Calibration of sightseeing tour choices considering multiple decision criteria with diminishing reward

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Abstract
For an increasing number of cities, managing tourism becomes an important task and accordingly better understanding of touristic travel patterns is required. We model the sightseeing-tour choice within a city as a utility maximization problem. For this, attractions and their intrinsic utilities as well as tourists’ preferences are evaluated over multiple dimensions in order to explain the variance in tourists’ choice of POIs (points of interest) including the visiting order. Furthermore, the choice of destinations is considered “history-dependent” in that there is diminishing marginal utility gained by visiting additional POIs. Given the many potential sights, this leads to a large combinatorial problem. We solve this with a variant of a TTDP (tourist trip design problem) with the modified distance that evaluates omitted POIs and geographical distance between estimated and observed tours. The approach is applied to revealed-preference survey data from Kyoto, Japan, where tourists stated their visited attractions among 37 touristic areas. We discuss model fit and scenarios with the existing and a modified transport network.

Keywords Tourist preferences · Tourist trip design problem · Diminishing marginal utility · Bootstrapping

Introduction
City tourism is a major business across the world and has become an essential part of the economy. At the same time, its steep growth is creating congestion inside cities. In Kyoto, Japan, for example, the number of tourists exceeded 55 million in 2016 (Kyoto City 2017). Although stalled due to COVID 19 pandemic, the tourism travel demand is expected to grow further. The resulting crowding, especially at points of interest (POIs), leads to frustration among tourists. Furthermore, many Kyoto residents perceive the large number of tourists often as negative and avoid visiting the city centre. The “positive” impact of the COVID-19 crisis related reduction of foreign and domestic tourists in early 2020 has highlighted this issue in that slogans such as “Kyoto as it used to be” became popular in social media and newspaper articles reported about the enhanced tourism experience of...
Kyoto without the inconvenience caused by crowds (see CNN Travel (2020) for an English article).

To manage the increasing number of tourists, in particular if crowding is perceived not only as an inconvenience but, a health risk due to possible COVID infection risks in crowded situations, a new concept of travel demand management is required. The basis for this is the ability to estimate and predict tours made by tourists. However, there appears to be limited literature describing the travel behaviour of tourists inside cities, partly because choices are difficult to estimate and partly because traditional travel surveys tend to focus on residents instead of tourists (Zheng et al. 2019; Schmöcker 2021).

This research aims to reduce this gap by defining a choice model that describes the tours of tourists. Such a behavioural model implies an abstraction of the underlying motivation (driving force) that explains tourists’ decision-making process as well as their sensitivity to environments, i.e. travel costs to a next location versus the potential satisfaction to be gained.

Specifically, we use non-aggregate methods to model the tourists’ behaviour in making tours. We model their decision-making process in choosing destinations and determining the appropriate order of visits, while taking into account their preferences for city attractions as well as a ‘fatigue’ or ‘accumulated satisfaction’ factor. Since we aim to estimate the order of POI visits, leading to a large choice set, we draw on a heuristic tour solving approach. Once able to predict tourists’ tours, this model allows us to simulate tourism management strategies under various scenarios. Our goal is to evaluate tourism demand management strategies, policies, and transit facility investments in order to get sustainable tourists distribution in a city.

Therefore, our main contributions include the formulation of a modified “tourist trip design problem” (TTDP) that considers estimated multi-dimensional tourists preferences and intrinsic utilities of POIs along with a diminishing utility effect of longer recreational tours. This new TTDP is different in a number of aspects from those that we found in the existing literature. Furthermore, the paper includes an application of the model to Kyoto. The case study illustrates the feasibility of the model and potential improvements compared to common TTDP formulations.

The remainder of this paper is organized as follows: The next section reviews both trip-based and activity-based approaches to tour estimation, discusses past studies concerning behavioural formulation in the operations research domain, and concludes with the rationale for our approach. In the subsequent section “Problem formulation” the concepts and mathematical form of the behavioural model are presented. The solution approach and key modules for the model calibration are elaborated in “Solution approach” section. In the following “Kyoto data” section then the various data used for our case study are described. The "Case study results" section presents the model calibration results, discusses on the estimated parameters, and tests the effectiveness of TDM strategies under various scenarios. The “Conclusions” section concludes this paper and discusses specific ideas for future research.

**Literature review**

Two types of travel demand methods have been widely used: trip-based and tour or “activity-based” travel demand forecasting models. Trip-based travel models use individual person trips as the fundamental unit of analysis. Shortcomings such as independent entities,
omission of spatial–temporal constraints are well known and, among others, reviewed in Rasouli and Timmermans (2014). Activity-based travel demand models instead are based on the assumption that travel is a derived demand from the need to participate in activities (Bowman and Ben-Akiva 2001). Accordingly, activity-based travel demand models simulate the activity-travel decisions of households and individuals that collectively result in the observed activity patterns. The disaggregate, often agent-based, models lead to a more realistic replication of actual traveller decisions than the aggregate trip-based models, as well as to greater sensitivity to transportation, investment policies, and TDM strategies (Castiglione et al. 2015). Despite their wide application for urban planning, such models are mainly used in the context of resident travellers. We find limited work in literature discussing tourist behaviour inside urban areas with either trip or activity-based approaches. Part of the reasons is, arguably, that there is a fundamental difference regarding the objectives in tour selection of tourists and residents for daily activities.

In activity-based models of daily activities, household members decide and schedule their activities before departure. They are assumed to follow certain activity types from a fixed, constrained activity set (Ben-Akiva and Bowman 1998). It is reasonable to assume that residents have flexibility for some trips but that there are also a number of mandatory trips with no or few destination and time choices. In contrast, tourists often dynamically optimize the activities by themselves, i.e. destinations to visit as well as what activities to engage in. Some tourists might have fixed, pre-decided itineraries but many might evaluate the satisfaction from the places visited so far en-route, which will, in turn, affect the choice of the next destination. Sometimes it is not even a particular, singular destination the tourist aims to reach but generally, the goal is to explore a city or an area of the city within a given time (and with a given budget). Therefore, this study aims at developing a tour estimation, where travellers’ choices are determined based on their preferences as well as on the satisfaction they have received from the activities carried out so far.

Operations research literature describing individual tourist behaviour through utility functions sees the decision of choosing a specific tour as a process of solving an optimization problem. The general problem is called orienteering problem (OP), in which players start from a fixed origin point to visit check points, each associated with a unique score, before returning to the origin point within the time limit. The winner of the game would be the one with the highest score. In the context of sightseeing, it is often named as the tourist tour design problem (TTDP), referring to a personalized route planning problem for tourists interested in visiting multiple POIs, with each visit contributing a satisfaction score in the utility maximization formulation (Vansteenwegen et al. 2007). Solving the TTDP can be the foundation to provide personalized route recommendations (Kinoshita and Yokokishizawa 2008; Huang and Bian 2009; Herzog and Wörndl 2016).

Gavalas et al. (2014a) provide a comprehensive review of TTDP related literature and discuss that the following input data is required: Firstly, a set of candidate POIs, each associated with a number of attributes, e.g. opening and closing times, as well as the “profit” to be determined based on the objective (intrinsic utility) and subjective importance to each tourist according to his/her personal preferences. Secondly, activity duration at each POI; thirdly, the mode-specific travel time and cost to reach POIs and, fourthly, constraints like starting and ending locations of an itinerary, including a time limit that a tourist wishes to spend on visiting sights, etc.

Since the complexity of the orienteering problem (OP) and its TTDP variant are well-known to be non-reducible to polynomial runtime (NP-hard), heuristics are used for deriving an optimal tour, searching for results that may have higher utilities until the constraints are reached (Lu et al. 2011; Souffriau et al. 2008). Vansteenwegen et al. (2011) modelled
the TTDP with a team orienteering problem with time windows (TOPTW) and presented a greedy randomized adaptive search algorithm (GRASP) to solve it. They also included lunch break as a virtual POI. With improvements in heuristics, additional variables are introduced to simulate more realistic TTDP scenarios. For example, Abbaspour and Samadzadegan (2011) introduced a multimodal transportation network with time-dependent travel time. Lu et al (2011) developed a system for the integration of tourist packages and single attractions with time-dependent interest levels. Garcia et al. (2013) integrated public transportation into personalised electronic tourist guides to recommend routes in real-time. Cenamor et al. (2017) presented an application that generates tourist routes based on the data from social network sites. They added restaurants for meal stops considering the hunger drive, which is represented by a time window during which a tourist can eat. Herzog et al. (2019) suggest that traveling between POIs can also be part of the pleasure and proposed several attributes to be considered when integrating route attractiveness into tourist route recommendation system. Gavalas et al. (2014b) extended the scope of TTDP by optimizing the hotel areas and distribution of the length of stay at different destinations.

Despite the above-mentioned advances, obtaining appropriate behavioural parameters remains a main challenge for practical applications of the TTDP. We suggest this is, in particular true for city-tourists who are often unfamiliar with their surroundings and therefore their behaviour is difficult to capture in optimizing approaches. Seddighi and Theocarous (2002) proposed a framework in which the destination choice is determined by both the objective characteristics of destinations and tourists’ perception/preference, whereas Becken et al. (2003) highlighted that tourists’ travel choices are closely associated with demographic and trip-related variables. Furthermore, encounters and events during one’s trip and adjusting plans to these are part of the fascination of city-tourism. At the same time, the onset of tiredness can lead to changes in trip plans as discussed in Ko et al. (2019). They proposed that “fatigue” should be taken into account in the tour design. We also note the work of Li et al. (2018) who suggested, based on experiments that “aesthetic fatigue” is an issue for city tourism. In other words, once a few attractions have been visited, the likelihood of skipping attractions will increase even if there is still sufficient time remaining.

Furthermore, POIs might be classified into several dimensions. For instance, a hiking area with spectacular scenery could have a high score in terms of natural beauty and outdoor exploration but should not be labelled as a place rich in entertainment and shopping activities. Similarly, museums and galleries are given high scores in terms of cultural and art activities but will have relatively low values for natural sceneries. Not only does the destination have a range of intrinsic utilities in multiple dimensions, but also the preference of tourists varies with respect to these dimensions and a tourist might want to satisfy several of these dimensions at least to some degree over the course of his/her tour. To reflect this, the Generalized Orienteering Problem describes a network in which each POI has a score with respect to a number of attributes, and tourists have multiple interests (goals). Therefore, the overall objective function might comprise any combination of the different benefits (Wang et al. 2008; Silberholz and Golden 2010). Alternatively, the multi-objective Orienteering Problem suggests that POIs can be assigned to different categories and contribute different profits to each category. Therefore, its goal is to calculate alternative tours that are Pareto efficient under different objective functions (Schilde et al. 2009).

In order to determine the categories that can be assigned to each POI, Becken et al. (2003) used factor analysis to reduce attraction categories into 5 dimensions (factors). Kinoshita and Yokokishizawa (2008) collected eleven significant adjectives paired with opposite meanings for expressing the characteristics of tourist attractions and reduced
them subsequently into three categories using factor analysis. Also with reference to Japan, Sasaki and Nishii (2010) summarized sightseeing facilities into three categories “Downtown”, “Shrine and Temple” and “Natural beauty”.

Following this review, in our research, we follow the Generalized Orienteering Problem approach. Our study suggests that the satisfaction obtained by tourists is determined by how well the intrinsic utilities of each node in different categories match the tourist preference. We evaluate both intrinsic utilities of POIs and tourists’ preferences for these dimensions using the data categories suggested in Gavalas et al. (2014a). Different from the reviewed literature we also introduce a diminishing marginal utility achieved along a tourist’s tour. We partially follow here ideas of Ko et al. (2019). Whereas that paper looked mainly at fatigue in terms of tiredness after visiting several sights (of any type), we interpret this in terms of satisfaction. For example, in Kyoto, our case study city, there is a choice between a large number of national and world heritage temples. Most tourists prefer to see only some temples on a given day and mix this with visits to other attractions. In the following section, we describe the resulting problem formulation of obtaining tour utilities with such characteristics on a complete directed graph before discussing our heuristic solution approach.

Problem formulation

Our problem focuses on the selection of POIs and their visiting order in a tourist’s tour. It must be noted that we do not model the route and mode choices between the selected POIs. We, therefore, denote a complete graph network as \( G = (V, E) \), where the vertex set \( V \) is a combination of the POI (attraction) set \( Q = \{v_1, v_2, \ldots, v_{|Q|}\} \), and the origin and destination set \( S = \{v_{|Q|+1}, v_{|Q|+2}, \ldots, v_{|Q|+|S|}\} \). The edge set \( E \) represents the paths connecting the vertices \( V \). To obtain such a reduced network we pre-process the transport network to find the mode-specific shortest paths between different POIs, origins and destinations and consider this as the edge cost.

We base the tour calibration on the assumption that each tourist is a rational decision-maker and model the tourist movements as a problem of tourism experience (utility) maximization. The objective function of the traveller is thus to decide on an ordered combination of POIs which maximize his/her interests including consideration of the route costs. We describe the tour of a person \( n \) with a binary matrix \( X^n \) of size \( V \times V \) with elements \( x^n_{ij} \) where non-zero entries denote travel from vertex \( i \) to \( j \) that are taken on a tour. Each row has at most a single non-zero entry and as we consider that each node is only visited once, \( X^n \) describes hence a unique tour for each tourist. The objective function is formulated in (1), where origin \( o \) and destination \( d \) (e.g. a common entry point to the city, or a hotel) of the person are given; \( i_k \) denotes the \( k \)th POI visited which can be extracted from \( X^n \). The tourist aims to maximize his/her utility by visiting a number of attractions before reaching his/her destination. We note that by maximising with respect to \( X^n \) also the number of points visited by a tourist, denotes as \( m_n \), is determined. \( m_n \) is equal to the number of non-zero entries in \( X^n - 1 \) excluding one for the destination.

The utility \( u_{n,i}^+ \) denotes the positive attraction of person \( n \) to visit POI \( i \) which is assumed to be a function of the previously visited POIs. Further, \( u_{ij}^- \) defines the negative utility of travel costs from \( i \) to \( j \). The travel costs and node attractiveness are obtained with Eqs. (2) and (3). Each edge is associated with a non-negative travel time \( t_{ij} \) and cost \( c_{ij} \). We assume a linear time and cost function as in (2) where \( a = 1/VOT \) (value of time) is to be estimated. Parameter \( \beta \)
weighs the relative importance of visiting attractions compared to the travel cost. In general, we expect a large positive value of $\beta$ for tourists, i.e. persons who have made a commitment to come to a city for sightseeing purposes.

In Eq. (3), the utility of visiting the POI $i$ at the $k$th position in the journey for person $n$, $u_{n,i_k}^P$, is decided by the interest of a tourist in a specific POI (personalized score of the location), which is determined by both the tourist’s preference and the intrinsic utility of that POI. It is assumed that the preference of a tourist $n$ can be characterized by a vector $p_n = (p_{n,1}, p_{n,2}, \ldots, p_{n,r})$, with entries describing preferences for each of the $r$ dimensional attractiveness of a POI. Correspondingly, each vertex $v_i$ in $Q$ has an intrinsic utility vector denoted as $y_i$, of size $r$ where each entry has a value describing the objective attractiveness of the POI across these different categories.

The ‘$\circ$’ mark in (3) stands for the entry-wise product of two vectors. $A_{n,k}$ is a vector with $r$ entries that represents the accumulated utility across the $r$ utility categories gained from the POI visits before arriving at the $k$th POI, $i_k$. $F(x;\kappa, \theta)$ describes a diminishing marginal utility function and is the cumulative distribution function of a gamma probability distribution where $\kappa$ and $\theta$ represent the shape of the “discount factor”. It is assumed to be negative since more cumulated satisfaction is reducing the benefit of visiting another similar place. We further introduce $F(A_{n,k};\kappa, \theta)$ as a vector of diminishing utilities for all elements of $x$. That is, in our case, $F(A_{n,k};\kappa, \theta)$, with the $r$ elements $F(A_{n,k,r};\kappa, \theta)$, describes the diminishing utility of category $r$ for person $n$ after visiting $k$ nodes.

A gamma form distribution is chosen as it represents a universal and flexible form for the discount factor. With the skewness, offset and sharpness coefficients that control the shape of such utility function, it can vary from the normal exponential form which drops sharply in the very beginning, to a rather general logistic form. The sharpness parameter represents the discount factor of accumulated utility and indicates how quickly people perceive fatigue. Those with small discount factors, e.g. $\kappa = 0.5$ and $\theta = 1.0$, tend to make very limited visits in a journey but would decide carefully where to visit first. For tourists with larger discount factors, their first few visits will not have much impact until the total utility obtained accumulates to some threshold. The curve will be very flat with large values of $\kappa$ and $\kappa/\theta$, which then indicates very limited influence of previously visited sites on the utility to be obtained from visiting next destinations.

\[
\max_{x_n} U_n \theta, d = \max u_{0,l_1}^d + \sum_{k=1}^{n-1} \left( u_{n,k}^P + u_{i_{k+1}}^d \right) + u_{n,m_n}^P + u_{v_d}^d 
\]

\[
u_{ij}^d = -(d_{ij} + ac_{ij}) \]

\[
u_{n,k}^P = \beta p_{n}^T(y_i \circ (1 - F(A_{n,k};\kappa, \theta))) \]

where $F(x; k, \theta) \sim \Gamma(k, \theta) \equiv \text{Gamma}(k, \theta) = \int_0^\infty f(u; k, \theta)du = \frac{\gamma(\kappa, z/\theta)}{\Gamma(k)}$
Constraints for the problem are:

\[ \sum_{i=1}^{Q} x_{id}^{n} = \sum_{j=1}^{Q} x_{oj}^{n} = 1 \]  \hspace{1cm} (4)

\[ \sum_{j=1}^{Q} x_{ij}^{n} \leq 1 \forall i \hspace{0.5cm} (5) \]

\[ \sum_{i=1}^{Q} \sum_{j=1}^{Q} x_{ij}^{n}(t_{ij} + T_{i}) \leq r_{\text{end}}^{n} - r_{\text{start}}^{n} \]  \hspace{1cm} (6)

\[ x_{ij}^{n} = \begin{cases} 1 & \text{if going from node } i \text{ to node } j \text{ is part of the tour;} \\ 0 & \text{otherwise} \end{cases} \]  \hspace{1cm} (7)

Constraint (4) ensures that the tour starts from an origin \( o \) and ends at a destination node \( d \). Constraint (5) implies that no attractions are visited more than once, and tourists could travel at most once among two nodes. Constraint (6) guarantees that the time budget of the tour is satisfied where \( T_{i} \) denotes the expected time spent at a POI, \( r_{\text{start}}^{n} \) the tour starting time of a person and \( r_{\text{end}}^{n} \), the desired end time. We note that \( T_{i} \) is taken as zero for origin and destination nodes. Constraint (7) defines the binary nature of our decision variables.

To summarize, we model tourists’ tour choice given a time budget, preferences across several categories as well as starting and ending points. We formulate this as the problem of finding optimal POI visiting sequences \( X^{n} \) for each person that maximise a tour utility. There are four parameters, \( \alpha, \beta, \kappa, \theta \) to be calibrated in the problem leading to a two-level problem for tour determination and parameter selection. This framework and the solution approach are described in the following section.

**Solution approach**

**Overview**

We employ the framework illustrated in Fig. 1 to calibrate the proposed model. The bi-level framework is obtained through two loops: The inner loop enumerates all tourists from the survey and utilizes a problem-specific heuristic to predict optimal tours. Then the predicted paths are compared to the observed ones and the prediction errors for each person are summed up to obtain a solution fitness value defined as the inverse of the prediction error. The outer loop generates alternative parameters in order to reduce these total errors.

In the following we first discuss the inner problem, which is solving the TTDP for a given set of parameters, before we deepen our discussion on the parameter calibration in the subsequent section.
Solution heuristic: a TTDP solving algorithm

The tourist tour design problem (TTDP) is known to be NP-hard and can be formulated as an integer programming problem. Exact solutions based on branch-and-bound, branch-and-cut are only feasible for small-scale graphs (Gavalas et al. 2014a). As our problem is large in terms of network size as well as number of tours to be solved for each set of parameters, developing a fast algorithm is essential. We exploited the Iterated Local Search (ILS) as a heuristic for predicting the best tours (Vansteenwegen et al. 2009a, b). A general flow of the heuristic is illustrated in the below pseudo-code.
The cost function: a path similarity evaluation metric

Usually in discrete choice problems, model parameters that represent the utilities of alternatives are estimated via methods like maximum likelihood estimation, where the logarithm of the probability for choosing the observed route is maximized. Since we cannot enumerate and find choice probabilities of all possible ordered combinations of the attraction areas, we describe tourist behavior as a non-discrete choice problem and generate a set of possible tours for each tourist in a deterministic way. Consequently, there is no probabilistic metric to distinguish between alternatives other than a metric that evaluates similarities between the most possible tours and the observed one. We therefore can only select or “calibrate” – but not statistically estimate - the best-fit parameters.

Let \( R_n \) denote the best fitting tour among the set of possible tours, i.e. \( R_n = \{ r \in R \mid \max U_r \} \). Our goal is to find the vector of parameters \( \Theta = \{ \alpha, \beta, \kappa, \theta \} \) that minimize the spatial difference between observed tours \( \hat{R}_n \) and calibrated tours \( R_n \). We note that we do not evaluate further based on time differences as this would require us to also estimate stay durations at the zones which we consider as a possible extension of the here presented approach. Neither do we estimate activity types conducted at the nodes. Tourists visit specific areas of the city usually for a range of activities and we remind that we accordingly estimate the multidimensional utility gained by visiting a specific area.

There are various kernel functions and similarity coefficients that compute the pairwise similarity between sequences as described in Rieck et al. (2006). For example, Zhang et al. (2012) used the longest common subsequence (LCSS) to group travellers with similar patterns. Such metrics, however, only measure the number of matches. In other words, predicting either the right or “wrong” path does not measure how close we are to the ground truth. To overcome this we exploit the Levenshtein Distance, one of the best-known string metrics.
widely used in areas like computer science, as a similarity metric or a measure for the “distance” between strings. The algorithm defines three basic editing operations to transform one sequence into the other, the Insertion cost, Deletion cost, and Substitution cost. A common form of the Levenshtein Distance $L$ between two strings $a$ and $b$ is formulated in Eq. (8). The indicator function $I(a_i \neq b_i)$ is equal to 0 when $a_i \neq b_i$ and equal to 1 otherwise. Although it is most common to set the cost of all three operations to 1, we can assign different weights or costs to each editing operation to represent a more flexible difference metric.

$$L_{a,b}(i, j) = \begin{cases} \max (i, j) & \text{if } \min (i, j) = 0, \\ \min \left\{ \begin{array}{l} L_{R_n,R_n}(i - 1, j) + 1 \\ L_{R_n,R_n}(i, j) + 1 \\ L_{R_n,R_n}(i - 1, j - 1) + 1(a_i \neq b_i) \end{array} \right\} & \text{otherwise.} \end{cases}$$

For our problem we suggest a modified Levenshtein Distance metric that integrates geographic interpretation into this assessment. It not only measures the number of different entries among the two sequences but also to what degree the entries are geographically apart. To implement this, we define two types of costs.

Firstly, $C^D(i)$ as an integration of “deletion cost” and “insertion cost”, which represents the penalty when the algorithm predicts one more visit or misses one visit (compared to the real situation). An intuitive implementation is to set the penalty according to the additional travel distance required in order to visit the inserted (or omitted) place. However, due to the nature of the algorithm, we do not know between which two points the new place is going to be inserted. In other words, the algorithm cannot determine which previous and next nodes to refer to. Therefore, to weigh the importance of this POI insertion or omission, we take the central point of the tour as a reference point and obtain $C^D(i)$ as the crow-fly distance between this central point and the inserted/omitted POI $i$. In other words, $C^D(i)$ is an approximation of the omitted/added spread of the tour compared to the approximated one.

Secondly, $C^S(i, j)$ stands for “substitution cost” of visiting area $j$ instead of area $i$. In many cases, travellers tend to choose between alternative destinations that belong to the same category, are close to each other, and are similar in terms of the utility to be obtained, while keeping the additional travel impedance within acceptable limits. Intuitively, the penalty for replacing a destination to another should depend on the spatial difference between them. Therefore, we define the substitution cost as the geographical distance between the centre nodes of the replaced and observed attraction areas. With these modifications we obtain Eq. (9) instead

$$L_{R_n,R_n}(i, j) = \begin{cases} \max \left( \sum_{k=0}^{i} C^D(k), \sum_{k=0}^{j} C^D(k) \right) & \text{if } \min (i, j) = 0, \\ \min \left\{ \begin{array}{l} L_{R_n,R_n}(i - 1, j) + C^D(i) \\ L_{R_n,R_n}(i, j) + C^D(i) \\ L_{R_n,R_n}(i - 1, j - 1) + C^S(i,j) \end{array} \right\} & \text{otherwise.} \end{cases}$$

We implemented obtaining $L_{R_n,R_n}$ for each tour through standard dynamic programming as described in Wagner and Fischer (1974). The fitness function hence becomes

$$L^*(\Theta) = \min_{\Theta} \sum_{n=1}^{N} L_{R_n,R_n}$$

There does not appear to be a closed-form formulation for the fitness function discussed and hence no analytical gradients for the objective function. Thus, we adopted a genetic
algorithm (GA) like meta-heuristic to search for the optimal solutions. The initial solutions (first generation) for further optimization are generated from a “grid search”: We first sample the solution space at certain intervals to roughly understand in which area optimal solutions can be expected. Specifically, we adopted a half-logarithmic increment to sample from a reasonable range for each parameter. Grid points are determined by an exhaustive permutation of all the values.

Parameter values with relatively low prediction error are taken as the first population that will reproduce offsprings through a loop of the three fundamental GA phases: selection, mating/crossover, and mutation. Through repetition and iterations, a set of parameters is derived that eventually best describes all tourists’ behaviour in the model. Despite the long computation time for a single set of parameters, the parallel evaluation nature of each parameter set allows us to apply multi-process programming, which speeds up the evaluation by more than 10 times.

**Goodness of fit evaluation**

To measure how well the proposed behavioural model reflects the tourists’ decision-making process, we would like to obtain confidence intervals of the parameters. This requires, however, a probabilistic formulation of the problem so that likelihood measures can be derived from which in turn standard errors can be derived. As explained above, this is, however, not available for our approach.

We therefore conduct a “bootstrapping” approach; a resampling technique that iteratively resamples a dataset with replacement. The data set is repeatedly split randomly into two sets. A fixed percentage \(x\%\) of samples is assigned to the training set and the remainder to the validation set. The behavioural parameter set is then calibrated on the training set and tested for performance on the validation set. A general flow of this approach applied to our problem is illustrated in the below pseudo-code.

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**Algorithm 2: “Bootstrapping” evaluation pseudo code**

For each \(i\) among \(N\) tests:

1. **Split** tourist samples into **Training set** and **Validation set**
2. **Step 1**: In-sample evaluation
   - Cold start: Perform “grid search” on Training set to obtain initial solutions
   - Model calibration: Perform “optimum search” on Training set
   - Return calibrated model parameters: \(\Theta^i\)
3. **Step 2**: out-of-sample results
   - Calculate Fitness \(L_{\text{ext}}^i\) for the calibrated model on Validation set
   - Calculate Fitness \(L_{\text{lop}}^i\) for zero case on Validation set

Return: Summary statistics and goodness of fit of all models
The main goodness of fit measure we obtain is $L^*$ from Eq. (10). In analogy with relative performance measures as used in e.g. Ji et al. (2015), we evaluate the improvement of model fit by considering the behavioural characteristics with a “zero case” where behaviour is not considered. The orienteering problem extensively discussed in the literature describes this case. It represents a scenario where tourists do not have personal taste differences over different types of destinations and where accumulated satisfaction is not considered in the choices. This leads to a problem where Eqs. (2) and (3) are reduced to Eqs. (11) and (12). In the absence of any preferences for different kinds of POI, \( \sum_{r} y_{i,r} \) denotes the normed attractiveness as sum over all attraction types \( r \). The \( \beta^{OP} \) in (12) is then calibrated with this simplified formulation with the same framework as in Fig. 1. We note that we suggest this one parameter formulation is a better comparison as a true zero case without any parameter. \( \beta^{OP} \) can be considered as a scale parameter between travel cost and attraction utility; omitting this, would lead to an arbitrary weight of sightseeing compared to travel between sites.

\[
u_{ij}^t = -t_{ij}
\]

\[
u_{n,k,i}^P = \beta^{OP} \|y_i\|_1
\]

We denote the orienteering problem goodness of fit as \( L^{OP} \). We then utilise the \( L^* \) and \( L^{OP} \) to obtain the relative improvement \( S^L \) to evaluate in how fare the parameters \( \Theta \) contribute to better model fit. The improvement score \( S^L \) or \( S^L_i \) for each bootstrap test \( i \), is denoted in (13). For this we calculate \( L^* \) and \( L^{OP} \) on the validation set of each model to avoid in-sample evaluation which will over-estimate the model performance. We report the average improvement score \( S \) over all tests in the case study.

\[
S^L = 1 - \frac{L^*}{L^{OP}}
\]

As a second measure of goodness of fit, we consider, \( \Upsilon \), which denotes the accuracy in terms of visit frequency of attraction points or areas as in (15) where \( y_i \) are the calibrated visits to a touristic area and \( \hat{y}_i \) are the observed ones. \( y_i \) is obtained with (14) from the predicted tours for each person \( n \), which depend on the parameters to be calibrated. The relative performance indicator for node visit frequency in (16) is then defined in the same way as (13). We note that a model that will correctly predict all tours has performance indices equal to 1. Indices of zero would mean that no improvement is observed compared to the OP case and negative values would indicate that the OP model is a better estimate.

\[
y_i = \sum_{n=1}^{N} \sum_{j \in V} x^p_{ji}
\]

\[
\Upsilon = \sum_{i \in Q} (y_i^* - \hat{y}_i)^2
\]

\[
S^\Upsilon = 1 - \frac{\Upsilon^*}{\Upsilon^{OP}}
\]
Kyoto data

The framework is implemented through a number of input data in line with the required data discussed in Gavalas et al. (2014a). In this section, the usage of three types of data sets for estimation of tourist preferences, evaluation of attractiveness, and description of the travel costs are introduced. For brevity we keep this section fairly short and we refer interested readers to the thesis of Shen (2020).

Survey data: revealed tours and tourist preferences

In the absence of recent data, we obtained observed tours as well as tourist preferences from a survey of tourist movements in Kyoto city, conducted in November 2006 (Urban Planning Bureau of Kyoto City 2006). Though the survey is clearly fairly old, we note that the tourist attractions as well as the transport network in Kyoto have not undergone major changes in the last decade. There has been no construction of additional rail or subway lines, only bus schedules have been adjusted. We acknowledge, however, that the decision-making about which areas to visit and how to travel might be different nowadays due to the increasing availability of mobile phone applications that provide advice to tourists. This can change the perceived travel costs and attractiveness of some of the areas.

The questionnaires were distributed in attraction areas and train terminals. The survey included (a) socio-demographics such as age, gender, occupation, ownership of vehicles, home city, etc.; (b) tour related attributes such as travel purpose, schedule, travel group, frequency of visiting Kyoto city, comments and discontents, etc.; (c) a trip diary of detailed trip chains that consists of destinations, travel time and mode choice. We note that the starting and ending points of the tour were not asked as precisely as we would have preferred for our model. This issue will be discussed further in the result section. A total of 3456 responses were obtained out of which 1265 could be used for the tour estimation. With origin and destination excluded, most tourists visit two (28%) or three (26%) of the 37 areas with touristic attractions of the city during the tour (average 2.8, variance 1.9). The longest tour we observe consisted of visits to seven areas. The areas and their location are illustrated in Fig. 2. We observed the most frequent tour in the sample are those that include a visit to points of interest near Kyoto Station (Area 29), but also these tours only make up 2% of the whole sample demonstrating the diverse range of tours and the scale of the challenge we aim to address.

Tourists’ preference determines the subjective importance of each POI (how different categories of POIs match the tourist’s taste). Since tourists did not describe explicitly which type of sights they favour in the survey, we use “travel purpose” to reflect travellers’ tastes in attraction types. In the survey respondents were asked to choose up to three out of 17 options for their main reasons for coming to Kyoto. According to these answers, dummy variables are created presenting the presence or absence of that attribute. We first reduced the number of choices from 17 to 9 by merging less-chosen options into semantically similar and frequent equivalents.

This grouping and the (up to) three purposes stated by tourists for their trip are then used for K-means clustering with the Hamming distance as a sequence difference metric (Hamming 1950). We obtain stable results for K = 3 so that we presume the preference vector \( p_n \) and accordingly utility vectors \( y_i \) and \( A_n \) also have a dimension of three. The centroids of the clusters, representing the dominant choice patterns, and the proportion of
travellers assigned to each cluster are illustrated in Table 1. We note that the survey was conducted in autumn and that “autumn foliage tours”, is for many a main purpose to visit Kyoto in November as the city is famous for its foliage season when red coloured maple trees in combination with historical sites are a major attraction.

The clustering result revealed a dominant proportion of tourists with interest mainly in sites where autumn foliage as well as temples and shrines can be seen. Such result is reasonable in that the studied city has the most traditional Buddhist and Shinto culture in Japan, with a number of national and world heritage temples and shrines. Clusters A and B clearly overlap in their purposes but we suggest it is worth distinguishing these two groups as those in Cluster B with the additional “gourmet” objective, tend to structure their tours differently. Furthermore, we found that socio-demographic differences between the clusters are evident. We estimated a multinomial logistic model in which such socio-demographics of the visitors as well as travel-related attributes are used as explanatory variables, while the preference label is used as the categorical dependent variable (see Appendix 1). The overall model fit is moderate (Mc Fadden pseudo $R^2$ of 0.11) indicating the wide range of different preferences among tourists. We suggest attitudinal questions or more detailed “lifestyle” questions could improve the model fit but would also make applications more cumbersome as planners are unlikely to have this information for their visiting tourists.

Fig. 2 Location of attraction areas in the survey
Our subsequent analysis will show that the rough categorisation based on simple sociodemographics of tourists contributes to explaining their tours. With significant factors from the socio-demographic data, we predict the probability of belonging to each of the clusters using multinomial logit regression. The probability of belonging to each cluster is used as the preference vector $p_n$ for each tourist.

**Evaluation of attraction utilities**

The intrinsic utilities of destinations $y_i$ are also estimated and taken as input for the tour prediction. In the survey, the destination is defined as a large area around one or several main sights as shown in Fig. 2, which may include multiple different types of POIs. To calculate the utility of the attraction areas we avoid using the frequency of visits to the attraction as this would lead to endogeneity issues. We further remind that for each attraction point or area we require an intrinsic value along the three dimensions established with the cluster analysis.

To do so, we searched for POIs in each area utilizing “keyword search” in Google Map and OpenStreetMap Places Query APIs and considered both the number of reviews as “popularity” and the average rating score as “quality”. For each area, a total score in a specific dimension is calculated by a weighted sum: A summation of the average rating score multiplied by the number of reviews for each related POI in the area. For instance, we queried the number of reviews and user ratings from Google Map Places API when assessing the intrinsic score in the dimension of “temples and shrines”. For the “gourmet” dimension, we considered both the ease of finding a place to eat, i.e. the number of ordinary restaurants, bars and pubs as well as the number of high-end restaurants in the area. Similarly, attraction intrinsic scores in the “leisure activity” dimension are evaluated by enumerating the number of facilities associated with leisure activities in each area. These are the number of shops, museums and art centres. For dimensions for which the related keywords might be ambiguous (e.g. autumn foliage), we looked for information such as rankings assessed by tourist websites and magazines over the past few years. Finally, the tourists’ preference vectors and attraction intrinsic utilities are normalized such that all elements in a vector are scaled to have a value between 0 and 1. Figure 3 illustrates the attractions’ intrinsic utilities in bars stacked by values in the three dimensions respectively.

On “manual inspection”, the authors’ experience of the sightseeing area scores in Kyoto is largely in agreement with those found by the above approach though there are some exceptions. In particular we note the low score of “Katsura Imperial Villa (Area 30)”, despite it being recognized as an “Important Cultural Property of Japan”. The reason is that there are no restaurants and only one souvenir shop in its vicinity. Furthermore, it has not been on the list of red leaf sites recommended by travel websites and magazines. Nevertheless, it is clearly visited by more tourists than the score suggests. We avoid manipulation

| Cluster # | Interpretation                                      | # of observations | Proportion % |
|-----------|-----------------------------------------------------|-------------------|--------------|
| A         | Autumn foliage & temples and shrines                | 668               | 19.3         |
| B         | Autumn foliage & temple and shrines & gourmet       | 2142              | 62.0         |
| C         | Leisure activities (shops, cinemas, museums and art centres) | 646               | 18.7         |
of the scores but suggest that this shows that further work can explore alternative scoring approaches.

**Network edge properties**

We then linked the attraction areas with arcs describing average costs to travel between the areas, thus creating a complete and undirected graph network. To evaluate the attributes such as time, distance as well as the cost for traveling on each edge, we utilized the Google Maps services: Direction API for evaluating the mode-specific - in our case transit - travel time, distance, and transit fare between any two areas. We defined the nodes for generating and absorbing traffic as area centres or main transit entrances. Matrices of travel time, distance, and fare are measured and averaged from different periods (7:30, 12:30, and 17:30) throughout a day.

**Case study results**

**Comparison to orienteering problem**

We focus our results on the tourists coming to Kyoto by transit. Furthermore, for those being in Kyoto for several days we take their activities during their first day of tourism. The best set of parameters is shown in Table 2. We furthermore conduct the Bootstrap algorithm (Algorithm 2) for 30 times; we note that each run requires about 50 h on a

![Fig. 3 Obtained intrinsic utilities of attraction areas](image-url)

**Table 2** Obtained intrinsic utilities of attraction areas
standard PC until convergence as each time the full framework shown in Fig. 2 is invoked. Grid computation and approximation of good starting values for the parameter search can though significantly reduce the run time. The ranges of the parameters for these 30 runs are also shown in Table 2 and a histogram of parameters is reported in Fig. 4.

Since $\alpha$ is equivalent to the inverse of the value of time (VOT) that transfers the monetary public transport fare into time, the mean VOT was calibrated as 32.26 JPY per minute (around 19 USD/h) for tourists using transit. The value appears reasonable, if not slightly low, given that the VOT used in Japan ranges from 36 to 57 JPY/min for infrastructure projects (MLIT 2010). We further note the left-skewed distribution with more observations that have a small VOT. We suggest this is due to many tourists possibly not being very price sensitive to the public transport prices in Kyoto (at the time of the survey a single bus ride costs around 200 JPY, about 2 USD), in particular if they have purchased daily travel passes (available for around 800 JPY). Further, compared to commuters, tourists might be more willing to endure detours and do not emphasize on time, possibly due to relatively flexible time schedules. With this interpretation, the value appears fairly reasonable.

To be noted is further, that in general the concept of a “touristic VOT” is clearly difficult to define. If the transportation service itself is considered part of the journey low or even negative VOTs can be reasonable. Walsh et al (1990) review and discuss touristic travel time as opportunity costs related to one’s wage and highlight that consumptive values of travel time are important. With a survey they discuss cases where one is willing to pay to travel longer for “road trips”. Though this is not likely the case for trips between tourist

| Variable [unit]                      | Mean   | Range [min, max] |
|-------------------------------------|--------|------------------|
| Monetary travel cost $\alpha$ [min/JPY] | 0.031  | [0.011, 0.042]   |
| Importance of attractions $\beta$ [min]     | 124.13 | [80.84, 153.3]  |
| Diminishing Utility, Shape $\kappa$ [1]    | 0.820  | [0.249, 1.300]  |
| Diminishing Utility, Scale $\theta$ [1]    | 1.002  | [0.713, 1.344]  |
| Importance of attractions $\beta^{OP}$     | 31.109 |                  |

| Sample size N                     | 1265   |
| # Est. Bootstrap models          | 30     |
| Relative improvement $S^C$        | 0.120  |
| Relative performance indicator $S^Y$ | 0.733  |

Fig. 4 Histogram of bootstrapping model parameters
sites within a city we suggest this discussion highlights why there appear to be no strong guidelines as to what VOT values are reasonable in the context of tourism.

The intercept of the node utility visit is calibrated as 124.13 min. This represents an upper boundary of the utility a tourist can gain from visiting nodes, as each entry in the intrinsic utility vector of attraction has been normalized between 0 and 1. We note the two-peak distribution for this parameter in Fig. 4, possibly suggesting that in further research one might not only distinguish tourists according to their preference vector but also distinguish tourists paying much or little attention to the presence of attractions in a touristic area.

We now turn to our parameters describing the cumulative satisfaction impact. Due to the diminishing marginal utility gained by visiting additional POIs throughout the tour, the gains for visiting extra destinations will drop quickly once the accumulated utility reaches an expected value of $\kappa \times \theta = 0.82$, which is generally around visiting one or two places, depending on the attraction utility. Such a diminishing marginal utility shows the importance of considering “fatigue” or “accumulated satisfaction” in the model as it helps to predict the correct number of visits compared to the algorithms using greedy insertions. Noteworthy are further the different distributions of the parameters $\kappa$ and $\theta$ found with the bootstrapping approach. Whereas $\theta$ appears to be fairly normally distributed, $\kappa$ is not. Hence, also here at least two different tourist groups might be distinguished in further research according to the how quickly one is satisfied with the attractions seen so far.

Figure 5 illustrates visit frequency of different attraction areas from in-sample and out-of-sample prediction. In the figure, we group the areas shown in Fig. 3 into larger areas for better visibility. When comparing with the observed visit frequency, both in-sample and out-of-sample predictions tend to over-estimate the number of visits to the most popular areas and under-estimate the visit frequency to less-visited areas. The calibrated behavioural model tends to overpredict the visits to the most frequently visited areas though the overall trend is well captured. We also compare the improvements to the ordinary Orienteering Problem. We observe a clear improvement in in-sample and out-of-sample predictions in that the overestimation of visits to the most popular places is significantly reduced. Positively to note is further, that there is no significant difference in the estimation between the in-sample and out-of-sample predicted visit frequencies. This indicates that our model is not overfitted.

In the calibration and in Fig. 5 we needed to assume the origin and destination of the travellers since these were, for most respondents, not stated accurately in the survey as noted afore. In the absence of better information, we assumed that the tour origin and the tour destination are near the first and last attraction respectively. This is clearly a favourable assumption improving our model fit, in particular for correctly estimating the first and last place visited. For a fairer comparison, in Fig. 6 we therefore also show the model fit ignoring the first and last POI for each tour. We observe a generally reduced fit but also in this case our model significantly outperforms the OP case.

**Simulation of network changes**

To illustrate the potential application of our model, we close this section by modelling the effects of an improvement in the transport network. This will impact the travel cost to and from an area and hence alter the resulting tours. We model a 10%, 20%, and 30% decrease in the travel time between Sagano (Area 14 in Fig. 2) and central Kyoto (Kawaramachi,
Area 25). In the qualitative part of the survey the unsatisfactory connection to Sagano was frequently mentioned.

Figure 7 shows a Sankey diagram to illustrate the change in the previous and next places that tourists visit and to understand whether the strategies help reduce or increase the traffic to the most crowded areas. There is a large number of trips between Sagano and nearby Arashiyama (Area 23). The two areas might be considered as complementary in terms of intrinsic utilities, and tourists often visit the two together. After improving the connection to Sagano, some visitors now tend to visit the two areas in reversed order: more trips from Arashiyama to Sagano while there are now fewer trips in the opposite direction. Furthermore, more trips are generated towards the city centre (Area 25) due to a shortened travel time. The example shows the wide-ranging changes that the proposed approach predicts given a cost change for a single link. One could further model the effect of changes in attractiveness in the area by changing the intrinsic utility of areas in one or more of the utility dimensions. One must be careful, however, in predicting how, for example, additional shops will influence the perceived utility so that we suggest in general, and in particular for
such scenarios, the proposed approach should be mainly used to estimate expected tendencies in trip patterns.

Conclusions

We contribute to studies in urban tourist travel demand estimation by proposing a tour-based model for estimating the attractions and in which order they are visited by tourists. The framework is formulated with an inner and outer loop where the inner loop solves a variant of the TTDP and the outer calibrates the required parameters. Specifically, we extend the existing literature in the following two aspects:

First, we introduce a multi-dimensional formulation of the TTDP to evaluate the preference of tourists and the utility of attractions in different categories. Literature shows that tourists are a very diverse group with different preferences and our analysis also shows this. Our model application confirms that multiple evaluation criteria, in our case study

![Diagram showing before and after effects of improving access to the Sagano area](image)

**Fig. 7** Effect of improving access to the Sagano area

(i: 10% ii: 20% iii: 30%) decrease in travel time
three, help us to better explain the variation in tourist choices. In particular, considering the diversity will help to explain the spread of tourists among the potential attractions. We compare our selected parameters to an orienteering problem formulation which tends to overestimate visits to the most popular places.

Secondly, we suggest that the choice of destinations needs to consider already accumulated satisfaction. We model this with a diminishing marginal utility gained by visiting additional POIs throughout the tour. We find that including this aspect helps us to better match the estimated number of POIs visited by a tourist with data observations. Ignoring accumulated satisfaction leads to an overestimation in the number of visited attractions.

We suggest that an attractive point of our framework is that the model remains fairly simple in that we achieve these improvements with only four parameters. Clearly, though, in its current form, the model should not be used to predict the choices of individuals with confidence. If this is the goal, one needs to integrate not only additional socioeconomic characteristics but also further information on attitudes and past experiences as sociodemographics alone do not explain the tour choices well.

Instead we suggest that the here proposed framework is rather a planning tool to observe aggregate patterns. We demonstrate how the model allows us to simulate the effect of transport network improvements. Furthermore, the parameters calibrated by our framework might be used to give suggestions to travellers on “realistic” routes they might take given an input of preferences. Testing existing tourist guidance applications and guide books, our perception is that they tend to give “ambitious” suggestions ignoring fatigue aspects.

The data required for applying our framework are a sample of tourist trips and a survey that can indicate their preferences. Through mobile applications and sensing technology, it becomes nowadays increasingly feasible to obtain such tour samples. Some applications further ask users to participate in a quick survey. If such preference data are not available, an alternative approach might be to extract preferences from the tour itself through clustering and taking the propensity to belong to a certain cluster as (latent) preference vector. In addition, the utility of areas needs to be estimated. We used in our example the number of POIs in areas as well as their ratings by travellers. We avoid using the number of visitors due to the endogeneity problem with estimating tours but note that one might argue that rating data are also to some degree endogenous to the tours made. We suggest one area worth further work is to explore more attributes that describe the attractiveness of an area but are clearly independent of the trips made.

Our paper focuses on the modelling aspects and we use the Kyoto case study only to demonstrate our model as the data are fairly outdated. Nevertheless, we suggest it is worth noting that the results appear to be reasonable and deliver insights: We find that Kyoto tourists can be distinguished as to whether they are interested in the temples/shrines only, whether they come to Kyoto in order to also visit one of the numerous, often famous, restaurants or whether these are tourists coming to Kyoto for other leisure activities, such as, for example, visiting museums, the zoo or shopping areas. We show dominant tour patterns and how they might be modified to reduce the overcrowding in parts of the city. This is likely to be an even more important goal in times when travel restrictions are reduced in the “new-normal” since COVID (Schmöcker 2021).

We close by noting that a recently increasingly popular approach for problems similar to ours is the formulation of activity chains within a recursive logit (RL) framework (Zimmermann et al. 2018; Hidaka et al. 2019; Västberg et al. 2020; Gao and Schmöcker 2021). With such an approach path or activity choice probabilities can be obtained for large network applications. As a result, and in comparison to this work, with the RL approach a log
likelihood measure and better interpretable parameter confidence intervals are obtained. Since the RL approach relies on recursively solving a set of Bellman equations, however, diminishing utilities according to accumulated satisfaction cannot be defined. Furthermore, the likelihood measure does not evaluate directly the added or omitted tour spread as we do with our Levenshtein distance measure. Therefore, we suggest comparative studies of the two model fit measures as another further work direction.

Appendix 1

(See Table 3).

Table 3 MNL of sociodemographic factors to estimate cluster membership shown in Table 1 (Cluster A is the reference)

| Variable                  | Level          | Cluster B Parameter | Std. Error | Sig. | Cluster C Parameter | Std. Error | Sig. |
|---------------------------|----------------|---------------------|------------|------|---------------------|------------|------|
| Intercept                 |                | − 1.797            | 1.05       | 0.086| − 17.5             | 6295.3     | 0.998|
| Travel group composition  | Single         | − 0.710*           | 0.349      | 0.042| 0.242              | 0.273      | 0.375|
|                           | Couple          | 0.112              | 0.287      | 0.697| − 0.723**          | 0.260      | 0.005|
|                           | Family          | 0.196              | 0.289      | 0.497| − 0.199            | 0.246      | 0.419|
|                           | Friends/colleague | 0.656*            | 0.283      | 0.021| − 0.376            | 0.252      | 0.135|
|                           | Sightseeing group | 0                |            |      | 0                   |            |      |
| Visit frequency           | First time      | − 0.247            | 0.215      | 1.330| − 0.598**          | 0.226      | 0.008|
|                           | 2–3 times in 5 years | − 0.144          | 0.191      | 0.569| − 0.421*           | 0.182      | 0.021|
|                           | Every year      | − 0.190            | 0.205      | 0.862| − 0.775***         | 0.207      | 0.000|
|                           | 2–3 times per year | − 0.110           | 0.185      | 0.350| − 0.449**          | 0.163      | 0.006|
|                           | > 4 times per year | 0                |            |      | 0                   |            |      |
| Living in Kyoto dummy     | Yes             | 0.502              | 0.810      | 0.384| − 1.162*           | 0.639      | 0.069|
|                           | No              | 0                  |            |      | 0                   |            |      |
| Length of trip            | Day trip        | − 0.625*           | 0.246      | 0.011| 0.186              | 0.308      | 0.366|
|                           | 2-day trip      | − 0.287            | 0.213      | 0.178| 0.179              | 0.287      | 0.390|
|                           | 3 days trip     | − 0.408*           | 0.217      | 0.060| − 0.209            | 0.301      | 0.482|
|                           | 4 days and more | 0                  |            |      | 0                   |            |      |
| With children dummy       | No              | 1.217***           | 0.347      | 0.000| − 0.138            | 0.233      | 0.351|
|                           | Yes             | 0                  |            |      | 0                   |            |      |
| Budget on food (Japanese yen) | 0–2 k           | − 1.329***         | 0.274      | 0.000| − 0.789*           | 0.313      | 0.012|
|                           | 2–5 k           | − 0.709***         | 0.270      | 0.009| − 0.695*           | 0.314      | 0.027|
|                           | 5–8 k           | − 0.148            | 0.300      | 0.620| − 0.454            | 0.361      | 0.208|
|                           | 8–15 k          | 0.281              | 0.318      | 0.377| − 0.091            | 0.385      | 0.814|
|                           | 15 k and above  | 0                  |            |      | 0                   |            |      |
| Model fitting pseudo R²   | a. Cox and Snell: 0.181; b. McFadden: 0.110 |
| Sample size               | 2818            |                     |            |      |                     |            |      |

Significance level: *0.05 **0.01 ***0.001
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Declarations

Conflict of Interest. All four authors confirm that there is no conflict of interest.

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