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Online and in-person activity logging using a smartphone-based travel, activity, and time-use survey

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ABSTRACT

With increased internet connectivity, there are more opportunities to substitute physical, or "in-person", activities with online activities. With this, changes to household and individual travel/activity patterns are to be expected. For example, the increased adoption of e-commerce can affect individual travel destinations and frequency. To study these shifts, we enhance an existing smartphone-based travel/activity diary to capture online activities, with a focus on activities that can replace passenger trips. Furthermore, we expand the options to report shopping details, to better understand the influence of e-commerce on in-person shopping. In this paper, we detail the data collection tool development strategy and user-experience findings. Moreover, we provide insights from a pilot deployment in Singapore during 2020, which allowed measuring travel/activity behavior, expenditure, and time allocation changes during various COVID-19 pandemic travel restriction periods.

Introduction

Internet access and the use of internet-connected devices have become ubiquitous in many cities. At the start of 2020, nearly 60% of the world's population has access to the internet, with the average internet user spending 6 h and 43 min online daily (KEMP, 2020).

Some online activities, such as virtual meetings and online shopping, can influence the internet users' daily activities. Online shopping activities are of particular interest, given the potential to influence both passenger and freight trips (Rotem-Mindali and Weltevreden, 2013). By *online shopping* and *e-commerce,* we refer to the process of buying and selling physical goods via the internet. We disregard details about the payment process or mode of delivery that follows. The number of e-commerce-derived business-to-consumer shipments has been growing at a faster rate than non-e-commerce business-to-business (retail) shipments worldwide for the past two decades. From 1999 to 2017, e-commerce sales increased from less than 1% of the total U.S. retail sales to more than 9% (ATRI, 2019). The annual growth of e-commerce has ranged between 13% and 16% from 2013 to 2018, outpacing the 1% to 5% annual growth in traditional retail sales (Hooper and Murray, 2019).

Despite the increasing relevance of e-commerce, its impacts on passenger trips remain unclear. First, e-commerce transactions tend to be smaller in value and are associated with increased variability of the demand patterns (Canetta et al., 2013), which already creates significant differences when compared to in-person shopping. Second, the academic literature reports contradictory findings (Rotem-Mindali and Weltevreden, 2013) regarding the extent of substitution, complementary, induction or other impacts of online shopping on in-person shopping. Rotem-Mindali and Salomon (2007) and Cao (2009) concluded that it was too complex to predict the impacts of online shopping on travel behavior.

The COVID-19 pandemic has accelerated the adoption of e-commerce (Dannenberg et al., 2020), and might leave a lasting effect (Han et al., 2020) on passenger and freight travel demand. Thus, to understand present and future travel demand patterns, there is a need to better understand individual choices between performing online versus in-

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person activities, and the resulting trips. Moreover, there is a research gap in tools that allow the simultaneous capture of both online and in-person activities with high resolution and accuracy. To this end, we enhance a state-of-the-art data collection tool – the Future Mobility Sensing (FMS) mobile application (Zhao et al., 2015) – and apply it in a pilot survey to capture trade-offs between online/in-person activities, and the associated impact on travel and time use. We expand the smartphone-based activity/travel diary with the ability to record online activities, expenditures, and online/in-person activity time allocation. The mobile application was piloted in Singapore in 2020. The influence of the COVID-19 pandemic and various restrictions on individual movements make it an ideal test bed for the proposed pilot.

In this paper, we detail the development and application experience of the data collection tool, providing unique insights that can be leveraged in similar developments by other researchers/practitioners. We also demonstrate the ability of the tool to capture online/in-person activities, travel behavior and time allocation changes.

Literature review

This literature review aims to cover two domains which are relevant for this research. First, the current knowledge on the online/in-person activity trade-offs and implications on travel, focusing on the impact of e-commerce. Second, the state-of-the-art in tools to collect online/in-person activity, travel, and expenditure data. We define *expenditure* as the value of goods/services used and paid for by a household, excluding loan repayment, taxes, or large purchases such as that of houses or vehicles. (Department of Statistics, 2019).

Online activities' influence on in-person activities and travel

Passenger and freight data collection efforts are typically disconnected. For example, passenger travel surveys do not capture shopping activities in detail, and freight-targeted surveys largely skip details about the end receiver. Prior research stressed how this situation leads to partial views on the subject, highlighting a research gap in jointly studying passenger travel and freight demand generation (Rotem-Mindali and Weltevreden, 2013; Suel and Polak, 2017). We agree this is key to understand the impacts of e-commerce on net mobility.

There are several hypotheses on the nature of the relationship between online and in-person shopping (Rotem-Mindali and Weltevreden, 2013). Examples are whether shopping online leads to a reduction, increase or no change to the number of shopping person-trips and person-distance travelled. Influence is typically characterized in four types (Cao, 2009; Ferrell, 2005):

- Substitution – passenger shopping trips are replaced by online shopping;
- Complementarity – due to online shopping, shopping trips increase;
- Modification – owing to online shopping, trips to physical stores are not replaced but are altered, and;
- Neutrality – online shopping has no effect on shopping travel.

There is a lack of consensus over the most prevalent relationship type. One argument is that the influence might be related to different product types. As grocery and other daily items are purchased frequently, many studies have focused on this goods category. A substitution effect was reported by some studies (Hoogendoorn-Lanser et al., 2019; Joewono et al., 2019; Suel et al., 2018, 2015) whereas one study reported neutral effect (Calderwood and Freathy, 2014), except for residents living in non-urban areas. For these residents, a substitution effect was reported. With regards to other product types, substitution effects have been reported (Rotem-Mindali and Salomon, 2009; Shi et al., 2019), but also complementarity (Cao, 2012; Cao et al., 2010; Ding and Lu, 2017; Farag et al., 2007) and neutrality (Hoogendoorn-Lanser et al., 2019), except for frequent e-commerce users. In summary, the results are mixed (Rotem-Mindali and Weltevreden, 2013). This can also be because behavior and impacts are either context dependent or are influenced by underlying modeling methods (e.g., definition of categories, assumptions, sample selection), or both. Still, as with predicting travel and activity generation, modelers seek to use socio-demographics and land-use factors as predictors of online shopping frequency and quantities (Department of Statistics, 2019; Russo and Comi, 2020; Shi et al., 2019). So ultimately, robust data collection remains crucial.

Data collection tools and processes

Methods to collect travel and activity diaries have evolved since the 1970s. Still, there are no defined standards for this purpose (Aschauer et al., 2019). Various media exist, ranging from mail-back questionnaires to telephone interviews to online questionnaires and smartphone app-based reporting. The relevance of digital tools, particularly GPS-enabled smartphones, is increasing. Whereas a complete record of trips allows some inference of activities, detailed activities are better captured through time use surveys. These place emphasis on the time dedicated to each activity, including travel as an activity type. Among other details, activity and time use surveys collect location, concurrent activities, and individuals involved (Aschauer et al. 2019). The use of smartphone apps to capture both travel and activity details is increasingly popular, including Future Mobility Sensing by Zhao et al., 2015, and Daynamica, by Fan et al., 2015.

With regards to expenditure surveys, these can focus on expenses made during the survey period or those that were incurred in some period before (Aschauer et al., 2019). Typically, these surveys are performed at the household level and not mixed with other data collection efforts (To Nhien and McBride Brett, 2013)). These surveys can also distinguish between the channel (in-person or online) used to perform the purchases (Department of Statistics, 2019; Stanford University, 2020).

The combination of the above-mentioned surveys is still rare, although there are some novel research experiments. Aschauer et al. (2019) highlighted the need to understand the trade-off processes between travel activities, non-travel activities and budget assignments. For this purpose, the authors proposed a survey design which integrated elements from travel surveys, time-use surveys, and consumer expenditure surveys. These are denominated as MAED, a Mobility-Activity-Expenditure-Diary. The value of the MAED method is highlighted in Jokubauskaitė et al. (2019), who claimed that data on expenditures allow for the specification and subsequent performance of a continuous-discrete model for a joint time-use, expenditure, and mode choice model. However, the supporting data collection relied on self-administered mail-back questionnaires with telephone support and incentives. Given the considerable data to be collected, Aschauer et al. (2019) highlighted design challenges so that quality information can be balanced with low response burden. Applying this in two pilot studies, the authors identified the omission of parallel activities as a serious downside of their approach. However, their method is quite comprehensive in some dimensions, e.g., fine expenditure details (trips, long-term expenses, etc.). Schmid et al. (2019) developed a multi-survey method to study the degree of mode choice, time allocation and activity pattern changes due to generalized transport cost changes. Their survey combined eight questionnaires, including: household, vehicles, individual, travel diary, trip planning, online diary and expenditures. In addition, two stated preference surveys were administered. The survey shares in scope several commonalities with that herein proposed, such as the use of a timeline to connect trips and activities. Huynen (2015) reported the use of a web-based expenditure survey with a smartphone-based pilot using Optical Character Recognition to digitize purchase receipts. The Harmonised European Time Use Surveys (HETUS) are also worth mentioning. Traditionally conducted via forms (Eurostat, 2020), there are ongoing developments of smartphone–based apps to perform

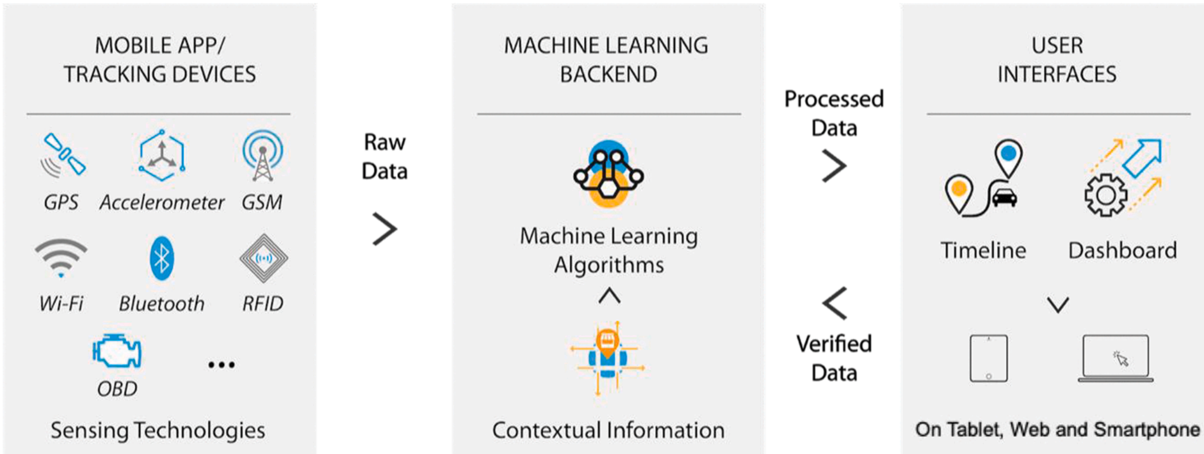

Fig. 1. Future Mobility Sensing (FMS) platform architecture.

similar functions (Zeni et al., 2019). Regarding similar applications, Mesaric et al. (2021) deployed a survey in Singapore to collect data on shopping behavior after the outbreak of the COVID-19 pandemic. The survey was limited to one month and focused on capturing self-declared shopping trips and parcels received. In summary, there is progress in combining these types of surveys, but we identify a gap concerning the existence of a tool that combines travel, activity, and expenditure surveys in a fully digital and integrated manner.

With regards to best practices of applying digital surveys, Harding et al. (2020) investigated the performance of 17 smartphone applications as travel/activity diary data collection tools, comparing them against ground truth data. The authors concluded that trip ends (stops) detection is performed with high accuracy but mode inference, in general, requires improvements. Thus, having users verify the information is an important step particularly when there are multi-modal trips. Moreover, it is recommended to ask about anchor points, such as home and work locations, and usual modes. Typically, collected data includes the start/end time of trips, along with locations, trip purposes and modes taken.

Concerning incentives to the participation in the surveys, we found some variation in incentive levels and awardees (individual or household), which makes it challenging to derive best practices. Closely linked to participation is survey duration, with Rizzo and Erhardt (2016) recommending 2–4 days as ideal depending on the cost of an additional day

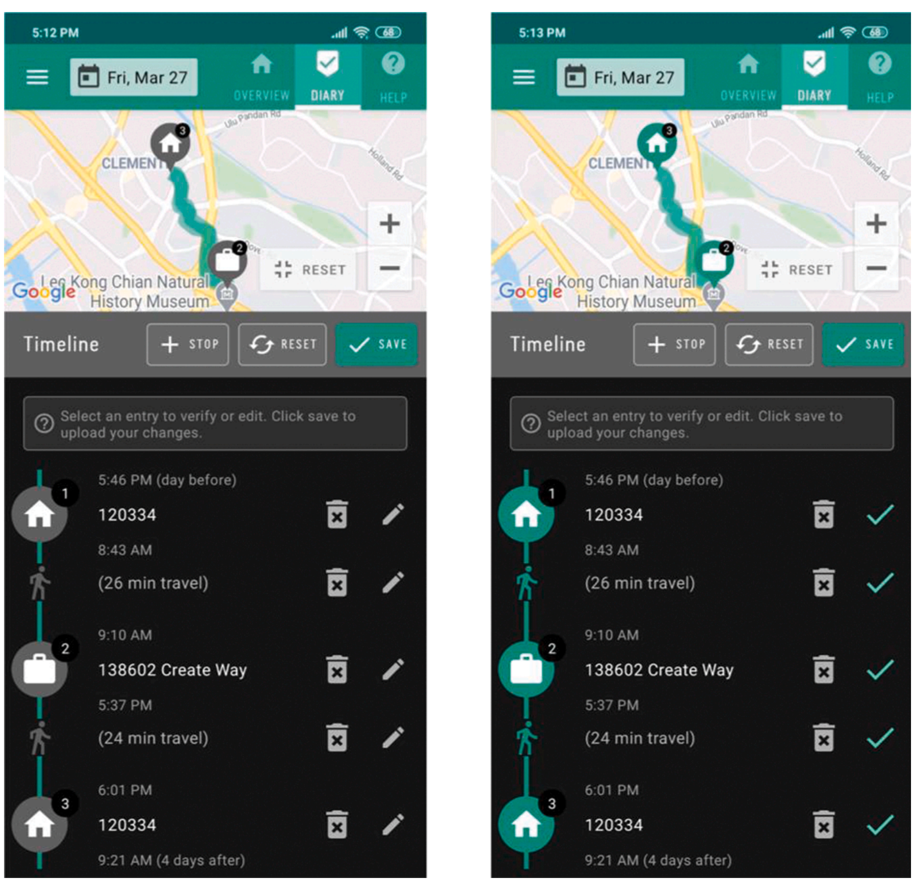

Fig. 2. FMS app screenshots of the user's trip timeline before (left) and after user verification (right).

Table 1
Summary of past projects which applied FMS platform to collect data.

Project Name	Location	Description
FMS pilot test (Zhao et al., 2015)	Singapore	• In conjunction with Singapore Household Interview Travel Survey • ~1500 participants
Happiness survey (Raveau et al., 2016)	Singapore, Melbourne, Seoul, Boston (USA)	• Passenger travel survey with prompts to collect real-time happiness levels from users. • Aimed to study real-time and retrospective happiness related to travel and activities • ~500 participants
Transit Satisfaction Survey (Li et al., 2017)	Boston, USA	• Event-driven real-time survey to study passenger satisfaction to Boston's Silver Line buses. • ~70 participants
Tripod SP (Danaf et al., 2019)	Boston, USA	• Stated Preference (SP) survey for a travel incentive project promoting energy-efficient choices. • ~350 participants
AMOD SP (Seshadri et al., 2019)	Singapore	• SP survey for Autonomous Mobility on Demand • ~350 participants
Commercial vehicle survey (Alho et al., 2020)	Singapore	• Survey on freight establishments' goods movements, shipments, and vehicle flows • 1,510 freight vehicles and 987 drivers completed the verification of their daily timeline for 5 days

versus additional sampling units. In this case, we challenge the generic recommendation given that recurrent shopping patterns can be hypothesized to take place over a week.

Overall, our literature review allows us to conclude that there are relevant arguments for research that seek to better understand the influence of online activities' on in-person activities and travel. Thus, incorporating mechanisms to capture online activities in activity/travel data collection is key. While some survey tools have been progressively digitalized, we were unable to identify a single tool which is able to fulfill the data collection requirements in a way that can capture high-resolution data, with high accuracy and minimal user burden.

Methods

FMS platform and applications

We build on an existing digital activity/travel diary platform, Future Mobility Sensing (FMS), where respondents detail their travel and activities using a smartphone. Developed at the Massachusetts Institute of Technology (MIT) Intelligent Transportation Systems Laboratory and the Singapore-MIT Alliance for Research and Technology, FMS is a data collection and visualization platform that leverages mobile sensing technology, machine learning algorithms and user verification, to capture and display high resolution data of travel/activities. Fig. 1

FMS consists of three distinct and interconnected components illustrated in :

- A mobile app/tracking device that leverages various sensing technologies.
- A backend consisting of a server system with a database and custom algorithms to infer stops, trip modes and purposes, and other trip details, for reducing user burden; and
- User interfaces, both mobile and web-based, used for verification of activities by respondents. This allows collecting additional information and displaying summarized information. Users can visualize their activities/travel in a daily timeline, overlaid in a map (Fig. 2), and verify their trips that are automatically detected.

FMS has been applied to collect data in various instances (Table 1).

Pre-survey

Base questions

The first step in using FMS is user registration. In this step, key socio-demographics as well as other relevant details are collected. In the *pre-survey* section, the questions included:

- Personal information
  - o Contact details
  - o Age
  - o Gender
  - o Marital status
  - o Employment status
  - o Workplace (Fixed, non-fixed)
- Frequent places
  - o Workplace / school
  - o Residence
- Household information
  - o Total members
  - o Total children
  - o Vehicles
  - o Household income range
  - o Whether individual oversees grocery shopping
  - o Whether household has a domestic helper

The sample universe were households in Singapore. We emphasize that the household-level information was only to be completed by an appointed point-of-contact household member, while the reporting of travel/activities targeted all household members with a smartphone (more details in section 3.3.1). The last question is specific to the pilot application in Singapore. Households with a domestic helper anecdotally might have this person in charge of grocery shopping, which is relevant to know when trying to understand shopping activity at the household level.

Data collected in the timeline includes the following:

- Travel interval: start and end time, origins, and destinations, modal choice.
- Stop interval: start and end time, activities performed.

Travel and stop intervals are detected by a stop detection algorithm (Zhao et al., 2015)

The full list of travel modes available for selection is:

- Taxi, Mobility on Demand
- Car, Van
- Motorcycle
- Train
- Bus
- Bicycle, Personal Mobility device
- Walking
- Air
- Other

The full list of in-person activities is:

- Change Mode/Transfer
- Maintenance/Home
- Work
- Work-related
- Education
- On-site Shopping
- Window Shopping
- Return Items

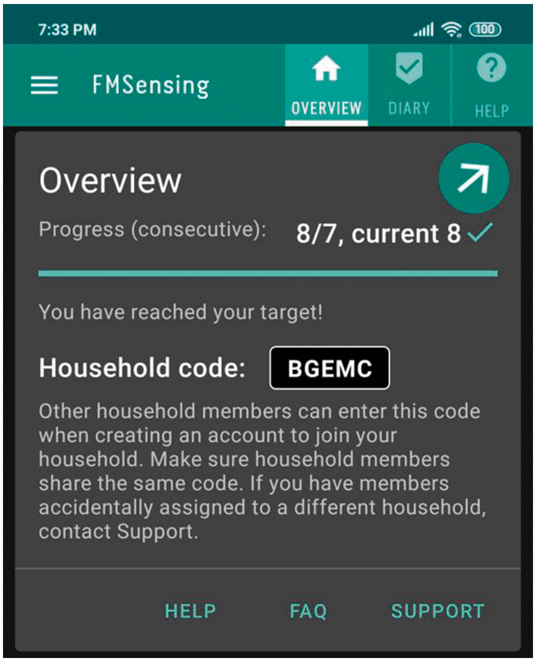

Fig. 3. Example of household code.

- Receive/Pickup Delivery
- Pick Up/Drop Off
- Social
- Recreation
- Health Care
- Meal
- Entertainment
- Sports
- Personal Errand
- Accompany Someone
- Other

The full list of commodity type for shopping activities:

- Consumables
- Durables
- Food & Beverages
- Meals
- Others

The application allows capturing multiple activities occurring simultaneously. Moreover, it allows specifying the time dedicated to each activity, as it will be further detailed in section 3.3.2. *'Time allocation between activities'*.

Survey burden

It takes around 5 min to fill the pre-survey. Following the pre-survey, users need to learn how to verify their data and provide detailed information. To help users, video tutorials were provided. These tutorials require a maximum of 30 min to be watched. Daily, it takes around 5–10 min to fill the timeline for the day including reporting shopping details, if any.

Platform enhancements

We have extended the FMS platform to collect additional information with respect to user's socio-demographics as well as online/in-person activities. The extension was performed in its two main sections, the registration *pre-survey,* and the *timeline* diary.

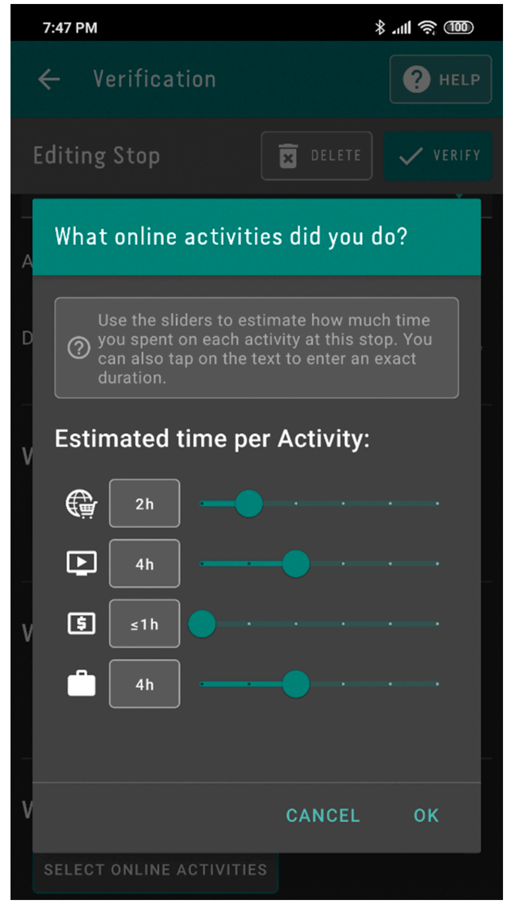

Fig. 4. User interface for specifying the duration of online activities.

Household-level surveying

Household-level activity responsibilities can be split across household members. In case of asking details (e.g., activity frequency) to a household member who is not responsible for a given activity (e.g., shopping) this might lead to biases/errors. On the other hand, not capturing them might also be problematic. For example, shopping online by a household member could save a shopping trip by another. Thus, to analyze the influence of other household members' activities on a given subject, it is required to capture household membership of survey respondents. This functionality was added to the *pre-survey* component. A unique household code is generated after the first user in the household fills the pre-survey (Fig. 3). The remaining household members can use the generated household code as a reference when they fill the pre-survey.

Time allocation between activities

One important consideration is the fact that online activities might not be performed for the entire duration of a travel or stop interval. One relevant example would be understanding the trade-off between the time spent shopping online versus its in-person counterpart. Given the challenge of specifying precise time estimates post-activity, we designed the interface such that the maximum activity duration is pegged to the interval duration. Moreover, the suggested activity duration intervals are adjusted dynamically. This means that longer intervals would allow using progressively larger gaps. However, the user can specify precise time estimates (to the minute). The interface for specifying activity time durations is shown in Fig. 4.

Online activities

A key dimension of the research at hand was capturing online

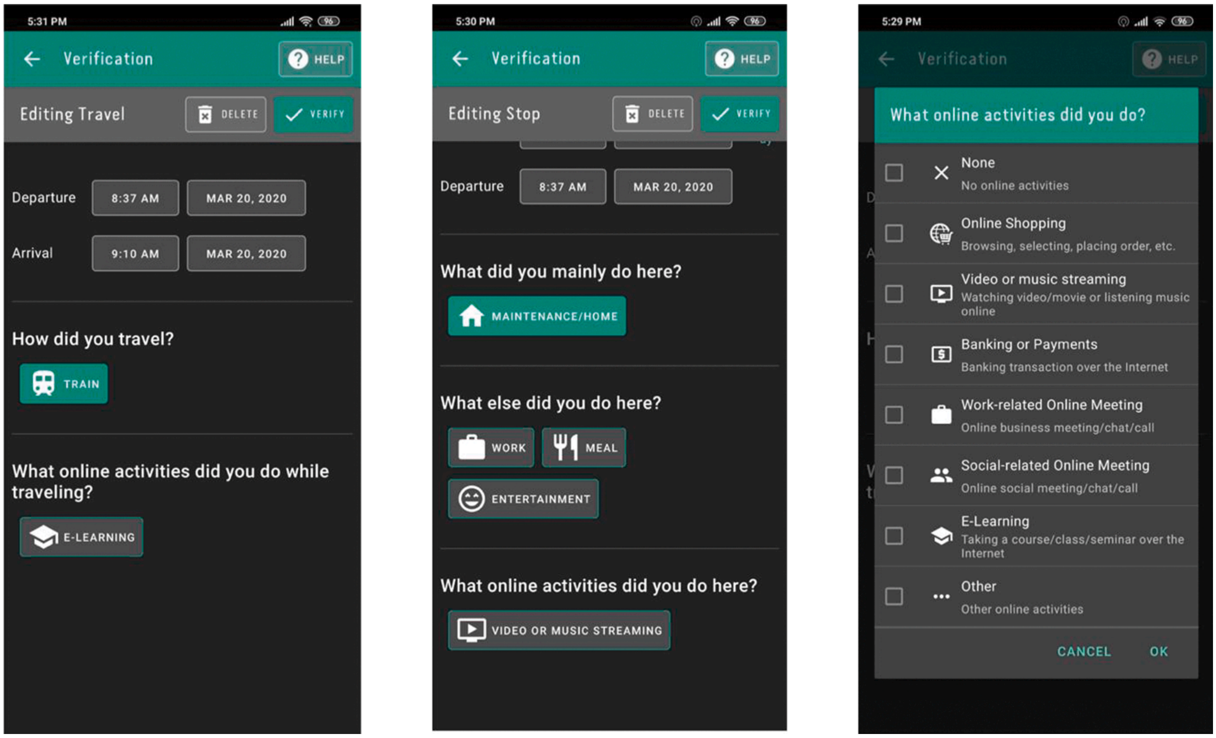

Fig. 5. Reporting details about travel (left), activities during a stop (middle), and online activities list (right).

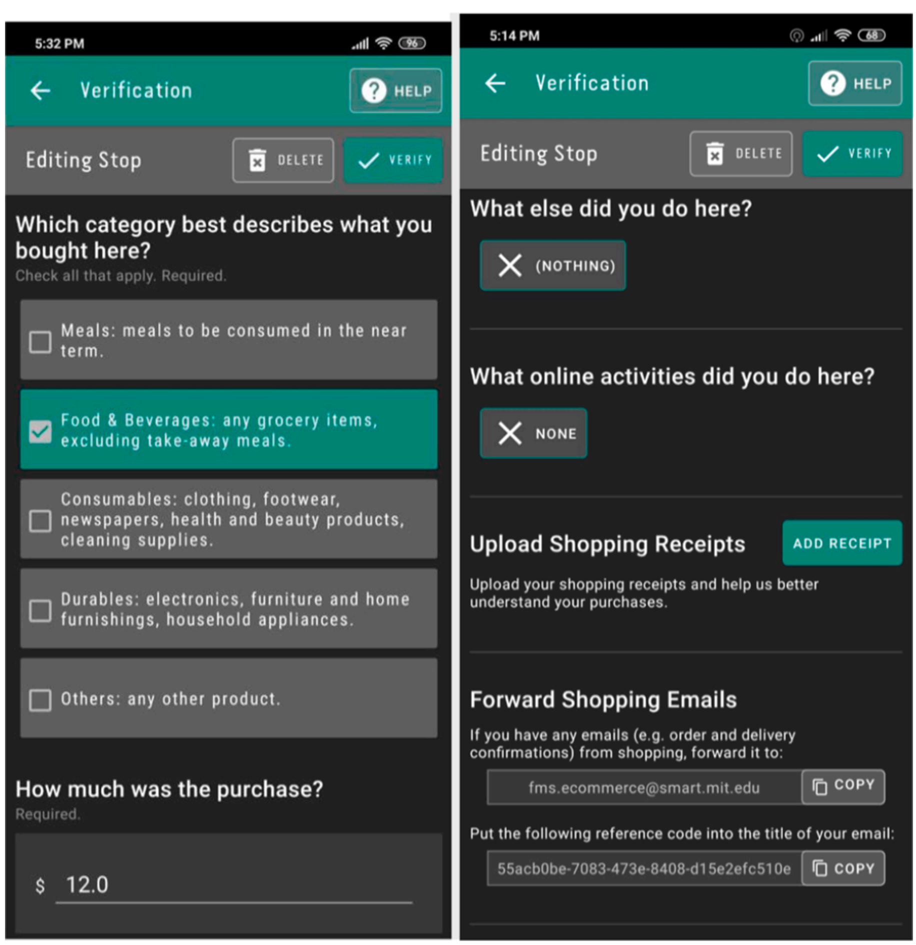

Fig. 6. (Left) Interface to specify details of goods purchased – type and value; (Right) Interface to upload shopping receipts or to forward e-mails related to online shopping.

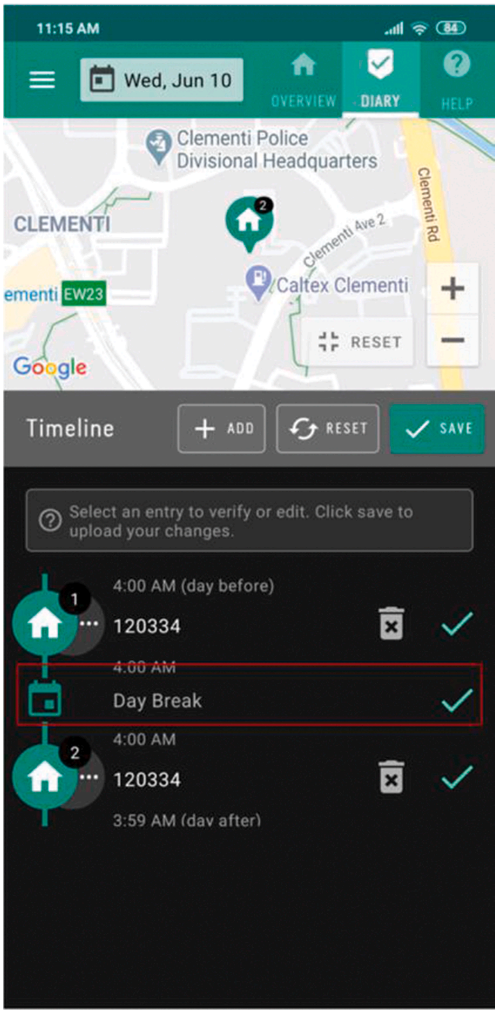

Fig. 7. Day break example.

activities in addition to in-person activities. A list of relevant in-person activities was compiled and the option to report the online activities was added to the *timeline.* Fig. 5 demonstrates key elements of the online activity reporting. Users can report online activities during travel or in addition to stop-level activities. Being able to peg activities to specific travel and stop intervals allows users to better recall the day's events.

Detailed shopping activities

Activity diaries capture shopping activities in a limited fashion. The definition of shopping activity remains vague, and with shopping details missing. For example, if one is concerned about goods flows, *Window Shopping* generates none, whereas *Online Shopping* will eventually trigger a freight vehicle trip. We recognize that a shopping activity can encompass multiple types of activities such as:

- Browsing but not purchasing, i.e., window-shopping.
- Browsing and purchasing or placing an order for subsequent delivery.
- Receiving/Picking up goods, i.e., curbside, in-store pickup, locker pickup.
- Returning an item to the store/other location.

Thus, these options have been added to the in-person shopping options. Then, to capture detailed goods type purchased, we specified a short but comprehensive list of items. Longer lists would result in users having to scroll and consider multiple selection, which we wished to avoid. The list of options is illustrated in Fig. 6 (left), consisting of Meals, Food & Beverages, Consumables, Durables, and Others, along with details to guide users.

We acknowledge the burden of completing these sections. Thus, we added the option for users to upload receipts or forward e-mails related to their purchases. We aimed at easing the process further by allowing for:

- Receipt scanning: with the phone camera without having to switch applications. This feature can be further expanded with an Optical Character Recognition (OCR) algorithm which could read and store in the database the contents of a receipt. Note that the OCR feature was not tested in this pilot.
- E-mail forwarding: users could forward e-mails related to confirmation of online shopping orders to a pre-specified general e-mail address. The activity associated with the online shopping would be linked by an identification field allowing us to map each e-mail to the activity that triggered it.

The user interface of these features is shown in Fig. 6.

Day-level break

The deployment of the survey took place during a period where shelter-in-place confinements were mandatory due to the COVID-19 outbreak. Thus, long presences at the same location (in this case 'home') presented a new challenge to the survey tool. FMS relies on travel activity, i.e., user-movement to specify an end of the stop activity and the beginning of a travel activity. Similarly, the end of a travel activity specifies the beginning of a stop activity. With survey respondents not traveling, the outcome in the timeline would be a single stop with long permanency. Consequently, it would be challenging for users to report the time allocations for their activities. Due to this, we introduced a "day-level break", which forces long (e.g., overnight stops) to break at a specified time. For our pilot, we broke the long stops at 4 am every day. An example of the outcome of this feature is shown in Fig. 7.

Other app developmental considerations

A few other developmental considerations took place, based on user reported feedback and data analysis, which will be further reported in the *Results* section. For example, when selecting online/in-person activities, at least one option must be selected. This is to avoid menu hopping without completing the questions. We provided a "None" option which is exclusive (i.e., selecting none will deselect and deactivate all other options). Lastly, it is worth mentioning that we trialed a survey design version where the expenditure report was separate from the timeline. However, this was more prone to disengagement, given that it would require switching between different sections of the app. We merged the feature into the timeline as it has the advantage of presenting our questions as part of the daily recall process.

Survey deployment

The survey was self-administered, with respondents being provided with support through help pages, instructional videos, and a contact e-mail/phone number. The recruitment for the pilot survey, in a convenience sampling fashion, was performed predominantly through posters and e-mail lists placed on university campuses in Singapore. The engaged individuals were requested to verify their timeline for a period of 7 days. If participating as a household, the data collection would have to be concurrent for all adult household members over the same period.

Deployment period

It is relevant to provide some context to different stages of business availability and mobility possibilities during this pilot, in Singapore. There were four key phases, detailed in Table 2 and further explained on

Table 2
Different stages of the pandemic during the survey pilot.

Stage	Period	Data collection time	Sample size (user week)	Number of unique users	Number of unique households	Average number of verified intervals per user	Response rate (%)	Updates to method	National pandemic measures
Before lockdown	Before pandemic	1 January – 31 March	73	64	58	66	54%	No major enhancement	● No special requirements
During lockdown	During pandemic	7 April – 1 June	25	24	22	35	83%	No major enhancement	● Only essential businesses/ services are allowed
After lockdown, Phase 1		2 June – 18 June	27	22	21	50	90%	Add day-break interval	● Some businesses to re-open with Safe Management measures ● Households can receive 2 visitors per day ● Primary and Secondary school graduating cohorts to attend school daily ● Essential care services are allowed
After lockdown, Phase 2	Post pandemic	1 July – 31 July	21	21	20	71	70%	Improved day-break interval	● Retail, F&B, personal health and wellness, home-based services, sports and public facilities to re-open ● Social interactions and family visits are allowed (Limited to 5 people) ● Schools open from the end June 2020
		1 August – 31 August	11	11	11	81	37%		
		1 September – 30 September	14	15	15	71	47%		
		1 October – 31 October	16	14	14	60	53%		

the website of Ministry of Health in Singapore (MOH, 2020a, 2020b). During the "Before lockdown" stage, when the survey started, social distancing was advised with some anecdotal evidence of the population at large staying indoors especially on weekends and after work. The "lockdown" stage was followed on by eased restrictions in Phase 1 and Phase 2, where the latter remained into 2021 Q1.

Incentives

The incentive strategy was revised during the survey period as it will be further explained.

1) Short-term commitment

The first stage was intended to be a one-off one-week participation, which ended at the end of March 2020. In this stage we first attempted to leverage any potential respondent also as a recruiter. We incentivized any individual referring households that completed their survey with SG $10 and allowing for up to 3 households to be referred. Any engaged household, regardless of size, would receive SG$50, including the household of the recruiter. This strategy had two pitfalls, the first is that recruiters were dependent on households' participation to receive their incentive, and the incentive was not commensurate to the size and effort of a larger household. As a result, we adjusted the strategy to compensate any individual with SG$50, and for households completing the survey a lottery took place to further award SG$50 to two households.

2) Long-term commitment

In the second part of the survey, we contacted users who participated in the first part of the survey to ask if they want to continue participation for 6 more months. This second stage of the survey required a longer commitment where households reported their activities for one week per month over 6 months. In this case, the prior incentive strategy would be too costly. Instead, we offered a lottery to win a tablet computer by a popular consumer brand, conditional on survey completion.

Technology

The app was developed and available for download exclusively in the Google Play Store, meaning it was only possible to engage with Android phone users, representing around 72% of total mobile phones as of March 2021 (statcounter GlobalStats, 2021). Using a flexible cloud-based database and computational host for the algorithms allowed us to adjust storage and computational power according to the number of users participating in each stage, keeping running costs to a minimum. The primary server was responsible for hosting the survey's website and providing an API to communicate with the Android app. A secondary server held the database and handled data processing tasks.

Results

We present the results and findings of our survey in two parts. The first is related to the deployment of the survey, user feedback and learnings from this process. We then provide some data analysis demonstrating the potential of the tool for developing insights and deployment at a larger scale.

Deployment, learnings, and user feedback

The survey deployment yielded a total sample size of 188 user-weeks, with 73 unique participants. The breakdown of user-weeks according to the outlined stages of the pandemic is:

- Before lockdown: 73 user-weeks
- During lockdown: 25 user-weeks
- After lockdown, Phase 1: 27 user-weeks
- After lockdown, Phase 2: 62 user-weeks

Key learnings from the survey deployment which are worth highlighting are:

- The recruitment process and incentives specification to trigger household-level participation were two of the major challenges. Reason being that if one household member did not have an Android phone or did not want to participate, this would disqualify the household. Whereas the first could have been addressed with larger scale development and a iOS app version, the latter remains a

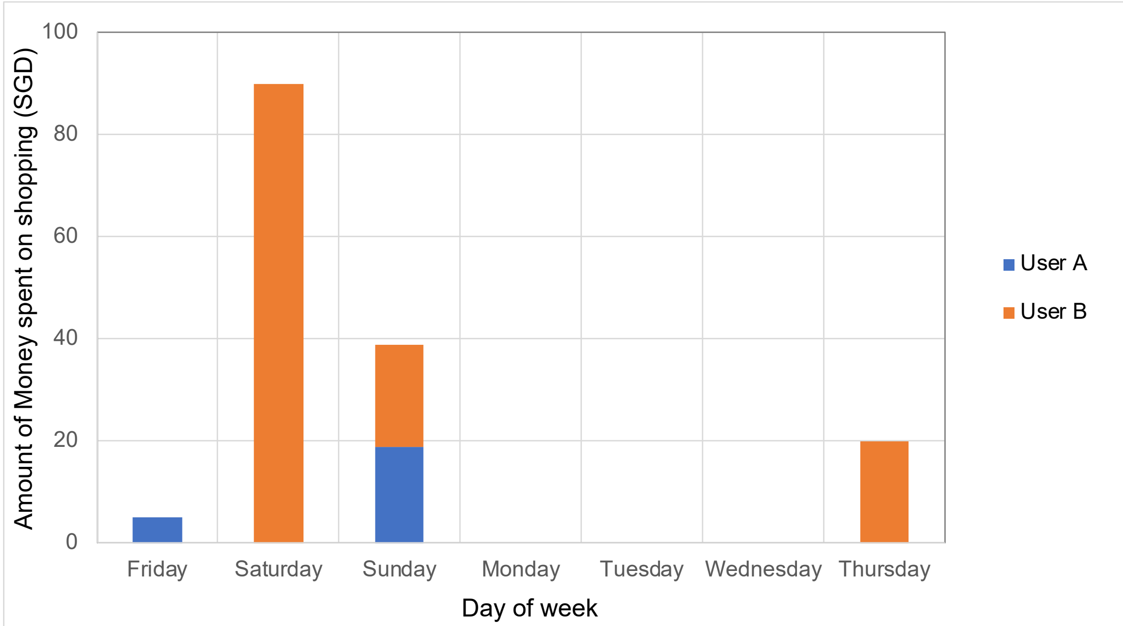

Fig. 8. Household-level distribution of shopping expenditure over a week.

challenge that can only be addressed via suitable incentives, commensurate to the household size.

- The FMS app needs to be running as a background activity all the time, and some phones limit such app configuration by default, and specific settings need to be changed to ensure smooth running of the app. There were some challenges related to defining the steps needed to allow FMS to run in the background in multiple smartphone brands. This posed a considerable burden on the research and development team to produce instructions specific to each phone make and model as well as step-by-step guides for less tech-savvy individuals.
- Most respondents praised the ease of using the app and the ability to quickly fill their activity diaries, but questions remained regarding the expectations of data precision. For example, some users would specify their transit trip access legs in high detail, whereas others would skip them all together. The same was observed for activities reported. Some users would report activities done for a very small amount of time (e.g., watching a video on the internet for 5 min), whereas other users chose to ignore this. Such expectations should be declared a priori.
- Through the analysis of multiple users' data, some specific user patterns appeared unusual. However, without having the means and ability to verify these, we had to take them as truthful. Developing further the ability to automatically detect improper verification can enhance the accuracy of collected data.
- To reduce survey burden, some users may choose to not declare shopping activities to avoid filling in the shopping details. Thus, further incentives/control mechanisms are required to motivate people to report their shopping activities, without leading to over-reporting.

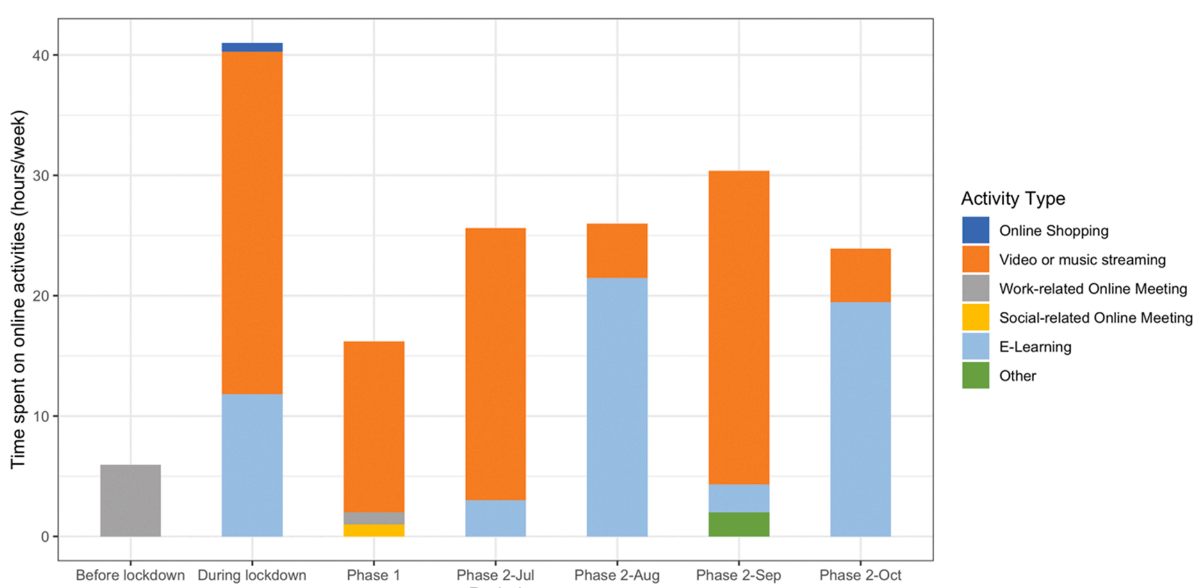

Fig. 9. Weekly time spent on online activities for one individual.

Table 3
Time allocation for activities at a single location "home", during the lockdown period, for one individual.

Activity type	Time (hours/week)
Work	64
Meal	9
Sports	2
Video or music streaming	3
Social	1

Data analysis

In the pilot survey, we collected data in Singapore over different stages of pandemic-related restrictions. We will use this section to illustrate how the proposed enhancements to the FMS tool can bring additional value to a data collection effort. For this, we will focus on key highlights, rather than perform a statistical analysis, exploring changes related to time allocation, expenditure, and travel/activity.

Household-level surveying

The hypothesis that activities might not be well captured by surveying one individual can be corroborated by the example in Fig. 8. Therein, it is shown that surveying either household member (User A or B alone) would only provide a partial view on the household-level shopping expenditure for the selected week.

Online activities

Adding the ability to capture online activities allows one to observe changes, such as those triggered by the lockdown, during which total online activity durations increased (Fig. 9).

Time allocation between activities

We are also able to illustrate the differences in time allocation for different activities in the same physical location, as shown in Table 3.

Detailed shopping activities

Asking for detailed shopping activities allows revealing activities otherwise not captured or distinguishable. The frequency of various shopping activities for selected individuals, commodity details and expenditure per shopping channel are shown in Table 4. In addition, we have received 88 shopping receipts and 3 online shopping emails.

Conclusions

We presented an enhanced smartphone-based travel/activity diary platform which allows individuals to record both online and in-person activities, as well as expenditures. By detailing the tool development and application considerations, we expect that this study can be of use for other researchers and practitioners aiming to develop a similar tool. The pilot application in Singapore demonstrated that the added features helped to capture missing behavioral dimensions in typical travel/activity surveys. Despite a limited sample size, which does not allow deriving conclusions on trade-offs between travel and online/in-person activities, we consider the pilot successful. The experience underlines the platform's capability of collecting high-resolution data, which can be used for behavior change analysis and travel demand model estimation. The tool itself did not demonstrate any major scalability concerns. However, although a comprehensive set of instructions to circumvent smartphone manufacturers' restrictions to app background usage was developed, a non-negligible amount of support had to be provided to users.

Table 4
Summary of on-site and online shopping details for one individual.

Period	Frequency of shopping-related activities (times/user-week)					Shopping frequency by commodity type (times/user-week)					Shopping expenditure ($SGD) by shopping channel	
	On-site Shopping	Window Shopping	Return Items	Receive/Pickup Delivery	Online Shopping	Consumables	Durables	Food & Beverages	Meals	Others	On-site shopping expenditure	Online shopping expenditure
Before lockdown	8	1	0	0	0	0	0	1	0	0	25	0
During lockdown	8	0	0	0	0	1	0	8	0	0	103	30
Phase 1	13	0	0	0	0	4	0	10	0	1	241	0
Phase 2 - Jul	8	2	0	1	0	1	0	6	0	1	602	0
Phase 2 - Aug	7	0	0	0	1	4	0	6	0	0	207	0
Phase 2 - Sep	8	0	0	2	0	1	0	8	0	0	103	0
Phase 2 - Oct	6	0	0	0	0	3	0	6	0	0	417	0

Learning from the pilot deployment experience, we envision several further enhancements to the tool and deployment strategy. First, there is room to increase the level of "sensing" ability to reduce user burden. While most users were accepting of the effort to fill all travel/activity details for one week, pre-filing assistance would be necessary for longer survey periods. Developing machine learning algorithms to support pre-filling would be a natural step forward, using variables such as time of day, prior and subsequent stops, location, among other factors. However, we also question if this can lead to users accepting the pre-filled values and lacking diligence to change erroneous predictions. Secondly, the current application allows users to scan receipts and reminds them to forward e-mails that confirm online shopping purchases. However, the detailed entries remain manual. Several technologies could be leveraged. Natural Language Processing (NLP) can be applied to scan the e-mails and extract the details related to online shopping purchases. Optical Character Recognition (OCR) can be applied to extract in-person shopping details from scanned receipts. Moreover, app usage tracking could trigger reminders to complete the diary if a purchase had been performed, and location data could be used to prompt the respondent about whether some shopping was done if at a location where this was recorded before. We do acknowledge that some of these technologies can raise concerns among individuals, who would have to provide consent to their use. Consent and participation are ultimately related to the individual's motivation to engage in the study. Thirdly, regarding incentives, alternatives to direct monetary incentives need to be proposed and tested. Such alternatives could be related to the provision of dashboards portraying respondents' activities and expenses akin to budgeting apps, which can help reduce survey costs. Finally, a complementary iOS app could allow us to recruit more participants and increase the sample size.

CRediT authorship contribution statement

André Alho: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Visualization, Supervision, Funding acquisition. **Cheng Cheng:** Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Dao Trung Hieu:** Conceptualization, Methodology, Software. **Takanori Sakai:** Conceptualization, Writing – review & editing. **Fang Zhao:** Conceptualization, Methodology, Writing – review & editing. **Moshe Ben-Akiva:** Conceptualization, Supervision, Funding acquisition. **Lynette Cheah:** Conceptualization, Writing – review & editing, Visualization, Supervision, Funding acquisition.

Declaration of Competing Interest

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

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