Dynamic Travel Behaviour: Findings of a Stated Adaptation Experiment and Modelling Framework

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Extended Abstract

1. Overview and motivation

The evolution of advanced, traveller information and the increased availability of travel alternatives -especially in urban settings- are altering the travel decision making process. While still constrained by unforeseen events (exogenous, such as weather and car malfunction or endogenous, such as congestion), individuals can better plan and subsequently act in a dynamic setting (1). In adverse conditions (e.g. ineffective short-term rescheduling, repeatedly increased travel time), individuals might evaluate their options based on real-time information and their accumulated experience (2), or even consider day-to-day and long-term adaptations. For instance, in the case of road closure, a traveller may make both short-term adaptations by modifying choice facets of his trip (e.g., departure time, mode, route), and/or account for this travel time fluctuation and accumulated experience when creating his future daily schedule (e.g. frequency of activity, work from home). Ultimately, individuals are found to progress towards a stable state (3) and (re)develop a set of day-to-day travel habits through the reinforcement of specific strategies.

The re-evaluation process described above is highly dynamic and often overlooked due to its high complexity, both in terms of data collection and modelling. The former requires panel data which are hard and costly to collect, with the literature thus focusing on -limited- stated adaptation experiments performed (4). The latter is usually based on the independent estimation of a set of models capturing aspects of the multi-level decision in a sequential fashion or loose coupling through the iterative feedback of inputs and outputs (5-6).

This paper aims to contribute to existing literature of travel decision making by, a) introducing a joint revealed and stated preference (RP-SP) adaptation experiment that captures within-day re-evaluation and day-to-day learning, tested with a panel of 282 individuals (3240 observations) in the Turin region (IT); b) proposing a modelling framework for the integration of travel behaviour dynamicity across temporal levels.

2. Survey, experiment design and data collection

The stated adaptation experiment is designed to explore people's adaptation strategies when faced with travel time fluctuation on their habitual schedule. The structure of the data collection experiment for dynamic demand shift consists of four main parts (Figure 1), i) RP data collection, including habitual activity and travel patterns, sociodemographic characteristics, and attitudinal statements on re-evaluation (e.g. resistance to change, tendency maximization, travel information seeking) ii) Backend functions, referring to the trip selection process (used as the adaptation reference point), choice of activity or en-route re-evaluation, and travel time ordering algorithms for the design of the hypothetical scenarios, iii) Stated adaptation experiment

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for integrating within-day re-evaluation and day-to-day learning and, iv) Feedback questionnaire for the assessment of response quality (e.g. complexity fatigue).

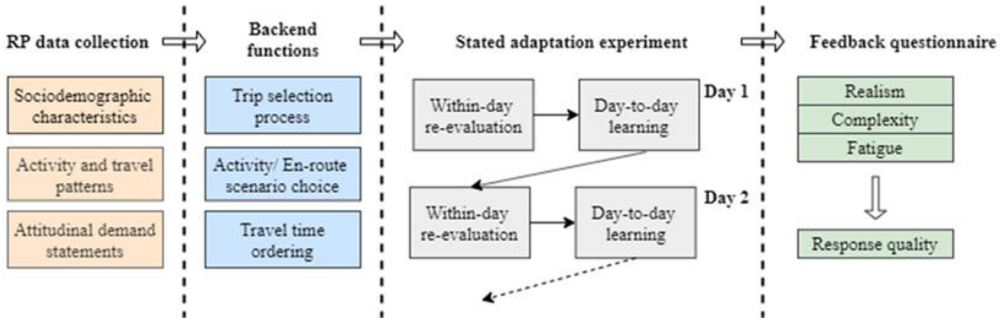

Figure 1 RP-SP data collection process for dynamic travel demand shift

To increase task realism, the stated adaptation scenarios are created based on the revealed preference (RP) setting. The participants are presented with hypothetical days for two different trips of their habitual schedule (see Figure 2 for an example). Each scenario is repeated for 6 hypothetical consecutive days with pivoting travel times based on the habitual travel time recorded in the travel diary. These scenarios refer to re-evaluation either during an activity, when the decision is taken prior to the execution of the trip, or en-route to the destination, in presence of live information. The stated adaptation scenarios are structured in a hierarchical process (Figure 3) that considers the following re-evaluation strategies: i) activity rescheduling (e.g. cancellation or replacement of an activity), ii) change of departure time, iii) mode shift, and iv) change of route. A sequence of binary answers determines the overall strategy, allowing us to capture multifaceted combinations of adaptation (e.g. change departure and mode). At the end of each hypothetical day, after the re-evaluation strategy is selected, the participant responds on his updated travel time expectation, as a result of the fluctuations experienced over the past days. The stated preference adaptation questionnaire was implemented using Ruby on Rails.

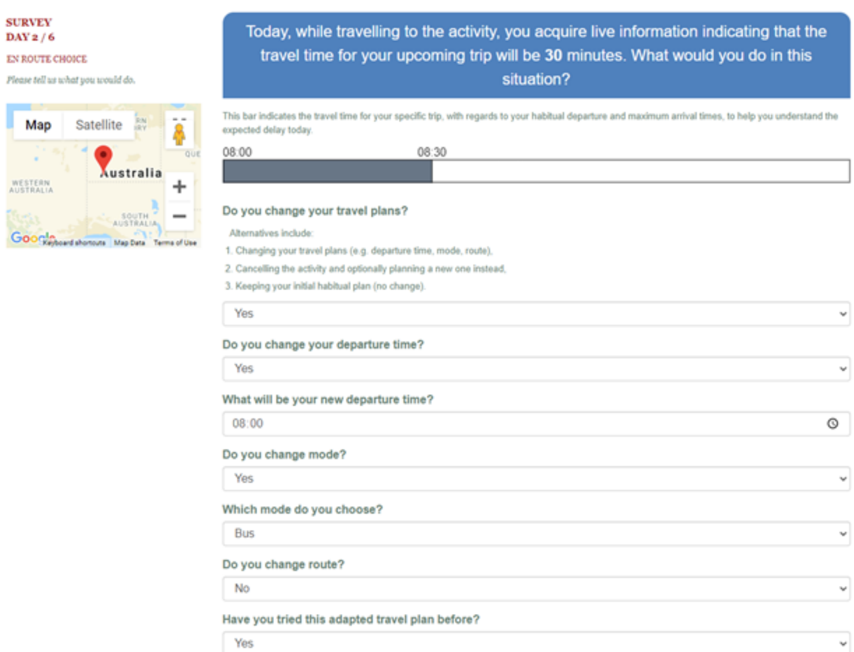

Figure 2 Stated adaptation scenario visualization

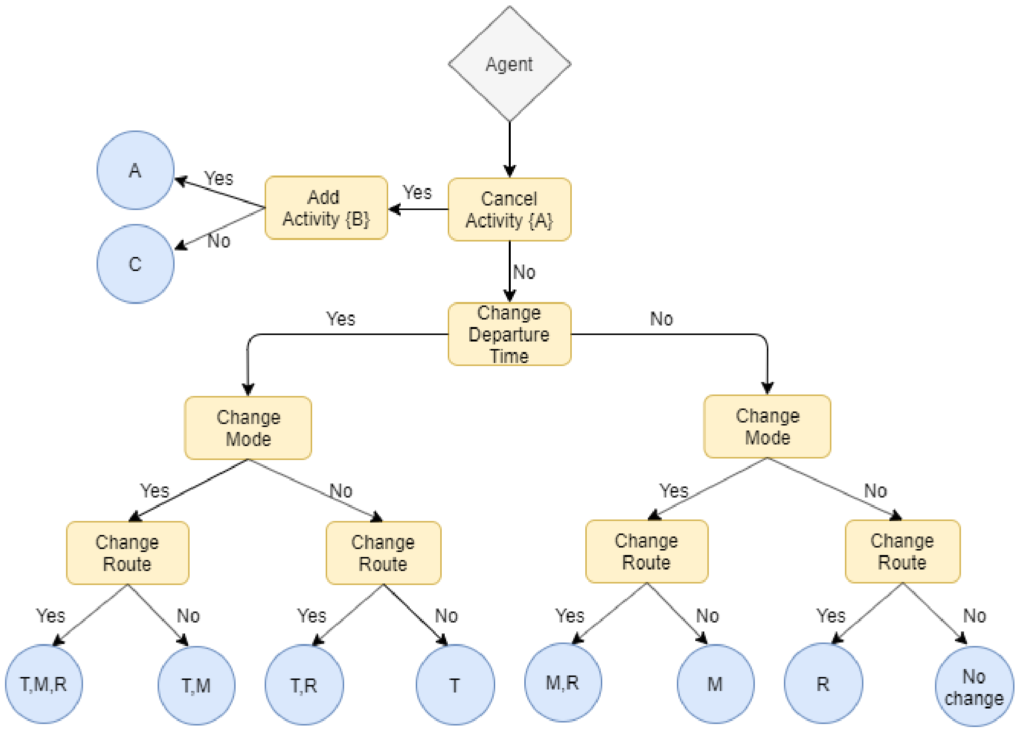

Figure 3 Within-day re-evaluation SP hierarchy and adaptation strategies (T: Departure time change, M: Mode change, R: Route change, A,C: Add/Cancel activity)

3. Modelling framework

Based on the theory of dynamic latent plan modelling, people make plans across different time horizons (short, medium, long term) and then select actions to execute those plans (7). Within the context of travel demand re-evaluation, those strategies have been distinguished into habit, adaptation, and exploration (6). The proposed modelling framework aims to capture this inherent dynamicity imposed by situational constraints and endogenous factors such as experience or inertia to change.

At the day-to-day level (Figure 4, left) the modelling structure is defined as an agent-based Hierarchical Hidden Markov model, where each state is a self-contained probabilistic model. Transitions can be vertical or horizontal. When a state is reached, the whole probabilistic model below is activated. Each level has a terminal state (*e.g. Day End*, *Change*) which when reached, control is sent back to the parent state that triggered this level. Some of the states lead to observations or actions (e.g. *Adapt*, *Explore*), whereas others do not (e.g. *Day Start*). These actions can be short-term adaptations (e.g. change departure time, mode, route), mid-term adaptations (e.g. change activity frequency) or even long-term adaptations (e.g. relocate, buy new car).

At the within-day level (Figure 4, right), a three-level decision process is envisioned for short-term replanning. The three stages are, choice of plan (e.g. habit, adaptation, exploration), tactic (e.g. change mode, departure time), and action (e.g. switch to bus, depart 10 min earlier). The agent selects a re-evaluation tactic conditional on the choice of plan. The chosen plans and intermediate choices are latent or unobserved and only the final actions are observed (8). While the sub-models are formulated as distinct models, the estimation is performed using the likelihood of the observed actions. After the trip is performed, the environment reward affects the choice of future plans and alternative attributes, through the process of learning.

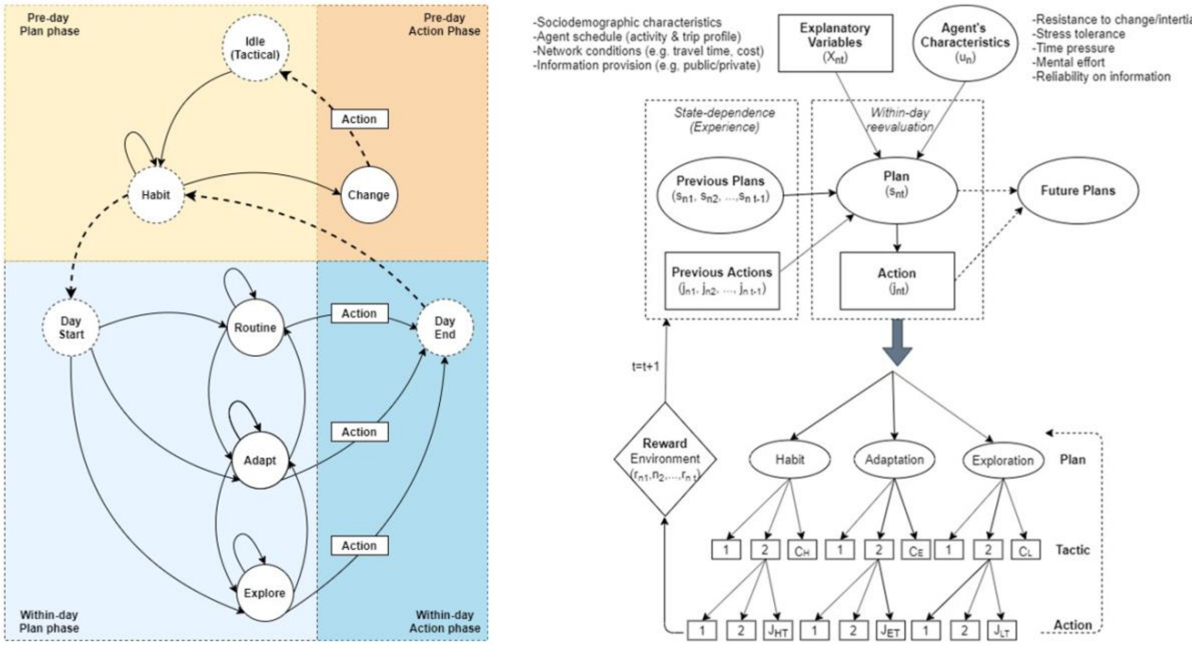

Figure 4 Integration modelling framework for day-to-day (left) and within-day (right) travel behaviour dynamics

4. Application and descriptive results

The stated adaptation experiment was applied in the metropolitan area of Turin (IT) between January and March 2022, as part of a wider travel demand survey. Recruited individuals formed a stratified sample of the travel survey participants, which is representative of the population in the Turin region (a survey company was hired for recruitment). The RP data collection was performed using a smartphone-based travel survey tool, the MobyApp. The habitual activity and travel patterns were tracked from the application in the form of travel diaries over the course of 7 days. At the end of the week, they were asked to complete the stated adaptation experiment and feedback questionnaire for 2 selected trips of their habitual schedule, based on a set of heuristic rules related to the frequency of the trip and activity type. In total, 282 individuals accessed the experiment and 270 of them completed it, resulting in 3240 adaptation observations. Descriptive results of the experiment are included below.

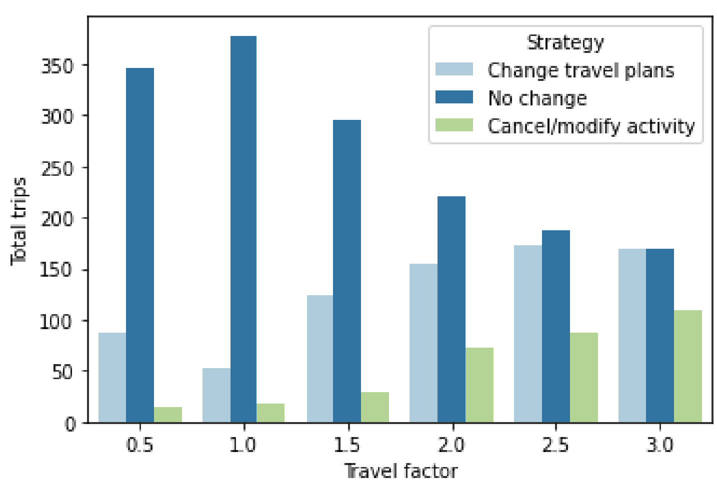

Figure 5 Resistance to change for different levels of travel time fluctuation

Our findings are in line with behavioural observations related to dynamic phenomena and specifically the concept of resistance to change or inertia associated with re-evaluation (9). Figure 4 presents the total trips by re-evaluation strategy, depending on the daily travel time fluctuation. The level of fluctuation is defined by the *travel factor* parameter {0.5, 1, 1.5, 2, 2.5, 3}, which is multiplied with the habitual (base) travel time for the selected trip of the participant, for a given scenario. For lower values of travel time fluctuation, 'No change' is the dominant re-evaluation strategy. It indicates that individuals might prefer a satisfactory habitual option over optimizing their schedule, often referred to as *satisficing*. As travel time increases, individuals opt for changing facets of their travel plan (departure time, mode, or route). For extreme values of travel time, we observe the highest chance for cancellation or replacement of the target activity.

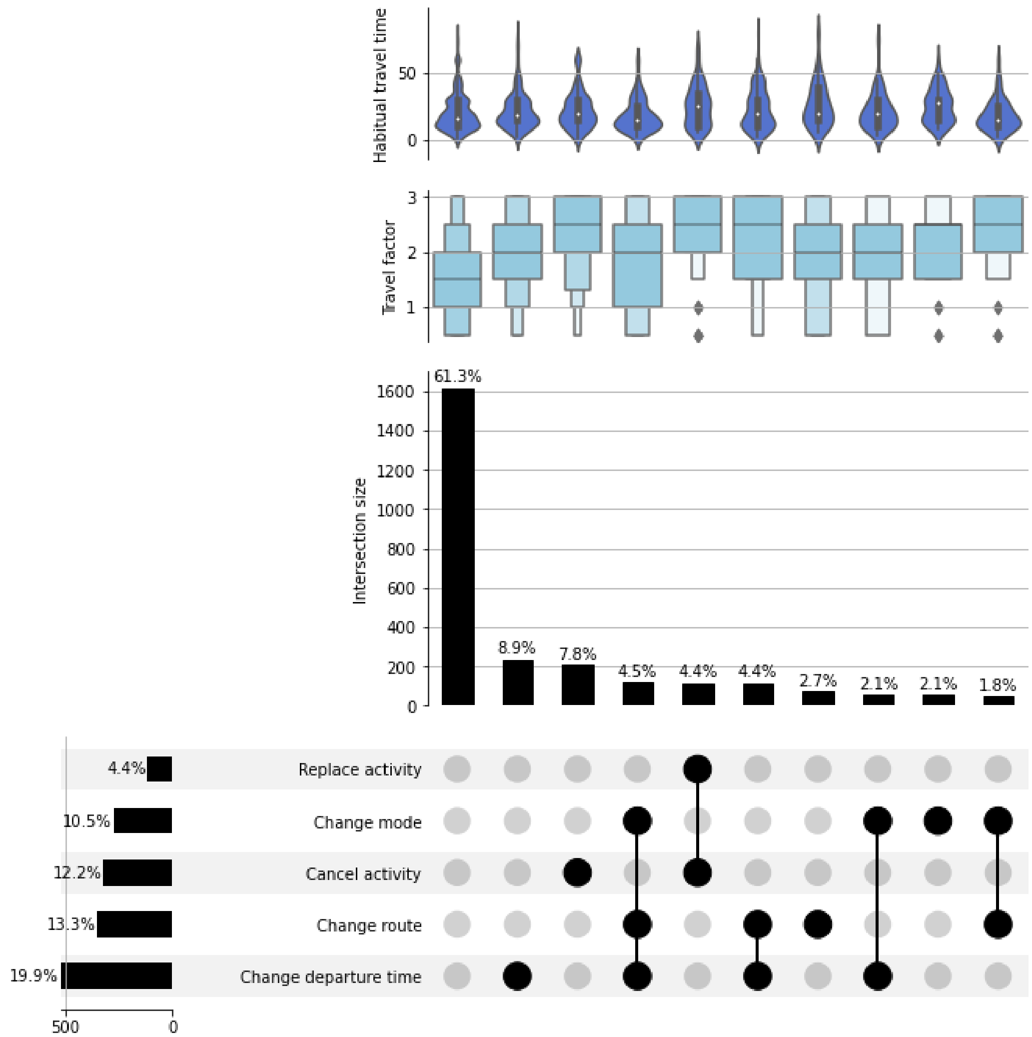

Figure 6 Upset figure of within-day re-evaluation strategies combinations over habitual travel time and its fluctuation

We proceed to analyse the disaggregate strategies of within-day travel re-evaluation. Figure 5 is an upset plot (read from bottom to top) that can provide useful insights on various aspects of the re-evaluation process. All possible combinations of re-evaluation strategies are depicted on the x-axis, including no-change, in addition to the cumulative percentage for modification of a specific choice facet. For instance, change of route occurred in 13.3% of trips among all possible strategy combinations. On the y-axis, we depict the intersection size among strategies, from which we can derive that the single modification of departure time is most often selected, occurring in 8.9% of trips as a single adaptation and in 19.9% of modified trips in total.

Each boxen plot provides information on the distribution of travel time associated with the re-evaluation strategy below it. It is apparent that cancellation and replacement of activity are associated with higher travel times, while 'No change', occurring in 61.3% of the presented scenarios, is linked with travel times closer to the habitual level. The violin plot includes information on the unscaled base habitual travel times (minutes), that are associated with a specific re-evaluation strategy below, while the mean of trip travel time for the sample is calculated at 20 minutes.

With regards to the feedback questionnaire, response quality was measured in a 5-point Likert scale. The results indicate that the design can sufficiently overcome the response burden challenges usually associated with these types of highly complex data collection experiments, with 64% of participants rating it above average in terms of complexity, 53% in terms of realism and 98% in terms of length and fatigue.

5. Conclusion

Experimental designs related to travel behaviour dynamics and its modelling are increasingly relevant with the emergence of advanced traveller information system and the use of live information that have shifted the focus of the scheduling process from the pre-day to the within-day level. Findings from the stated adaptation experiment are in line with the behavioural observations related with the dynamic concepts of travel re-evaluation and replanning. The full paper will include the estimation and validation of the proposed modelling framework for the regions of Turin (IT) and Oxfordshire (UK), using the data collected through the stated adaptation experiment. Ultimately, the design of robust data collection and dynamic modelling methods, will support the understanding of travel behaviour under uncertainty and assist towards policy analysis and simulation.

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