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Place Generator and Place Interpreter: a new methodology to collect data on regular mobility patterns

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Abstract
When observing the temporal trajectory of an individual, there is a high probability of them visiting an already-known place due to habit and routine in human mobility behavior. To collect data and understand these routine activities, we propose the Place Generator and the Place Interpreter, a survey adapted from the Name Generator and Name Interpreter methodology of social network studies for travel behavior. In the survey, we asked the participants to name the venues they regularly visit for leisure by category. This methodology captures the characteristics of the venues and the reasons to be chosen. We tested this method in the Zurich Metropolitan Area in Switzerland, focusing on leisure activities and the social environment of the venues. Hence, we ask the individuals to describe the reasons for choosing that specific location and the sociodemographic characteristics of the other visitors. This methodology worked well when compared with earlier long-duration GPS tracking surveys. Respondents report, on average, 9.85 locations for nine types of venues, mainly supermarkets and restaurants or cafes, and respondents can describe their similarities with other visitors to that location. The survey is complemented with a survey of sociodemographic characteristics and the respondent's ego-centric social network to get information on social connections and their impact on leisure activity.

Keywords Regular leisure activities · Socially motivated travel · Data collection

Introduction

Most of the demand for transportation is derived since mobility is mainly performed to satisfy a need (work, leisure, care) in a specific location (Ortuzar and Willumsen 2011; Jones et al. 1983). Therefore, to understand transport demand, it is essential to understand the motivations for choosing a specific location for a given activity, as it can help policy makers and practitioners define the optimal location to install new facilities to maximize visitors, reduce travel times or improve accessibility, depending on the social or private

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goals of the project. To accomplish this, the primary tool is the destination choice model; These models are probably the most underdeveloped ones in transport choice behavior, with the collection of data and the generation of choice sets being the main obstacles when developing them. There are different approaches to explain the motivations and factors that influence the decision to go to specific locations. The four main tools for collecting data on mobility patterns are GPS tracking, Global System for Mobile Communication (GSM) tracking, social media scraping, and survey diaries. Each of these methods has different strengths and limitations. GPS tracking can give precise information about the places visited, but it has high costs of implementation; GSM collects data on a substantial number of participants, but with limited details beyond location; social media scraping also can collect a large amount of information, but it is dependent on the information individuals voluntarily share; finally, personal interview survey methods can disentangle the motivations and attitudes of the individuals, but are highly dependent on memory recall.

The massification of mobile technology has helped researchers understand human spatial behavior and the laws of mobility patterns. Brockmann et al. (2006) proposed the first theories about spatial behavior using GSM data; they described mobility patterns as continuous-time random-walk processes with scale-free jumps, a similar pattern seen in other mammals (Ramos-Fernández et al. 2004; Viswanathan et al. 1996). However, as more data are collected, the new findings show that individuals tend to have a high degree of spatial regularity, with consistent and repetitive patterns (González et al. 2008). These can be observed when individuals are studied for longer periods, as the probability of finding a location that has not been visited before decreases over time (Song et al. 2010). One of the explanations for this phenomenon was proposed by Schönfelder (2006), who theorizes that the habitualization of spatio-temporal behaviors is a mechanism to avoid uncertain decisions that could lead to suboptimal experiences. These new understandings of the regularity of travel generate the need to design new methods to measure and analyze these patterns to understand how individuals choose to include specific venues in their routines.

Because human mobility has regular patterns, we hypothesize that asking participants which locations they regularly visit can be a valid methodology for understanding frequent mobility patterns, which, complemented with questions about each place, can generate an understanding of the underlying motivations to go to those locations. In this case, we want to focus on the social aspect of leisure mobility. For this, we adapt the *Name Generator & Name Interpreter*, which is widely used in social network studies (Wasserman and Faust 1994), to transportation research. In order to avoid confusions about the type of information collected and due to the lack of a general term, we have labeled this method *Place Generator & Place Interpreter*. The idea is to generate a reliable and low-cost data collection method that researchers can use for specific or general surveys to capture the motivations and latent constructs that can influence destination choice modeling. The survey starts with the *Place Generator*, which asks respondents to name the places they visit regularly; the second step is the *Place Interpreter*, which consists of a battery of questions that repeat for each of the locations named in the first part. We used a survey for data collection for two reasons: first, surveys allow to capture information about the personal motivations to regularly visit a place, which are essentially impossible to capture with GSM or social media scraping. Second, it allows capturing regularity in a longer period than GPS tracking (for example, an individual might visit a venue once a month, which cannot be captured as a regular venue in a 1-month GPS tracking). On the other hand, we focus on leisure travel because leisure is one of the most flexible types of travel in time and space (Ruiz et al. 2016) and the most important in terms of kilometers traveled (43% of the total kilometers traveled per year in Switzerland (Bundesamt für Statistik 2023)), with a wide range of types of activity and venues to perform it, and most individuals engaged in at least some leisure travel activities. Therefore, regularity in destinations for leisure activities is not imposed externally (as for work or education), but freely chosen. For this reason, the survey includes only leisure places that can be freely chosen and changed in the short term. We acknowledge that leisure can be performed at friends' houses. However, we have excluded them from the analysis as the motivations to perform leisure in those places are different from the motivations to go to a leisure venue (one would expect that going to a friend's house is more related to the friend's characteristics than on the house's characteristics).

The main motivation for designing this methodology is the need to improve destination choice models. Current models focus primarily on the aggregated characteristics of the destination zone and socioeconomic characteristics of the individual; whereas this survey will help collect information on latent motivations to choose specific destinations, which can improve our understanding of the decision-making process. Improving destination choice models can also have policy benefits, as understanding regular mobility patterns can improve techniques to measure how future urban projects can change the flows of people. The survey was conducted in Zurich, Switzerland.

The paper continues as follows; Sect. 2 includes a literature review on collecting data on destination choice, leisure, and socially motivated travel. Section 3 presents the structure of the survey. Section 4 reports the sampling and data collection methods. Section 5 shows the survey results, and later to finalize with Sect. 6 reporting the discussion and suggestions for future work.

Literature review

Collecting data on destination choice

In recent years, there has been an increase in smartphone-based surveys complemented with GPS tracking (Rieser-Schüssler and Axhausen 2014; Greaves et al. 2015; Molloy et al. 2022) and social media scraping. This methodology has gained prominence due to its smaller response burden, the capacity to account for all trips generated by the individual, and the benefit of not relying on memory recall (Janzen et al. 2018), while passively collecting data for extended periods is automated and not the individual's responsibility. GSM technology has also increasingly been used in recent mobility literature: the main benefit of this technology is its understanding of mobility dynamics (Doyle et al. 2014), large-scale mobility patterns (Calabrese et al. 2013), urban social connections (Phithakkitnukoon et al. 2012) and emergency behavior (i.e., shelter-in-Place behavior during Covid-19 (Carranza et al. 2021), and post-earthquake behavior (Bengtsson et al. 2011)). Although this technology has many benefits with respect to the amount of information collected and precision, data are rarely available as mobile phone operators do not share them due to industrial confidentiality, privacy concerns and the high price tag of data sets (Khatib et al. 2021). A third method to collect data on mobility patterns is analyzing voluntarily shared data on social media. This form of data collection can include many data points (Singh et al. 2014) that would not be possible to collect through an invitation to participate in a study. However, this method has some limitations as the individuals using and sharing trackable social media content can be behaviorally different from people that do not share this content and it depends on the willingness-to-share the venues visited. This problem is challenging for researchers when they want to generalize the population's travel behavior (Zhang et al. 2017).

These three ICT-based data collection methods have improved destination choice modeling, allowing researchers to progress from aggregate zonal to facility-based data. However, the primary model used to represent decision-choice processes, the multinomial logit model (MNL), which assumes that individuals derive their utility from choice alternatives, still rely on the built environment and the socio-economic characteristics of the destination zone (population, employment) as measures of the destination attributes (Clifton et al. 2016; Cascetta et al. 2006). However, it is hardly realistic that the individual utility derived from the activity at a destination is only dependent on the socio-economic characteristics of the zone, especially for spatially contiguous venues. New studies have used social media platforms to collect data on the choice sets (i.e., Foursquare (Molloy and Moeckel 2017) and Yelp (Wang et al. 2016)) to include information on the prices and quality of venues. However, these models could be hard to implement as there is no information available on the motivations to visit these venues and the situation when it was chosen. The difficulty of collecting data and modeling spatial behavior generates the need to design and test new methodologies that can help to understand mobility patterns. For this reason, more traditional survey methods are relevant tools to capture latent travel motivations.

Leisure and socially motivated travel

There are many definitions of leisure, from the "sphere of life not occupied in working, traveling to work, or sleeping" to the "largely discretionary time, to be used as one chooses. It excludes subsistence time, time spent in socially or group-determined activities in which the individual would prefer not to participate" (Veal 1992). Regardless of the differences in the definition, one common point is that leisure can be heterogeneous in form and function, and it can be performed in many different locations, such as the individual's house, the workplace, or places designed for leisure (such as bars or restaurants), making leisure travel intrinsically different from work or study travel. The former tends to be spatially more variable due to the dispersion of activity locations, making public transit often inefficient compared to private modes (Schlich et al. 2004). Although inefficient for the system, leisure travel generates health and well-being benefits (Fancourt et al. 2021; Sala et al. 2019) and social cohesion (Morata et al. 2021; Jennings and Bamkole 2019). Recent literature on leisure travel has also shown that social connections strongly influence individual mobility. For example, Cho et al. (2011) modeled the impact of social networks on short-range mobility, finding that social relations can explain between 10 and 30% of human travel. In addition, Grabowicz et al. (2014) predicted individual location choice using acquaintances' locations and predicted friendship status using temporal co-occurrences. An individual's social network abates the effects of changes in the generalized cost of travel, as the motivation to perform social travel generates stability in everyday mobility patterns (Puhe et al. 2021).

One of the most popular methodologies in the transport literature for analyzing socially motivated travel is the Name Generator and Name Interpreter. This methodology started in sociology to capture social network information from an egocentric point of view (with the respondent *ego* in the center and the *alters* around it). Kim et al. (2018) has identified three main research domains in the influence of social networks on leisure travel behavior: Network size (Frei and Axhausen 2007; van den Berg et al. 2009), geographical distribution of the residential location (Carrasco et al. 2008a; Frei and Axhausen 2007; Kowald 2013;

van den Berg et al. 2009), and frequency of social activity participation (Lin and Wang 2014; van den Berg et al. 2012). With respect to the network size, the participation of more activities is associated with more extensive networks. Elders tend to have smaller network sizes, and young children create opportunities for parents to establish new social connections. Concerning the geographical distribution of social networks, van den Berg et al. (2009) measured the geographic distance between the ego and each of the alters, exploring the connection between ego-alter characteristics and residential distances: relatives are associated with longer distances, while club members live closer. Regarding social activity participation, Lin and Wang (2014) found that social people tend to perform more social travel with alters that provide emotional support. This type of survey has been beneficial in understanding general patterns of socially motivated travel, such as the ones described above. However, it does not provide information on the importance of venues and their characteristics when an individual performs leisure travel.

Recent studies have proposed new methodologies for analyzing leisure travel. Han et al. (2023) has used a group-activity survey to incorporate group-level impedance into destination choice models; this methodology has captured the last eating-out venues visited by the individual and its clique and has allowed them to collect 2.5 destinations per respondent. Parady et al. (2023) developed a methodology called the Text-aided Group Decision-making Process Observation Method (x-GDP) to observe quasi-natural decision-making processes among groups. These two methodologies have been implemented in eating-out activities and can be implemented for any activity. The first methodology asks for the last places the individual has visited, while the second focuses on the decision process; but none of these methodologies differentiates between first-time visits and venues that are part of the individual's routine.

Due to the current state of the literature on data collection for destination choice, it is important to design new methodologies to collect data on regular activities. Besides, as we are interested in socially motivated travel, the contribution to the current literature is two-fold. It can capture data on regularity that is not possible to capture with study-period-constrained GPS or GSM tracking, while capturing the social motivations and personal interests to visit said location.

Survey structure

The Place Generator & Place Interpreter is part of a more extensive survey conducted in Zurich, consisting of three stages, the second and third stages sent 3 days after the previous one was completed. For completeness, we will describe the three stages and their results, but the focus will be on the second stage, which is the methodology of interest for this manuscript. Including the results of the first and third stages gives a comprehensive look of the data collected and the possibilities of analysis that the Place Generator & Place Interpreter gives.

First stage

The first stage of the survey consists of three subsections. The first subsection consists of socio-demographic information such as gender, age, education, family's country of origin, mobility tool ownership, and occupation. The second subsection asks questions about the individual's experiences in the city and potential mobility. Including questions about how comfortable the person feels using public transport, their ability to use location apps (i.e., Google Maps), and general knowledge of leisure activities in the neighborhood. The last section includes questions on the attachment levels to the city and the perceived capacity to influence one's neighborhood (von Wirth et al. 2016).

Place Generator and Place Interpreter

The second stage of the survey contains the methodology of interest for this article. In its first section, *Place Generator*, the respondents are asked to name restaurants or cafes, bars or nightclubs, cultural locations, sport-centers or gyms, parks or forests, and other leisure places they regularly visit. The idea of asking for specific categories is to create a structure for people to think about where they go for leisure, since an open-ended question would hardly collect as many locations as a more structured question (Carrasco et al. 2008b; Troncoso Parady et al. 2021).

A possible complication of working with open-ended questions is the possibility that people answer in any format they like. To avoid such answers, the survey must describe in detail the information required to be completed and the motivation for these questions. In order to comply with these requirements, the instructions request: avoiding using generic answers, providing detailed information about the address, excluding private homes, and leaving the space blank if they do not visit any location in one category. All these instructions were added because during the pre-test conducted, a substantial number of respondents answered "keine" (None), forcing them to answer the next section of the survey about no place. After the instructions, the survey continues to the next section, where the survey asks for the locations they regularly visit. The question has minor variants depending on the type of location requested. The restaurant and cafe version reads:

> Which Restaurants or Cafes do you visit on a regular basis? Please indicate the name of the Restaurant or Cafe, street and neighbourhood or zip-code. Try to be as specific as you can, please avoid generic answers such as "Zurich" or "McDonalds".

Each category offers three spaces to name venues. The limited space available could generate an underestimate of the actual number of regular venues visited by an individual. However, since the length of the following section depends on the previous answer, there is a trade-off between the number of venues and answer quality in the *Place Interpreter*.

After the respondent finishes naming all venues they wanted to include, the *Place Interpreter* section asks eight questions about each place. The questions are similar for each category, with slight variations to improve readability. The first questions are related to the temporal regularity of the visit. These questions include if they go during the week or on weekends, at what times, and how often. Later, a question on the mode of transport used to go to each venue, followed by the motivations to go to that specific place. For this question, we have included options like price; quality;[1] convenient location; environment, decoration & music; the social environment; easiness to meet new people; crowdedness; friendliness of staff; and because friends or family enjoy it.

The next question relates to the description of the social environment of the location. To collect this data, we asked the respondents to describe the location's visitors compared

[1] Depending on the type of location, "Quality" was specified differently. For example: in restaurants, the option was "Quality of the food & drinks" while in sport-centers was "Quality of the equipment"

to themselves. The possible options were: similar age, similar interests (i.e., leisure interests, political interests), similar socioeconomic status, similar cultural background, same neighborhood, mixed visitors, and *I don't know*. This question has the option for multiple answers. During the pre-test, some respondents commented that they did not know how to answer this question, so we included a text stating our interest to know whether they can describe the people that go to the same places as they go, which increased the quality of the answers. Finally, if the respondents selected *similar interests*, a new question would pop up asking to specify those interests. The options vary depending on the location, including enrichment interests (i.e., learning, coding, reading), sports and fitness interests, political interests, creative interests (i.e., music, films), social interests (i.e., networking, meeting new people), outdoor interests, and religious interests.

Name Generator and Name Interpreter

The third stage is the *Name Generator & Name Interpreter* survey based on previous work in Zurich (see Frei and Axhausen 2009; Kowald et al. 2010; Wicki et al. 2018). This methodology consists of questions about friends, family and acquaintances and the regularity of contact with them. The structure of the survey is similar to the second stage of the survey: it starts with the *Name Generator*, in which the respondent is asked to name up to 20 people with whom they either discuss important problems, are in regular contact, or whom they can ask for help. Later, we ask them to indicate other people they are in contact with in their free time, with space for up to 10 more people. The second question to name the contacts is, on one side, to collect information about the ego's core and the extended network. At the same time, it is also used as a prompt for respondents to give second thoughts about their social connections.

After both lists of contacts are filled, the survey continues with the *Name Interpreter*, which consists of 19 questions related to the alters named. The questions are the same, independent of whether the alters were included in the first or second list of people. The Name Interpreter starts with basic socio-demographic questions such as age, gender, country of origin, and education of the alter. Later, there is a map to locate the approximate home address of the alter. In addition, questions on the type and length of the relationship are included. Lastly, there were questions on the frequency of contact and the communication tools used. In this last part, the communication tools included were "face-to-face", text messages, phone or video calls, e-mail, and others. Following, a question on the regularity of contact for each tool. In addition, if the respondent answers "face-to-face", a new question asking for the locations they regularly meet pops-up; the options available are the locations stated in the *Place Generator* of the second survey, as well as the ego's and alter's house.

It is important to highlight that the *Place Generator & Place Interpreter* is an adapted version of the *Name Generator & Name Interpreter* to mobility behavior, therefore, it follows the same structure of asking the respondents to make a list of the elements of interest, followed by a set of questions repeated for each of the mentioned element.

To finalize the survey, we include a short *resource generator*, which consists of questions about specific instrumental resources the individual can access through their social network (Lin 2001). The interest of these questions is to find a relation between the ego's leisure acquaintances and social resources. The questions asked to choose which alters they would contact if they had a health problem, to help find a new job, borrow a large amount of money, and ask for a place to stay for a week. These questions can look for the correlation between the alters an ego would ask for help in different situations, and the alters to perform social activities.

The information collected on the geographic distribution of the ego's social network, combined with regularly visited locations and the information collected about house and work/study locations, the completed survey gives extensive information on the spatial distribution of the respondents' regular activities and social points of interest. This information helps to understand spatial behavior and the impact of social networks on individual mobility.

Sampling and data collection method

The sample consisted of a representative list of 10,000 randomly selected addresses in the Zurich Metropolitan Area. These addresses received an invitation letter with a link and a QR code to the survey and a six-letter code for personal identification. Two weeks later, a reminder letter was sent to the addresses that still hadn't started the survey. After the first stage of the survey is completed, there is an invitation to the second stage; if the invitation is accepted, we ask for an e-mail to send the invitation 3 days later. After finishing the second stage, we ask if the respondent is willing to participate in the third stage; if the answer is positive, we send a second e-mail with the invitation for the third stage. In addition, we sent a reminder to complete the second and third stages 2 weeks after completing the first stage. We offered a 15 CHF incentive after the three stages of the survey were completed.

There were three phases for the data collection: two pre-tests in May 2022 and September 2022; and a final version in November 2022. The first pre-test only included the Place Generator & Place Interpreter plus the Name Generator & Name Interpreter (leaving out the first stage of the survey). For the first pre-test, we invited 2000 individuals via mail. It was conducted to see if the methodology was appropriate to collect data and if they would give enough information to geocode the answers. This pre-test did not include the monetary incentive, and it is not included in the final database. Later, we carried out a second pre-test to include the first stage of the survey, where we invited 800 individuals in each city via mail. The third wave of invitations reached 7200 people.

Results

In this section, we present the main results of the methodology, including response rates and response times, the socioeconomic characteristics collected in the first stage of the survey, and the social network results from the third stage. Later we present the results of the Place Generator & Place Interpreter.

Table 1 shows the three stages' response rates and response times. Following the work of Schmid and Axhausen (2019), we have estimated the response burden and predicted the response rates of the survey. Using this methodology, the respective stages had 214, 535, and 1072 response burden points,[2] which, in combination with the 15 CHF incentive,

[2] The methodology assigns points to different questions depending on the length and type of answer required. For example, for multiple-choice questions with fewer than four options, the response burden is two. For open-ended questions, the response burden is six.

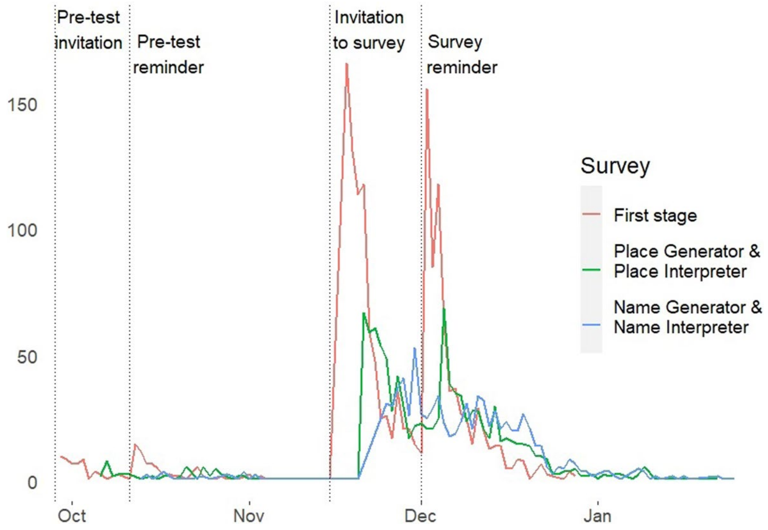

Fig. 1 Number of answers collected by day. We have excluded the first pre-test invitation as the length of the survey and incentive differ to the latest version

Table 1 Response rates and response times of completed sections

	Response rate* (%)	Drop-out** (%)	Total time spent (min)	Time spent Generator (min)	Time spent Interpreter (min)
First stage	20.65	13.67	15.42	–	–
Place Generator & Place Interpreter	59.04	15.23	15.66	6.78	8.88
Name Generator & Name Interpreter	81.28	16.12	23.48	3.00	20.48
Total	9.91	–	54.56	–	–

* The response rate is calculated as the total amount of completed surveys to the number of possible respondents. The first stage considers all people who have received a letter of invitation, and the second and third consider the number of people who finished the previous stage

** Survey drop-out is the share of people that started the survey but did not finish

predicted a final response rate of 10%, which was close to the final response rate of 9.9%. Regarding response times, the survey takes a median of 55 min to be fully answered, the social networks stage being the longest part.

The second and third stages have a high variance in response times, as they depend linearly on the number of answers given in the (Place or Name) *Generator* part of the survey; on average, the individuals mentioned 9.85 places and 12.7 alters. Comparing the response times of the *Generator* section, people take 6.78 and 3.00 min to answer each survey, respectively. The Interpreter part takes, on average, 8.88 and 20.48 min. This shows that people take longer to think about the places they regularly visit compared to the alters they are regularly in contact with. But, in the *interpreter* section, individuals answer on average 8.87 questions per minute in the *Place Interpreter* and 11.78 questions per minute in the *Name Interpreter*.[3] Therefore, individuals take longer to answer the questions related to their alters than about the places they regularly visit.

Regarding response times, Fig. 1 shows the temporal distribution of the data collection process separated by stage. The first stage has two significant peaks right after the invitation. In contrast, as the invitations for the second and third stages depend on finishing the first, the distribution of answers is flatter. In addition, the reminder has an essential effect on the response rate, helping to collect almost as many new responses as the initial invitation.

First stage

Table 2 reports the main socio-demographic characteristics that completed the different stages of the survey.[4] There is a high share of males and respondents between 51 and 60 years of age. During the three stages, the percentage share of socio-demographic characteristics remains stable across groups, except for the elderly, who increase their share in the third stage. Employed and retired also increase their share, which is correlated with the increase of elderly. Higher incomes also increase their share at the end of the survey.

Social networks

In the third stage, the first question was to recall the people with whom the respondent was regularly in contact, could talk about important problems, or could ask for help. The previous results of a similar survey in Zurich were 8.8 (Wicki et al. 2018), 19.9 (Kowald and Axhausen 2013) and 6.0 contacts (Frei 2012), while in this survey the number was 12.59. The difference in contacts can be explained by the survey method employed to collect data and the exact wording used in each of the surveys. In the case of Frei (2012), a phone interview was conducted, while Wicki et al. (2018) collected data through an online-based survey. Kowald and Axhausen (2013) used a snowball sample; However, because these snowball samples are not randomly drawn, a bias towards individuals with more alters is expected, as the respondents tend to have more contacts than the average population. As the survey by Wicki et al. (2018) is the most similar methodology, we expected a similar number of alters to the mentioned survey. Therefore, we can see an increase in the number of alters named by the respondents over the years. Table 3 compares the three surveys mentioned and the current one.

[3] Respondents answer eight questions on an average of 9.85 places mentioned which gives an average of 78.8 questions in total, divided by 8.88 is 8.87. For the alters, the methodology is the same, 12.7 alters multiplied by 19 questions divided by 20.48.

[4] To fix the socioeconomic bias, we have estimated sample weights using Bundesamt für Statistik (2023) as reference.

Table 2 Socioeconomic characteristics per stage finished

	First stage		Place Generator & Place Interpreter		Name Generator & Name Interpreter	
	Freq.	%	Freq.	%	Freq.	%
Gender						
Female	759	46.06	487	48.55	421	49.07
Male	883	53.58	512	51.05	433	50.47
Non-binary / other	4	0.24	4	0.40	4	0.47
Age						
18–30	55	3.34	32	3.19	28	3.26
31–40	163	9.89	91	9.07	76	8.86
41–50	350	21.24	201	20.04	169	19.70
51–60	642	38.96	386	38.48	316	36.83
Over 60	436	26.46	293	29.21	269	31.35
Education						
Elementary school or lower	26	1.58	13	1.30	12	1.40
Secondary school or orientation cycle	204	12.38	120	11.96	104	12.12
Gymnasium or high school	76	4.6	42	4.19	37	4.31
Vocational school or bachelor’s degree	727	44.11	454	45.26	391	45.57
Master’s degree or doctorate	613	37.20	374	37.29	314	36.60
Main activity						
Employed	1140	60.17	676	67.40	580	67.60
Care/domestic worker	66	4.00	43	4.29	34	3.96
Self-employed	192	11.65	113	11.27	91	10.61
Student/in-training	17	1.03	12	1.20	9	1.05
Retired	192	11.65	135	13.46	125	14.57
Unemployed	14	0.85	10	1.00	8	0.93
Other	25	1.52	14	1.40	11	1.28
Household income						
Under CHF 2000	11	0.67	11	1.10	11	1.28
2000–4000	42	2.55	27	2.69	25	2.91
4001–6000	144	8.74	96	9.57	85	9.91
6001–8000	226	13.71	147	14.66	127	14.80
8001–10,000	280	16.99	168	16.75	149	17.37
10,001–12,000	280	16.99	173	17.25	139	16.20
12,001–14,000	192	11.65	107	10.67	93	10.84
14,001–16,000	118	7.16	78	7.78	64	7.46
16,001–18,000	102	6.20	56	5.5	42	4.90
More than 18,000	172	10.43	90	8.97	78	9.09
I don’t know/I prefer no to say	79	4.79	50	5.00	45	5.24
Nationality						
Switzerland	1451	88.46	896	89.33	763	88.93
European Union	160	9.7%	94	9.37	70	8.16
Other European	22	1.3%	8	0.80	7	0.82
Other	11	0.66%	5	0.50	5	5.83
Car availability						

Table 2 (continued)

	First stage		Place Generator & Place Interpreter		Name Generator & Name Interpreter	
	Freq.	%	Freq.	%	Freq.	%
No	216	13.11	145	14.46	126	14.69
Yes, one	750	45.51	478	47.66	415	48.37
Yes, two	499	30.28	286	28.51	235	27.39
Yes, three or more	169	10.25	88	8.77	77	8.97
Bike availability						
No	282	17.11	181	18.05	158	18.41
Yes, one	239	14.50	157	15.65	136	15.85
Yes, two	404	24.51	246	139	210	24.48
Yes, three or more	723	43.87	419	41.77	354	41.26
eBike availability						
No	1,023	62.08	639	63.71	548	63.87
Yes, one	350	21.24	201	20.04	173	20.16
Yes, two	229	13.90	138	13.76	116	13.52
Yes, three or more	46	2.79	25	2.49	21	2.45

Place Generator and Place Interpreter

Place Generator

This survey stage starts by asking the respondents to name the locations they regularly visit by category. Initially, the survey had 11,336 answers, but after filtering answers that were too broad, such as “Zurich”, or negative answers, such as “none”, 10,219 places were geocoded using the R function from Kahle and Wickham (2013). This function gives 9885 locations, losing 3.3% of the specified answers. As this methodology has not been tried before, we had no data to predict the number of responses, so we were expecting a total of 7 or 8 locations per individual, which was surpassed as there were a total of 9.97 places named per person. For places that were correctly geocoded, information is available on geographic location and address, price level (if applicable), user rating (if applicable) and type of location. If we separate the number of locations per type, the three categories with the most answers are supermarkets and stores, with an average of 2.55, restaurants or cafes (2.04), and parks or forests (1.53). Table 4 shows the average number of locations per type mentioned by the respondents. When the number of locations visited is disentangled by socio-economic characteristics, there are no observable differences in the number of locations named.[5] Table 5 shows the total number of locations collected; since the options in a city are limited, two or more respondents are likely to answer about the exact same location. The most repeated types of

[5] Gender is the only sociodemographic characteristic that shows a difference, females tend to name 0.6 locations more than males.

Table 3 Number of alters by socioeconomic characteristics of the ego

	This survey	Wicki et al. (2018)	Kowald (2013)	Frei (2012)
Gender				
Female	13.9	9.4	8.26	6.4
Male	11.2	8.1	11.40	6.2
Non-binary/other	15.5	–	–	–
Age				
18–30	9.04	8.8	(0–20) 0.59**	7.1
31–40	10.3	8.2	(21–40) 4.35**	6.8
41–50	11.1	8.7	(41–60) 9.79**	6.7
51–60	13.3	*	(61–80) 4.46**	*
Over 60	13.7	8.9	(81+) 0.47**	5.6
Education				
Less than secondary school	12.7	6.6	***	5.5
Secondary school	11.8	8	***	6.5
Technical/professional degree	12.9	8.1	***	6.1
Bachelor's degree	12.6	9.2	***	7.2
Master's degree or Ph.D.	12.2	9.2	***	*
Household income				
Under CHF 2000	11.9	8.2	***	6
2000–4000	13.0	8.2	***	5.9
4001–6000	12.5	*	***	*
6001–8000	13.0	8.8	***	6.6
8001–10,000	13.0	*	***	*
10,001–12,000	13.0	8.9	***	*
12,001–14,000	12.2	*	***	*
14,001–16,000	13.4	9	***	*
More than 18,000	11.6	*	***	*
I don't know/I prefer not to say	10.8	*	***	*

* The ranges of socioeconomic characteristics differ in each survey. The points are part of the previous group

** The age ranges presented in the manuscript differ from the used in the other surveys. Age ranges in parenthesis

*** Values not available in the manuscript

place are supermarkets and cultural centers, while social or religious centers are the type of location with the highest percentage of uniquely named locations.

Table 6 shows the average distance to frequently visited locations by type of location visited. Most locations are closer than 5 km from the individual's house, with a reduction in the percentage of places as the distance increases. Except for *Other* locations for which the share of locations visited increases at the more than 20 km category, this can be explained because some individuals included out-of-town locations as their regularly visited locations, such as a camping site or a nearby lake. Supermarkets and parks or

Table 4 Mean and standard deviation of the number of locations named by the respondents

	Mean	SD
Restaurant or cafe	2.02	1.13
Bar or nightclub	0.52	0.94
Cultural center	1.28	1.20
Gym or sportcenter	0.78	0.90
Supermarket or store	2.54	0.73
Park or forest	1.52	1.11
Social or religious center	0.49	0.79
Other	0.70	0.98

Table 5 Total number of unique, repeated and total locations named

	Unique locations	% of unique locations (%)	Repeated locations	% of repeated locations (%)	Total
Restaurant or cafe	1306	64.4	722	35.6	2028
Bar or nightclub	317	61.7	197	38.3	514
Cultural center	365	28.4	918	71.6	1283
Gym or sportcentre	571	73.5	206	26.5	777
Supermarket or store	785	30.8	1765	69.2	2550
Park or forest	885	58.1	638	41.9	1523
Social or religious center	455	92.7	36	7.3	491
Other	597	85.8	99	14.2	696

Table 6 Percentage of locations by distance to home

	Less than 2.5 km (%)	Between 2.5–5 km (%)	Between 5–10 km (%)	Between 10–20 km (%)	20 km or more (%)
Restaurant or cafe	49.28	17.65	15.31	10.02	7.74
Bar or nightclub	43.63	16.63	15.12	13.61	11.02
Cultural center	32.56	17.40	17.13	17.85	15.07
Gym or sportcenter	48.01	21.35	14.88	9.57	6.19
Supermarket or store	67.63	16.54	8.83	4.24	2.76
Park or forest	59.31	17.13	10.25	6.88	6.43
Social or religious center	54.52	13.69	13.92	10.21	7.66
Other	36.44	14.87	13.56	13.07	22.06
All locations	52.43	17.10	12.90	9.39	8.17

Table 7 Average regular leisure activity space by survey

	Mean (km)	SD	t-value[1]*	*p* value[2]
Place Generator	103.8	442.5	–	–
MOBIS (r > 5)	155.0	511.9	3.40^{***}	< 0.01
MOBIS (r > 6)	135.50	470.15	2.11^{**}	0.03
MOBIS (r > 7)	109.78	421.74	0.40	0.689

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[1] T-value of the Student's t-test for comparison of medians, compared to the Place Generator database

[2] A significant *p value* means the average values are statistically different

forests are the two locations that have a higher share of places located close to home, while cultural centers are the ones that have a higher percentage of faraway places.

External validation

To validate the capacity of the survey to collect information on frequently visited locations, we compared the size of the activity space generated by the Place Generator with the activity space from the data collected by the MOBIS-COVID Project (Molloy et al. 2022). This project collected GPS data, tracking individuals in the German-speaking part of Switzerland between 2019 and 2022. As MOBIS-COVID data include all trips generated by the individuals, we have defined *regular activity* as any leisure location that has been visited more than *r* times, for at least 30 min each, while the study was being conducted. As there is no objective distinction between a regularly visited location and other locations, we have estimated the activity space using locations visited more than 5, 6, and 7 times. Table 7 shows the activity space for leisure activities that have been performed *r* or more times during the length of the study with its separate t-test comparing it to the Place Generator. The results show that the activity space of the Place Generator tends to be equal to GPS tracking data when considering a regularly visited location as a place visited more than 7 times during the duration of the study. We have only compared the results of this survey with GPS as it was the available data set with long tracking periods. On the other hand, social media data highly depends on people's voluntary *check-ins*, which might not happen every time the person visits the place.[6]

Place Interpreter

After the Place Generator is finished, the respondents are directed to the Place Interpreter, where they are asked to answer specific questions about the locations named. First, as mentioned before, one of the benefits of this methodology is that it can collect data on regular activities that could be hard to capture using study-period-restricted tracking data. Therefore, the first question to analyze is the regularity of visit of the places the respondents have mentioned. Table 8 shows how often each category is visited on average, few places are visited between four and seven times a week, while the number of places visited between

[6] For example, a person visiting a gym three times a week might not *check in* every time they visit it.

Table 8 Regularity of visit

	Restaurant or cafe (%)	Bar or night-club (%)	Cultural center (%)	Gym or sport-center (%)	Supermarket or store (%)	Park or forest (%)	Social or religious center (%)	Other (%)
Between 4 and 7 times a week	1.0	0.2	0.5	5.4	4.7	6.1	3.2	4.4
Between 1 and 3 days a week	12.0	3.6	0.8	53	42.2	19.6	33.3	15.4
Once every 2 weeks	13.9	8.9	2.3	17.9	26.9	21.5	15.6	14.8
Once a month	31.3	29.8	16.6	13.6	19.5	28.5	20.3	32.9
Less than once a month	41.8	57.5	79.8	10.2	6.6	24.3	27.6	32.4

Table 9 Reasons to visit each location

	Quality (%)	Price (if applicable) (%)	Convenient location (%)	Decoration, environment & music (%)	I like the type of people that goes (%)	It is easy to meet new people (%)	It is uncrowded (%)	Friendly or knowledgeable staff (%)	My friends or family enjoy it (%)
Restaurant or café	72.31	21.92	54.88	14.45	21.00	1.56	12.60	49.07	24.27
Bar or nightclub	26.14	6.44	42.80	53.22	49.05	12.69	9.85	29.92	30.49
Cultural Centers	66.31	6.92	39.08	11.23	18.77	2.85	11.92	14.23	21.62
Gym or sport-centers	39.37	20.89	59.37	7.09	27.34	5.70	23.67	27.59	19.87
Supermarkets	68.58	32.24	71.90	2.15	–	–	15.98	22.12	–
Parks or forest	29.05	0.52	56.98	78.85	5.68	1.63	31.66	–	23.17
Social clubs or religious centers	12.97	2.99	22.16	3.79	58.28	16.57	8.78	14.17	32.53
Other	57.99	8.77	41.16	17.68	23.62	5.23	16.27	11.74	23.34

The column names were simplified to improve readability, the text depends on the type of location stated (i.e., In the restaurant section “Quality” was written as “Quality of the food and drinks” while in the cultural locations was written as “Quality of the presentations (i.e., films, shows, art collections, etc.)

Table 10 Description of visitors of the places of regular visit

	They have similar age than mine (%)	They have similar interests than mine (i.e. leisure interests, political interests) (%)	They have similar socio-economic status than mine (%)	They have similar cultural background than mine (%)	They live in the neighborhood (%)	I don't know (%)
Restaurant or café	17.24	11.43	20.36	11.77	20.51	7.13
Bar or nightclub	31.06	19.51	17.05	15.34	11.36	3.79
Cultural Centers	14.15	33.62	14.08	24.31	5.85	8.46
Gym or sport-centers	19.87	46.96	10.38	6.58	17.59	5.06
Parks or forest	4.70	18.73	3.59	3.00	25.33	13.45
Social clubs or religious centers	25.15	64.67	18.56	27.54	25.75	1.80
Other	10.33	38.05	10.33	10.61	14.57	8.06

Supermarkets were excluded from this question as it is not considered "socially motivated travel"

1 and 3 days a week is higher, with more than half of the gyms and sport-centers being visited this frequently, supermarket or stores are also visited frequently, with 42.2% of the places being visited between 1 and 3 days a week. In terms of the less frequently visited locations, almost 80% of the cultural centers are visited less than once a month, while more 57.5% of bars and nightclubs are visited less than once a month, 41.8% of restaurants and cafes are visited with the same regularity.

Concerning the reasons to go to each location, respondents were asked: "Why do you normally go to [Name of location]? Mark all that apply". Table 9 shows the results in terms of the percentage of the option chosen. The most important reason to go to the stated locations depends on the category. For example, the Quality of Food and Drinks was the principal attribute to frequently visiting a restaurant, while Parks being conveniently located was the main reason to visit them. On average, quality and convenient location are the two most essential attributes, while price is among the least important attributes, combined with the ease of meeting new people. Some categories are not presented as possible answers. For example, supermarkets do not include social attributes such as *the type of people that goes* and the ease of meeting new people.

The following question was included to describe, in comparison to themselves, the perceived sociodemographic characteristics of the visitors to their regular leisure locations, this question is of interest for the project the survey is embedded in. Table 10 shows the responses to this question. The first conclusion that can be drawn is that people can make simple descriptions of the individuals that visit the same leisure locations as them; in most categories, less than 10% answered *I do not know*. The only exception is the category *Parks or forests*, where the answers are lower than the rest of the categories. In these areas, one can expect a lower density of people per square meter and a higher heterogeneity of individuals, making it harder to classify the people who visit those places. This question provides a first understanding of the importance of the city's social environment in leisure activities. The last two tables described are examples of questions that can be included in the survey and that can help understand the latent motivations to visit a place.

Discussion

The survey proposes a new methodology that can capture regular mobility patterns in activities that the individuals freely choose and the motivations to choose the specific place. The methodology is based on the *Name Generator & Name Interpreter* widely used in social network analysis and starts by asking the respondents to list the places they visit regularly. After they finish filling in the locations, a group of questions is repeated for each place the individual has mentioned. Individuals have mentioned, on average, 9.97 places. This methodology has proven to be effective in collecting data on regular activities, which can be hard to capture with GPS data. When individuals are asked about the regularity of visiting these locations, around 50% of the sport-centers and supermarkets are visited at least once a week. However, many cultural centers, bars, nightclubs, restaurants, and cafes are visited less than once a month and are considered *frequently visited* by respondents. Therefore, a GPS survey that is limited in time cannot capture the difference between these frequently visited locations and one-time visits.

Making a difference between regularly visited locations and one-time visits can improve destination choice models because the motivations and expectations to visit a venue are different when it is a first-time visit compared to an already known place. The information available when a person chooses to visit a place for the first time is limited mostly to friends' recommendations and online reviews. In contrast, the decision to choose a place as part of the individual's routine is more informed as the place has to be visited at least once before.

A second benefit of this survey, compared to GSM and social media scrapping, is the capacity to collect data on the reasons and motivations to visit a specific place, and the characteristics of the place itself.[7] Integrating place-specific questions, the researcher can disentangle latent motivations to perform leisure in that place. For example, in the survey conducted, around 25% of restaurants were visited because "My friends or family enjoy it," with many comments stating that they visited the location because their kids liked it; this type of behavior can be hard to capture using tracking data. In addition, integrating questions about the location can improve the choice set elaboration by collecting data about the locations that can be expensive or unavailable. For example, the main interest of this work is to understand the importance of the social environment of the location. That is why we have included a question to describe the type of visitors of the place, which can help construct an idea of the social environment of the places in the database. Concurrently, it can help gather information on other characteristics that are not easily available, such as crowdedness or cleanliness.

Finally, we want to point out some limitations of this methodology that can be improved in future work: frequently visited location boundaries are subjective and difficult to define. Some respondents consider the places they visit weekly, while others can reckon the locations they visit less than once a month, but have done it for long periods. Second, people might only easily recall some of the locations they regularly visit, leaving some locations out of the data collection. Third, the survey considers eight categories (Restaurants and Cafes, Bars and Nightclubs, Cultural Centers, Sports Centers, Supermarkets, Parks, Social Activities, and other locations), which can be too strict about capturing the variety of possible leisure activities for the individual. The purpose of this paper was to show the capacity of the methodology to collect data on regular mobility patterns. The data set is available on demand; please contact the corresponding author.

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[7] GPS surveys could also ask this questions by adding a small survey after the individual visits a venue.

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