing on the cost-effectiveness of each ad based on the amount spent per result. The analysis revealed that reaching females was approximately 1.21 times costlier than males, yet females clicked more frequently, making their cost per click roughly 0.69 times lower than males.

Age-wise, costs per 1000 reaches were consistent across all groups within each gender, though the oldest age group was slightly pricier. The cost per click increased with age, with those aged 55 to 65 and above costing twice as much as those aged 18 to 44, suggesting lower engagement from older demographics towards our travel survey ads.

Table 1
A summary of the broad recruitment's Facebook advertisement campaign.

Phase	Impressions	Reach	Link clicks	Amount spent (AUD$)
1	6,421	5,634	218	70
2	27,518	24,863	741	260
Total	33,939	30,497	959	330

Fig. 5 shows the A/B testing results between the 'reward' and 'research' themed ads during phase 2 of BR. It can be seen that 'reward' ads were more cost-effective, costing AUD$0.32 per click, compared to AUD$0.42 for 'research' ads. This 24% lower cost per click indicates a higher attraction to the reward-themed ads across all demographics. Additionally, a simulation by Facebook estimated an 87% probability that the 'reward' version would outperform if the test were repeated, further supporting its effectiveness.[3]

3.2. Recruitment results

To assess the recruitment efficacy, we focused on the number of participants initially recruited rather than those who completed the survey. This approach helps to minimise any biases introduced by study-specific factors. For instance, some participants might have dropped out after experiencing usability issues with our app or encountering difficulties during setup, feeling that continuing was not worth their effort. We acknowledge that the way we provided instructions may have influenced the recruitment outcomes.

Regarding campaign effectiveness, Targeted Recruitment (TR) operated over 16 days with a budget of AUD$5000, securing 66 participants at a cost of AUD$ 75.76 each. Conversely, Broad Recruitment (BR) ran for a shorter period of 7 days, achieving significantly greater efficiency by recruiting 150 participants at a substantially lower cost of AUD$ 2.20 per participant.

Another interesting recruitment result is a cross-check between the demographic characteristics of Facebook's audience data and the users' responses to our user profile survey. This comparison aimed to explore the reliability of data sources, posing the question: should we place more trust in Facebook's data about their users or in the users' self-reporting? In the second phase of BR, see Section 2.2 for details about this phase. All ads were assigned the same daily budget targeted at each demographic group. To capture which advertisement a responding participant clicked on to get to the onboarding survey, we used a URL query string to embed the advertisement ID that could be used to link back to the advertisement, as well as which age group and gender it was targeted. For example, the full URL can be:

"www.travelsurvey.com/onboarding?parameter1=advertisement_id"

where `travelsurvey.com` is a host name, and `onboarding` is a page, `parameter1` is the name of a parameter, and `advertisement_id` is the ID of the advertisement that can be linked back to Facebook. The cross-check result in Table 2 shows that 90% of users' gender matched between the two sources. In contrast, age groups are quite varied, with three age groups – 18–24, 25–44 and 45–54 – in the range of 90% alignment, 25–34 year old was 82.76% aligned, and the sample size of the two oldest groups are too small to render a meaningful observation.

Based on these findings, the potential impact of these discrepancies is multifaceted. Firstly, the high alignment in gender data suggests that, for gender-specific analyses, Facebook's and users' reported data

[3] https://www.facebook.com/business/help/166313650471318.

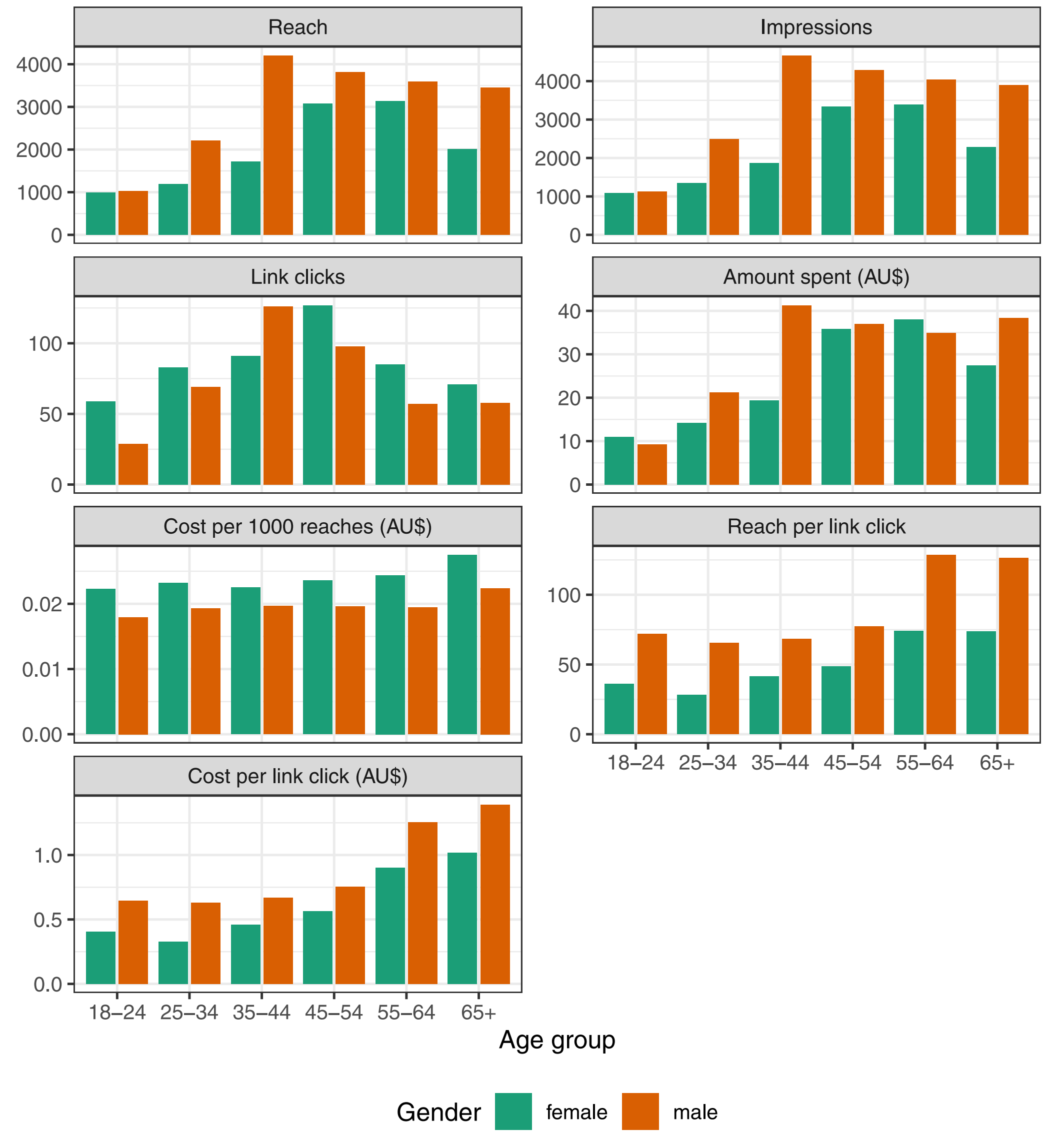


Fig. 4. Facebook Ads results of the broad recruitment. Note that, in phase 2 of the broad recruitment 2, the 'research' advertisements targeted at females aged 25–34 and 65+ were not approved by Facebook; hence, their reach and impressions are significantly lower than those of males of the same age groups.

are largely reliable, enabling confident interpretations of gender-based findings. However, the variability in age group alignment, especially the lower alignment in the 25–34 age group, underscores a potential source of bias in age-specific analysis. Such discrepancies could lead to skewed interpretations of age-related behaviours or preferences in travel patterns, particularly if the study's conclusions rely heavily on precise age segmentation. This underscores the importance of verifying the reliability of demographic data when using social media for recruitment and its impact on the study. Those who opt for this survey approach should strive to ensure that their findings are insightful and deeply rooted in a nuanced understanding of the data sources' strengths and limitations.

Fig. 6 shows the demographic distributions of the recruited participants of BR's second phase versus the implemented demographic quotas (see Section 2.2.1). We attempted to recruit a sample of 100 participants with the same age and gender distribution as residents of the Greater Sydney region. Note that these demographic quotas were based on Facebook's data of their users' demographic characteristics, not the users' own response to the user profile survey. The quotas for people aged 18 to 54 years old in both sexes were met, and some of the quotas were greatly exceeded, especially in the quota for females aged 35–44, which had almost twice as many recruited participants as its quota. However, with the time and budget we had, we were unable to prolong the recruitment. Hence, the quotas for people aged 55 and over were not met. As expected, this highlighted the difficulty in recruiting

Table 2
A cross-validation of the key demographic variables between Facebook audience profile data and the user profile survey responses of the recruited participants in Phase 2 of the broad recruitment.

		Sample size	Match
Sex			
	Female	54	96%
	Male	43	91%
Age			
	18–24	20	91%
	25–34	24	83%
	35–44	25	93%
	45–54	17	89%
	55–64	4	67%
	654+	1	100%

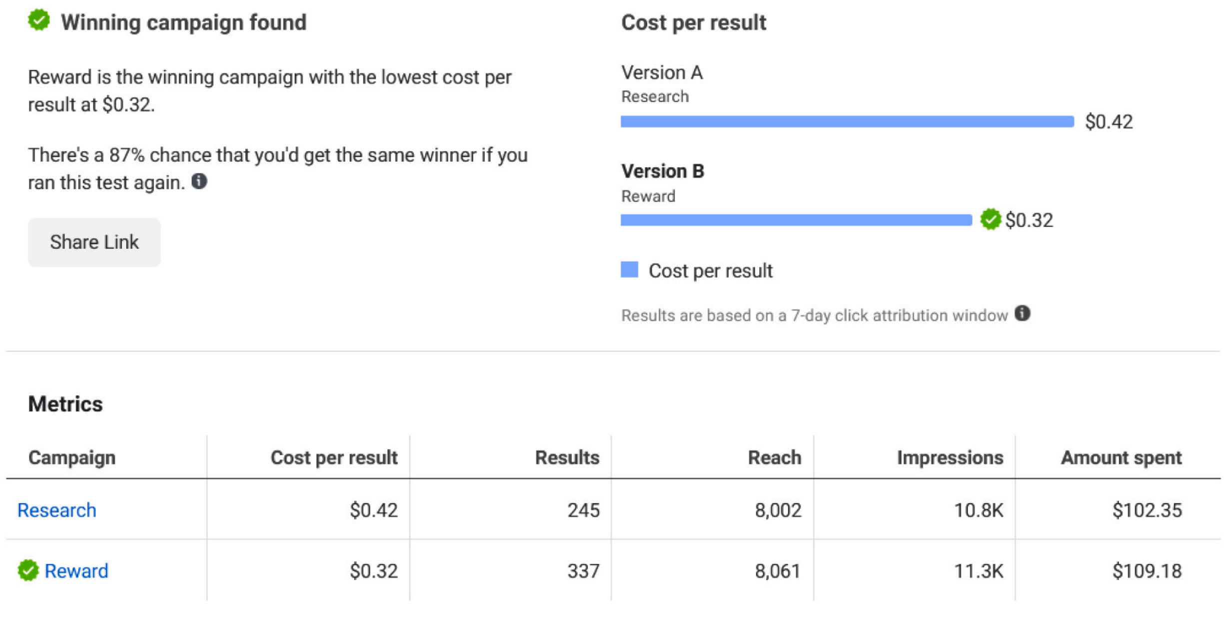


Fig. 5. Facebook A/B test results of the research advertisements versus the reward advertisements.

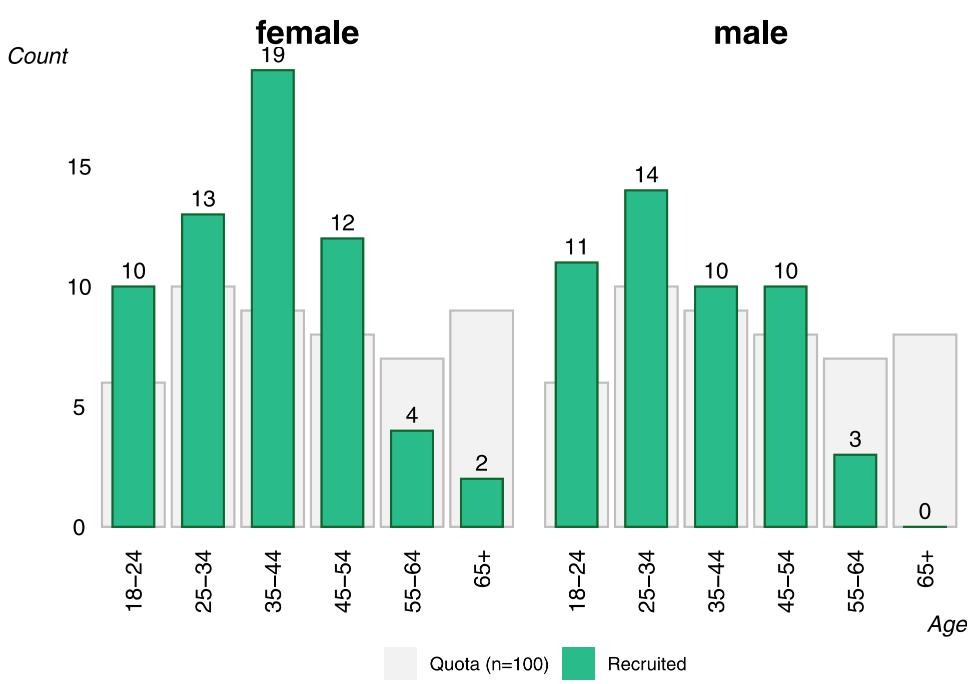


Fig. 6. Participants' demographic characteristics versus the demographic quotas from Phase 2 of the broad recruitment.

the older generations to join a smartphone travel survey through social media.

3.3. Recruited participants

Table 3 details the socio-demographic characteristics of participants from the smartphone travel surveys, derived from their user profile surveys. The Targeted Recruitment (TR) predominantly attracted females aged 25–34, all of whom were employed, as employment was a criterion for participation. In contrast, the Broad Recruitment (BR) had a more balanced gender distribution. A majority in both surveys held at least a bachelor's degree and came from couple-family households.

In TR, 50% worked in the "Health Care and Social Assistance" industry, one of three targeted industries, compared to lower participation from "Public Administration and Safety" and "Construction". This skew towards Health Care, a female-dominated sector in WGEA (2019), likely influenced the female majority in TR. In BR, no participants worked in Public Administration and Safety, with most reporting employment in Education and Health Care.

Income levels varied, with nearly half of BR's participants earning over AUD$1250 weekly, compared to 33.4% in TR, indicating a higher proportion of medium and low-income earners in TR.

Fig. 7 presents responses to nine attitudinal statements on a five-point Likert scale from the user profile survey, designed to gauge

Table 3
Characteristics of the recruited participants from the two recruitments who answered the user profile survey.

	Category	Recruitment	
		Targeted (n = 60)	Broad (n = 145)
Age			
	18–24	7 (12%)	35 (24%)
	25–34	23 (38%)	42 (29%)
	35–44	12 (20%)	39 (27%)
	45–54	8 (13%)	20 (14%)
	55–64	7 (12%)	7 (5%)
	65 and over	3 (5%)	2 (1%)
Employment			
	Employed, away from work	0 (0%)	11 (8%)
	Employed, worked full-time (35+ Hours per Week)	35 (58%)	76 (52%)
	Employed, worked part-time (less than 35 Hours per Week)	25 (42%)	39 (27%)
	Not in the labour force	0 (0%)	7 (5%)
	Unemployed	0 (0%)	12 (8%)
Gender			
	Female	37 (62%)	77 (53%)
	Male	22 (37%)	67 (46%)
	Others	1 (2%)	1 (1%)
Highest level of education attained			
	Year 12 or below	4 (7%)	20 (14%)
	Diploma and certificate level	8 (13%)	16 (11%)
	Graduate diploma and graduate certificate	5 (8%)	10 (7%)
	Bachelor degree level	30 (50%)	59 (41%)
	Postgraduate degree level (E.g. Masters and Doctoral Degree)	13 (22%)	40 (28%)
Household type			
	Couple family with children	13 (22%)	47 (32%)
	Couple family without children	19 (32%)	30 (21%)
	Group household	10 (17%)	20 (14%)
	Lone parent	3 (5%)	2 (1%)
	Other family	6 (10%)	13 (9%)
	Single person	9 (15%)	33 (23%)
Industry of employment			
	Accommodation and food services	2 (3%)	6 (4%)
	Administrative and support services	1 (2%)	6 (4%)
	Arts and recreation services	1 (2%)	5 (3%)
	Construction	1 (2%)	6 (4%)
	Education and training	4 (7%)	28 (19%)
	Electricity, gas, water and waste services	0 (0%)	1 (1%)
	Financial and insurance services	1 (2%)	8 (6%)
	Health care and social assistance	30 (50%)	21 (14%)
	Information media and telecommunications	0 (0%)	6 (4%)
	Manufacturing	1 (2%)	4 (3%)
	Mining	1 (2%)	1 (1%)
	NA (not Employed or not in the Labour Force)	0 (0%)	19 (13%)
	Other services	3 (5%)	4 (3%)
	Professional, scientific and technical services	5 (8%)	12 (8%)
	Public administration and safety	6 (10%)	0 (0%)
	Rental, hiring and real estate services	1 (2%)	1 (1%)
	Retail trade	1 (2%)	8 (6%)
	Transport, Postal and warehousing	2 (3%)	8 (6%)
	Wholesale trade	0 (0%)	1 (1%)
Weekly income			
	\$0	1 (2%)	8 (6%)
	\$1–\$399	2 (3%)	16 (11%)
	\$400–\$799	16 (27%)	31 (21%)
	\$800–\$1249	21 (35%)	21 (14%)
	\$1250–\$1499	7 (12%)	18 (12%)
	\$1500–\$1999	6 (10%)	29 (20%)
	\$2000 and above	7 (12%)	22 (15%)

attitudes towards data privacy, study interest, and technological literacy. Responses showed a general openness to data sharing for research and policymaking, strongly believing their data would be handled appropriately. Most participants were comfortable with technology and heavily relied on mobile phones, though opinions were mixed on commercial data use by companies like Google and Facebook. Notably, rewards were not the primary motivator for participation.

These insights suggest our average participant is receptive to data sharing, technologically adept, and trusts the researchers, but is cautious about commercial data exploitation. This aligns with findings from Keusch et al. (2019), who noted that intriguing, trustworthy studies with fair incentives tend to enhance participation.

We applied binary logistic regression models to investigate the effects of socio-demographic variables and recruitment type on attitudinal responses. These models predict the likelihood of participants agreeing or strongly agreeing versus other responses, expressed as:

$$log\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n \tag{1}$$

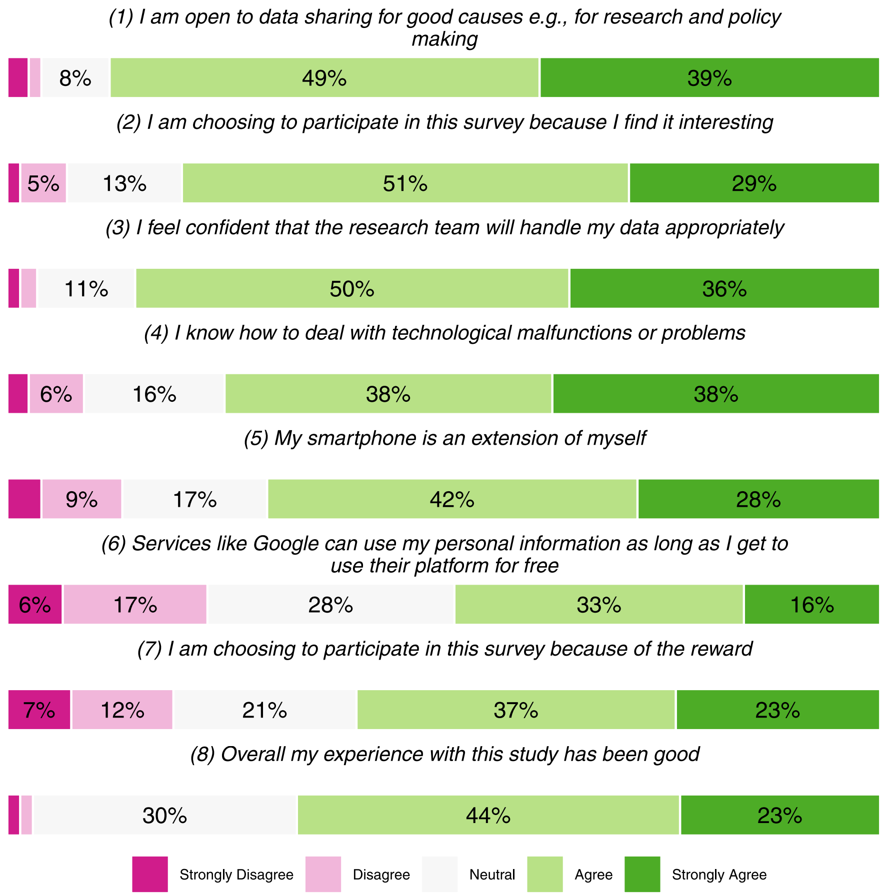


Fig. 7. Recruited participants' responses to the attitudinal statements in the user profile questionnaire.

Here $P(Y = 1)$ represents the probability of agreement, x denotes the explanatory variables, and β are the regression coefficients. Coefficients can be exponentiated to obtain odd ratios (Sperandei, 2014), facilitating interpretations such as "females are x times more likely than males to complete data collection".

Table 4 presents the odds ratios for each attitudinal statement from Fig. 7. Despite a limited sample size, few significant relationships were observed between the attitudinal responses and the socio-demographic variables or recruitment type. Participants not in the labour force were less likely to trust the research team with their data than employed participants. Those aged 45 and over were less comfortable managing technological issues independently than the youngest age group (18–24 years), used as the reference in the model. Moreover, participants from the targeted recruitment group and those aged 45–54 were more likely to participate for reasons other than rewards than participants from the broad recruitment group.

3.4. Data collection

Our method of administering smartphone travel surveys was designed to minimise researcher–participant interaction. During the onboarding stage, participants were instructed on using the app, including setting app permissions and confirming trips. Despite this, reminders were occasionally necessary to ensure participants completed various tasks throughout the data collection process.

The data collection procedure was consistent across both recruitment rounds. Although the mobile phone sensors automatically detected trips, participants needed to confirm each trip's travel mode and purpose and identify any spurious trips, which were frequently reported due to GPS sensor malfunctions. This trip confirmation step increased the data's reliability for subsequent analysis and provided richer context to the sensed data.

3.5. Completed participants

In total, 33 participants from the Targeted Recruitment (TR) and 90 from the Broad Recruitment (BR) completed our smartphone travel surveys, resulting in 50% and 60% completion rates, respectively. The combined cost of advertisement and incentives for these groups was AU$23.11 for TR and AU$174.70 for BR.

Participants completed a post-experience questionnaire within the app after at least four days of data collection. This allowed us to evaluate their experiences, perceptions of the incentive, and any changes in their initial user profile survey responses. Fig. 8 illustrates these responses. Most participants felt positive about the survey process; they felt safe, found the incentives fair, and did not perceive the data collection or trip confirmation steps as overly intrusive. The app received generally positive feedback, though there were mixed feelings about some of its features. Most participants reported a positive overall experience, trusting the research team with their data, and expressed willingness to participate in future studies or recommend the study to others.

Despite satisfaction with the data collected and the incentives, the app's usability of the app emerged as a key area for improvement in future iterations. Importantly, incentives were not the primary motivation for most participants, as their user profile surveys indicated. However, concerns about the app's accuracy were raised, particularly its mode inference model and trip segmentation algorithm. The model, originally developed with data from a US city, may not transfer well to Australian contexts. Addressing this, we aim to re-calibrate the mode inference model using data collected in this study to better suit Australian conditions. Participants also suggested the need for a trip editing feature within the app, which the *e-mission* community has not yet prioritised.

Table 4
The results of exponentiated logistic regression models of the attitudinal statements (agree/strongly agree).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	12.898***	3.532**	17.653***	7.170***	3.466**	0.658	3.020*	5.262***
25–34 years	0.830	0.635	0.296+	0.625	1.693	2.299+	1.358	0.588
35–44 years	0.483	1.137	0.620	0.402	0.745	1.007	1.301	0.389+
45–54 years	0.587	2.169	0.611	0.205*	0.435	1.526	0.313*	0.478
55 years and over	–	2.072	–	0.271+	0.806	1.482	0.430	0.894
Male	0.767	1.000	0.590	1.013	0.850	1.167	0.784	0.918
Not in the labour force	0.153+	0.530	0.056**	0.699	0.495	0.474	0.745	0.168*
Unemployed	0.231+	1.255	0.302	2.508	0.666	1.350	4.644	0.328
Targeted	1.088	1.586	0.694	0.729	0.573	0.823	0.168***	0.477*
Num.Obs.	203	203	203	203	203	203	203	203
AIC	153.7	215.1	170.2	231.7	253.1	291.8	244.4	263.5
BIC	183.6	244.9	200.0	261.5	283.0	321.6	274.2	293.3
Log.Lik.	−67.871	−98.527	−76.086	−106.857	−117.572	−136.910	−113.197	−122.742

Note:
Reference levels: 18–24 years, Female, Employed, and Board,
– indicates that the estimate is highly insignificant in the model,
+ = .1,
* = .05.
** = .01.
*** = 0.001.

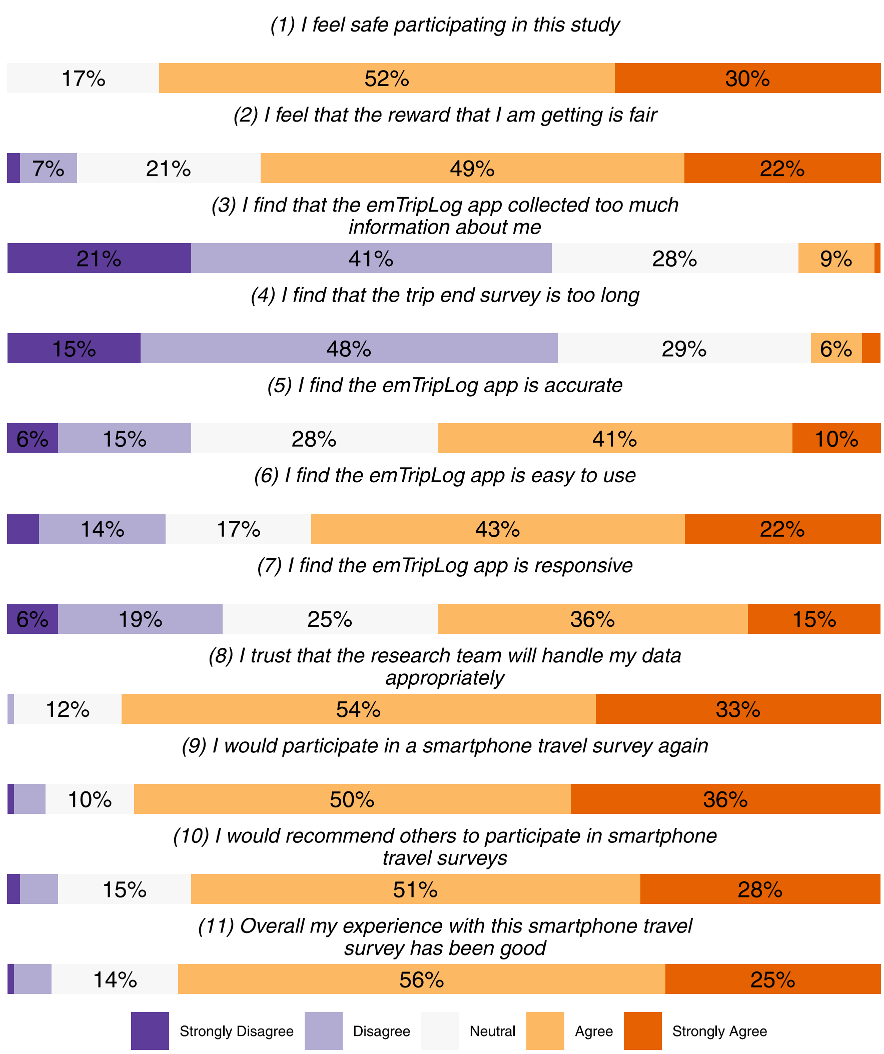


Fig. 8. Completed participants' responses to the post-experience questionnaire.

Table 5
Details of the three smartphone-based travel surveys.

Characteristic	Outsourced survey	Targeted survey	Broad survey
Study area	Greater Sydney, Australia	Eight greater capital cities of Australia	Greater Sydney, Australia
Period of data collection	14 September–12 December 2018 (89 days)	11 May–18 June 2020 (39 days)	24 August–12 September 2021 (20 days)
Recruitment channel	Qualtrics online panel	Facebook	Facebook
Data collection platform	rMove	e-mission	e-mission
Number of recruited participants	397	60	145
Number of completed participants	326	30	90
Number of trips	11,670	501	1026
Number of confirmed trips	11,358	484	1009

Additionally, the effect of participant characteristics and attitudinal responses (Table 4) on their decision to complete our travel survey was investigated. Utilising logistic regression analysis, we found that these factors are not statistically significant predictors of survey completion. This indicates that once participants agree to join the study, their initial perceptions, as shown in Fig. 7, do not significantly influence their decision to complete the survey.

3.6. Incentive schemes

Our targeted recruitment aimed to assess the effectiveness of different incentive structures based on the expected completion time for our survey. We estimated participants would spend about 41 min, including installing and learning to use the emTripLog app, completing an initial profile survey, daily trip-end surveys over four days, and a final post-experience survey. We calculated incentives based on an assumed hourly wage of AU$30, resulting in two schemes: a flat AU$20 upon completion and a more flexible AU$5 per day.

The flexible AU$5 per day option proved more popular, attracting more sign-ups and costing AU$10.66 and AU$11.9 per participant in two phases, respectively. This option also garnered more clicks than the AU$20 completion incentive and the no incentive option, which were significantly costlier per participant.

Our findings suggest that participants gradually prefer the option to earn rewards with the flexibility to opt out without losing accrued benefits. This insight was pivotal in refining our broader recruitment strategy, confirming that more flexible, incremental incentives can effectively enhance participation rates.

3.7. Comparison of smartphone travel surveys

This section contrasts three smartphone travel surveys (referenced in Table 5), focusing on their demographic quota fulfilment, spatial representativeness, and administrative costs. However, the “targeted recruitment” survey is largely excluded from this analysis due to its smaller sample size and methodological differences.

The purpose here is not to establish the superiority of one recruitment method over another, such as opt-in online panels versus Facebook advertisements, but rather to underscore each approach’s strengths and areas for improvement. It is important to note that this comparison omits several crucial aspects, including non-respondent analysis, the effect of incentives on completion rates, response quality, respondent biases, and the usability of mobile travel diary applications.

For the outsourced survey, we engaged a market research firm and a third-party to collect GPS-based travel data from 500 Greater Sydney residents aged over 18, over five days, using a developed app. This survey utilised quota sampling from an online panel based on age and gender. Though not contractually agreed, the firm also endeavoured to achieve spatial representativeness, which was not integrated with the demographic quotas. The stated incidence rate based on these quotas alone was 50%.

In contrast, our two in-house surveys handled recruitment and data collection, with participants documenting their travel for up to four days. The outsourced survey, which ran for three months, saw 326 completions from 1772 initial contacts, collecting 11,670 trips via the rMove app, with 97% confirmed by participants. As expected, the conversion rate from contacts to participants was notably higher than those recruited via Facebook, likely reflecting the opt-in panel’s characteristics.

The average number of trips was lower in recent surveys, likely impacted by COVID-19 restrictions. Trip confirmation rates across all samples were near 99%, with the targeted survey slightly lower at 97%. Detailed discussions of the two in-house surveys and additional information about their recruitment and data collection methods are available in previous sections of this paper and the supplementary document.

3.7.1. Demographic quota fulfilment

Table 6 compares the demographic quotas achieved in the outsourced and broad surveys, targeting Greater Sydney residents aged 18 or older. The initial targets were 500 and 100 participants for the outsourced and broad surveys, respectively, but both faced recruitment challenges.

The outsourced survey’s contractor initially aimed to recruit 500 participants for at least five days of data collection. However, they overestimated the panel’s interest, leading to a revised goal of 500 completions, regardless of demographics. This change resulted in a sample comprising younger and female participants, with male quotas remaining unfilled and female quotas mostly exceeded in younger age groups.

For the broad survey, quotas were only monitored during the initial screening due to budget and time constraints, affecting the ability to track completion accurately. To compensate, quotas were increased by 1.5 times and adjusted based on retention rates. Ultimately, quotas for participants aged 18 to 44 were fully met in both recruitment and completion. Many of these participants were recruited during the initial phase, targeting all adults over 18. The ‘optimisation for ad delivery’ setting on Facebook skewed this recruitment towards younger users more likely to engage with the ads.

Both surveys showed lower interest among older populations in smartphone travel surveys. Additionally, participants from the online panel displayed a higher commitment to completing the survey than Facebook-recruited participants. For instance, 42% of females aged 55–64 in the outsourced survey were retained in the final sample, compared to a 28-percentage point drop in the broad survey. This disparity may reflect varying levels of commitment between experienced survey participants and novices, as observed by Zhang et al. (2020).

3.7.2. Spatial representativeness

Spatial representativeness is crucial in travel surveys to ensure that the analysis of travel patterns is generalisable across different geographic levels. However, achieving this representativeness is challenging with opt-in online panels due to limited sampling frames and the high costs of selecting a spatially and demographically representative sample.

Fig. 9 displays the spatial distribution of completed participants from the broad recruitment study, indicating a concentration of nearly 90% in or near the “City and Inner South” area, with no participants from four regions. As detailed in Table 7, this distribution significantly

Table 6
Comparison of the demographic quotas filled in the outsourced and broad surveys. The population column denotes the percentage of the Greater Sydney population in each demographic category.

	Population	Outsourced survey (%)		Broad survey (%)	
		Recruited	Completed	Recruited	Completed
Female					
18–24 years	6%	157	113	317	183
25–34 years	10%	156	123	220	160
35–44 years	9%	151	132	233	178
45–54 years	9%	91	72	100	67
55–64 years	7%	42	36	71	43
65 years and over	10%	10	10	10	0
Male					
18–24 years	6%	48	23	267	117
25–34 years	10%	61	57	200	130
35–44 years	9%	72	63	189	111
45–54 years	8%	46	39	138	75
55–64 years	7%	68	68	29	14
65 years and over	8%	41	32	12	12

Table 7
Comparison of the target population's spatial distributions (place of residence), completed participants from the outsourced study recruited through an online panel, and completed participants from the broad recruitment recruited through Facebook.

Statistical area 4	Target population	Outsourced survey	Broad survey
Central Coast	6.8%	6.6%	0.0%
Baulkham Hills and Hawkesbury	4.7%	5.0%	2.6%
Blacktown	7.0%	6.9%	0.0%
City and Inner South	6.5%	9.9%	14.3%
Eastern Suburbs	5.5%	5.0%	6.5%
Inner South West	11.8%	10.2%	14.3%
Inner West	6.1%	8.5%	10.4%
North Sydney and Hornsby	8.4%	8.0%	18.2%
Northern Beaches	5.2%	4.4%	2.6%
Outer South West	5.4%	5.2%	1.3%
Outer West and Blue Mountains	6.4%	7.4%	0.0%
Parramatta	9.3%	8.8%	15.6%
Ryde	3.8%	5.8%	10.4%
South West	8.4%	6.1%	3.9%
Sutherland	4.5%	2.2%	0.0%

deviates from the target population, even at Statistical Area Level 4, just below the granularity of Greater Sydney.

The outsourced study, however, shows a more representative spatial distribution. The discrepancies in the spatial distribution of our Facebook-recruited sample can be attributed to two main factors. First, the coverage of the targeting area in our Facebook ads, marked by a grey circle with a 60-km radius from Sydney CBD in Fig. 9, did not include certain areas like "Central Coast" and "Outer West Blue Mountains". Second, the enabled "optimisation for ad delivery" option utilises machine learning to target users most likely to click on the ads, which skewed participant recruitment away from a representative geographical spread.

3.7.3. Costs

The administrative costs of three smartphone travel surveys reveal significant variations in recruitment and data collection expenses. The outsourced survey incurred AU$20,000 in recruitment costs alone, with each completed participant costing AU$61.35. This contrasts sharply with the insourced surveys, where the completion costs per participant were AU$151.52 and AU$23.11 for the targeted and broad surveys, respectively. Extrapolating the costs for the broad survey to recruit 500 participants would total approximately AU$11,555.56, showcasing Facebook advertisements as a more cost-effective method, approximately 1.7 times cheaper than an online panel.

For data collection, the mobility research company charged AU$25,000, including $50 per user for using their mobile travel diary app, data storage, server use, and data delivery. On the other hand, the insourced surveys used the cost-free, open-source *e-mission* platform. Management costs were calculated based on a casual university employee rate of AU$30 per hour. Server costs varied, with the targeted survey incurring AU$130 and the broad survey AU$585, due to the latter's use of a dedicated server via Amazon Elastic Compute Cloud (Amazon EC2) to support approximately 500 users.

These figures illustrate the financial implications of different recruitment and data collection strategies for smartphone travel surveys. The choice between outsourcing and insourcing can significantly affect data collection efforts' cost and scalability.

4. Discussions and conclusions

This paper presents the findings and lessons learned from our experience administering two smartphone-based travel surveys and recruiting participants using Facebook advertisements. . By combining these tools, we demonstrated that our smartphone-based travel surveys could be rapidly conducted during the COVID-19 global pandemic, as the entire process required no physical interaction between participants and researchers. Moreover, the proposed survey approach is highly scalable and budget-dependent, and allows for a highly customisable sampling frame using Facebook's comprehensive and rich audience profile database.

We observed that targeted recruitment cost AU$ 174.70 per completion, significantly higher than AU$23.11 per completion using quota sampling for a demographically representative sample. This suggests that while Facebook advertisements are generally more cost-effective than traditional opt-in online panels, costs can vary substantially based on the recruitment strategy and the urgency of advertisement outcomes.

The broad recruitment round's the response rate was approximately 0.3% (n = 30,497). In comparison, other smartphone travel surveys, such as Silvano et al. (2020), reported a 3% response rate (n = 2800) by randomly sampling from the official Swedish Population Address Register and 3.9% (n = 5085) using a web panel. Meanwhile, Bürbaumer et al. (2024) reported a 1% response rate (n = 1000) using postal recruitment and 4% (n = 1180) using personal recruitment at the doorstep. The response rates of surveys can vary significantly due to differences in recruitment methods, geographical areas (Stopher and Shen, 2011), the effort required to complete the survey, incentives offered, and even trust in the data collector (Svaboe et al., 2021). Despite these variations, understanding the reach versus response rate of the proposed method compared to other widely used recruitment methods is valuable.

Several lessons emerged from our data collection. For instance, flexible incentives enhanced participant engagement more effectively than fixed rewards. Additionally, we encountered challenges recruiting older adults, demonstrating higher costs per ad click and lower completion rates. Our findings also indicated a high accuracy (over 90%) in aligning participants' self-reported and Facebook-profiled demographic data for well-represented categories.

For travel surveys that require a diverse participant mix, we recommend the implementation of quotas within the screening survey. This method effectively limits participation once specific quotas are reached, allowing researchers to manage their study's budget more efficiently by avoiding the distribution of rewards to participants in already filled quotas. This approach not only streamlines data collection but also ensures a balanced representation of demographics, which is crucial for the reliability of survey results.

However, there are certain limitations to using Facebook advertising for recruitment, such as selection biases and the generalisability of results. Social media users inherently do not represent the broader population demographically, with significant variations observed across different platforms (Mellon and Prosser, 2017). These biases stem not only from recruitment through Facebook advertisements but also from

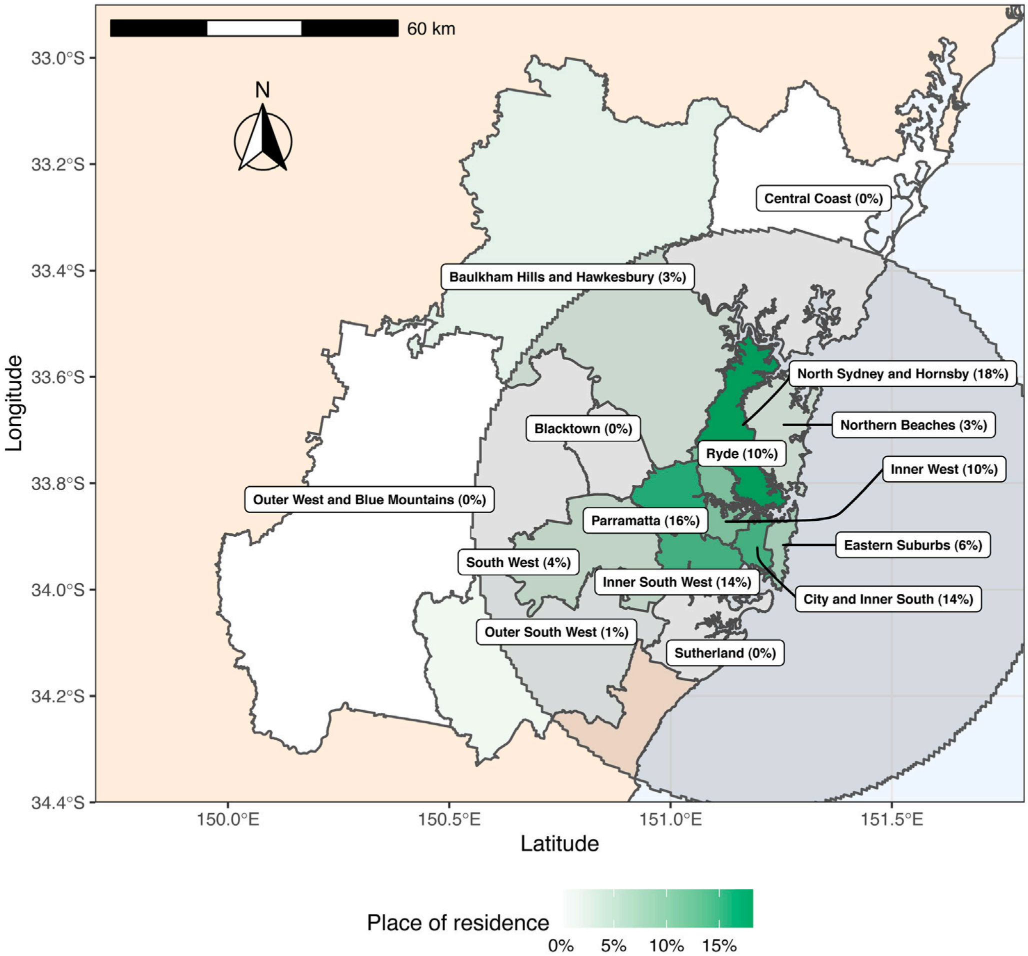


Fig. 9. Spatial distribution of the broad recruitment's sample based on the 2016 Statistical Area level 4 zoning system.

the inherent methodology of data collection. Therefore, interpreting results from the travel data collected using the proposed approach must be conducted carefully, recognising the potential biases in the sample. These biases may extend beyond socioeconomic characteristics to include participants' attitudes towards data privacy and technological literacy, as indicated by our findings in Sections 3.2 and 3.3.

Some issues we encountered when advertising on Facebook are worth mentioning. First, the success of an ad largely depends on Facebook's ad review process, which can display inconsistencies in approval decisions. We submitted 12 ads for review, all featuring the same picture and message, with the only variation being the target audience profile based on age and gender. Shortly after, we were informed that two ads were rejected due to an alleged breach of their ad guidelines, while the rest were approved. Whether this was due to inconsistencies in Facebook's review process or an oversight on our part, such scenarios can potentially delay time-sensitive data collection.

Second, we learned that targeting people based on their interests can lead to a significantly larger audience pool than targeting solely based on socio-demographics. In retrospect, Facebook has more detailed insights into its users' interests through the analytics of pages they have visited or 'liked', compared to the socio-demographic information that users provide.

Lastly, a cost control strategy, such as a bid cap, should be employed to prevent Facebook from rapidly depleting the allocated advertisement budget. In hindsight, we overlooked that our ad campaign was competing against many businesses, likely with greater spending power, bidding to promote their services and products on Facebook.

Future research could explore the relationship between incentive amounts and participation rates, the impact of different ad contents on engagement, and how samples recruited via social media compare to those obtained through traditional methods regarding travel behaviour and socio-demographics, similar to Mellon and Prosser (2017). Our small sample sizes underscore the experimental nature of our study yet provide a foundation for further investigation into this recruitment approach. We also advocate for the continued use and development of open-source transportation software projects, which are crucial for advancing research capabilities in the field.

In conclusion, exploring smartphone-based travel surveys and Facebook-assisted recruitment offers substantial insights and practical lessons. Despite its challenges, when strategically implemented, Facebook advertising can be a highly effective recruitment tool, offering a cost-efficient method for obtaining representative data in travel survey research.

Ethical approval

The ethical approval for this study was approved by UNSW Research Human Ethics (HC reference no: HC180687).

CRediT authorship contribution statement

Amarin Siripanich: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Taha H. Rashidi:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization. **Shankari Kalyanaraman:** Writing – review & editing, Software, Conceptualization. **Travis S. Waller:** Writing – review & editing, Resources. **Meead Saberi:** Writing – review & editing, Resources.

Vinayak Dixit: Writing – review & editing, Resources. **Divya Nair:** Writing – review & editing, Resources.

Declaration of competing interest

The authors declare no conflicts of interest.

Data availability

Due to the nature of this research, participants of this study were assured strict confidentiality and privacy of their data. As a result, and in compliance with the restrictions set out in our ethics approval, raw data cannot be made publicly available. This is to protect the privacy and confidentiality of the individuals who participated in the study.

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In the interest of transparency, we acknowledge that this article contains certain overlaps with one of the authors' doctoral thesis: Siripanich, A. (2021). "Emerging Data Sources and Advanced Microsimulation in Transport Modelling" (Doctoral dissertation, UNSW Sydney) [DOI: https://doi.org/10.26190/unsworks/2288]. The decision to include overlapping content was made to ensure wider dissemination of key findings and methodologies to the academic community beyond the scope of the thesis.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.trip.2024.101116.

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