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WHAT YOU SEE IS WHERE YOU GO: CRUISE TOURISTS' SPATIAL CONSUMPTION OF DESTINATION AMENITIES

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Abstract: Using tracking technologies to measure revealed preferences can help detect locations with potential for further expansion or with risks of tourism overgrowth and consequential externalities. Understanding consumer behavior in spatio-temporal dimensions can reveal what contextual factors influence the consumption of a destination. This paper aims to contribute to knowledge on behavior-based segmentation by disaggregating spatial behavior of tourists in an intra-destination context. Behaviors were explored focusing on cruise tourists in Visby using GPS loggers and a gridded sighting experience dataset. To identify points of interest, tourists' indicated their liking using GPS click-loggers. The results were compared to the spatial distribution of visible amenities and through a stepwise method, behavior-based segments grounded in movements and positive emotions were derived. The paper contributes to previous research on intra-destination tourist mobility by developing a method for identifying revealed behavior, and developing segments that can be used to match tourist interests to distribution of amenities. The method aims to provide stakeholders with tools that can facilitate their strategic management and marketing of a destination.

Keywords: Tourism; behaviour-based segmentation; GPS; amenities

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Introduction

Research attention has recently turned towards spatiotemporal analysis to understand tourists' observed behavior in general and their space-time preferences specifically (De Cantis et al. 2016; Sciortino et al. 2022). Developing research based on observed mobility provides insights can add to understanding tourists' behavior in a spatio-temporal context (Caldeira and Castenholz, 2020; Martinéz Suaréz, 2021). By using GPS trackers, it is possible to identify tourists' movements in time and space, and to identify which parts of a destination (such as an urban district or sight) show high concentration of visitors and which are neglected (Modsching et al. 2008; Navarro-Ruiz et al. 2020). This type of analysis provides insights to how destination management can direct and distribute the flow of tourists, and to design marketing to attract the attention of tourists (Shoval and Ahas 2016). Previous research has identified differences in behavior among tourists in terms of time spent at a destination (Jaakson 2004; Cessford and Dingwall 1994; Henthorne 2000; Brida and Zapata-Aguirre 2010; De Cantis et al. 2016; Navarro-Ruiz et al. 2020), distance moved (Jaakson 2004; De Cantis et al. 2016; Andriotis and Agiomirgianikis 2010; Shoval et al. 2020), and spending rate (Douglas and Douglas 2004; Henthorne 2000, Sciortino et al. 2022). Although spatio-temporal analysis provides insights into behavior, there is still a need to further our understanding of revealed behavior. One aspect is tourist movements in a spatio-temporal context, but understanding the active phase in the customer journey is argued to be equally important as this is where the customer engages in the experience process, and where value is created through participation (Moshe Yachin, 2018). To capture what positive emotions and thus revealed preferences during the experience can add knowledge to what and when tourists become engaged during a visit. We do so by combining spatiotemporal analysis and contributing by including a technique to capture the when and where the tourists become engaged during their visit. It contributes to the evolving research using GPS tracking techniques to understand tourism behavior (Domènech, Gutiérrez, and Anton Clavé 2020a; DeCantis et al. 2016; Martínez Suárez et al. 2021), develops a method for combining GPS tracking technologies, and adds consumers' emotion, limited to liking, towards specific characteristic amenities of the destination. By adding the emotional dimension in terms of the predisposition to like a place, a holistic understanding of tourists' behavior combined with perceptions is developed, helping to predict tourists' movements. The article adds to previous research by combining mixed methods with open data analysis, allowing the researchers to include spatiotemporal, emotional, and visual experiences, and thus what the tourists actually see and do. This research captures cruise tourists' behavior on an island where the entry and exit points are defined and the tourists' visit is limited in time. Combining geolocation analysis with what tourists actually see and like, and does so by presenting a systematic five-step method approach. By including the geographical location's specific amenities and combining that with points of interest measures, new segmentation variables are identified to understand individual behaviors in a given context. Despite the drastic changes in tourist movements due to the COVID-19 pandemic, this research contributes with important insights on how to identify and understand tourists' movements. The method is aimed at managing overcrowding, and thus can be used to develop safer tourist destinations and aid decisionmakers on managing and avoiding crowds.

Previous research on cruise tourist behavior

Clustering behaviors – segmentation

By identifying common characteristics, needs, and behaviors among consumer groups, the different consumption patterns can be classified to facilitate destination management, planning of marketing activities, and distributing the flow of tourists within a destination. Previous research has identified different segments where Hayllar and Griffin (2009) identified three different categories of tourists based on what they wanted to do while visiting a destination: *explorers*, *browsers* and *samplers*. Whereas *explorers* prefer to discover different experiences and like to stroll on their own, the *browsers* instead seek out known tourist areas and routes. *Samplers* lastly, focus on specific tourist attractions and are not interested in the different dimensions constituting a destination. Andriotis and Agiomirgianakis (2010) instead identified that the tourists could be divided into those that wanted to explore a historical site, calling this segment *exploration*, as opposed to *escape* oriented tourists who were seeking to relax and disconnect from everyday life. While the motivation was either to *explore* or to *escape*, temporal constraints limited the number of possible activities. Thus, categorization of tourists in general, and cruise tourists specifically, seems to depend on the logistic circumstances of the stay and the tourists' choices, rather than sociodemographic factors (Hayllar and Griffin 2009). Although these different categories provide insights on behaviors, it has been criticized for capturing predicting intentions of behavior and attitudes rather than observing actual behavior (De Cantis et al. 2016). The critique relates to the use of questionnaires or diaries as a method for capturing behavior, as these methods captures the attitudes towards behavior rather than revealed behavior.

Cruise tourists and GPS tracking

In contrast to previous research, GPS technology provides spatially and temporally rich data that offers information on tourists' movement paths, pace, and distance range (Edwards and Griffin 2013). By using GPS tracking, researchers identified areas exposed to visitor congestion versus those that are underutilized (Shoval 2008; Martinéz Suaréz et al. 2021). The GPS tracking is possible both on aggregated (Ahas et al. 2007; Ahas et al. 2008) and local levels (Modsching et al. 2008; Tchetchik, Fleischer, and Shoval 2009; Sciortino et al. 2022), allowing to explore movement patterns affected by spatio-temporal restraints (Grinberger et al. 2014). Tracking technologies also come with a number of disadvantages (Shoval and Ahas 2016). The spatial resolution of mobile phone data enables aggregated analysis at a national or regional level, but requires high density of antennas in an area of interest to enable sufficient spatial accuracy for a local analysis. Until recently, one of the most common techniques to document spatiotemporal movement was the use of self-recorded movement diaries. It often results in inaccurate data, as participants often fail to record information accurately on a continuous basis (Shoval et al. 2014). Overcoming the dependence on individuals' entry of information, a more precise methodology is to combine GPS tracking with questionnaires. GPS tracking combined with questionnaires gives insights into the dynamic process of tourists' movements as affected by space-time characteristics of the place being visited (Tussyadiah and Fesenmaier 2007). To understand the dynamic process, both 'objective' movements and the 'subjective' attitudes and experiences are essential. As concluded by Caldeira and Kastenholz (2015:92) "[o]n one hand, mobility constitutes an important part both of the tourism system and the tourist experience, eventually even being its center or goal". On the other hand, memories and experiences are at the core of tourism.

Movement patterns

While few previous studies on cruise tourists' behavior have used GPS technology (Domènech et al. 2020a; Domènech et al. 2020b; Sciortino et al. 2022), a number of different behavioral patterns, characteristic for tourists, have been identified, such as the difference between first-time visitors in contrast to returning visitors. First-time visitors tend to be more explorative, aiming to visit as many attractions as possible, compared to the selective exploit behaviors among the repeat visitors (Kemperman et al. 2004). First-time visitors tend to wander around, whereas repeat visitors tend to focus more on shopping and dining areas (McKercher et al. 2012; Grinberger, Shoval, and McKercher 2014).

The distance moved also differs among tourists. Hayllar and Griffin (2009) state that in urban destinations, tourists tend to be spatially concentrated to defined tourist areas rather than dispersed over the city. Cruise tourists in Mexico (Jaakson 2004) spend on average 110 minutes within 200 meters from the ship due to the stores' concentration in the port. Henthorne (2000) found instead that cruise tourists spend on average five hours at the destination, but that the duration of stay is dependent on whether they walk independently or go on guided tours. De Cantis et al. (2016) found that cruise passengers travelled from 500 meters to 58 km, with an average of 3 km from the port. They also found that length of stay is positively related to number of attractions visited and length of available tours. There is thus a discrepancy in research findings on how far cruise tourists move during a day. Although different distances were travelled on shore, the reasons behind those differences were not elaborated. One explanation for the deviation could be resource allocation trade-off between time and space (Grinberger et al. 2014). Tourists plan their explorations based on how much time they perceive they have at the destination. Grinberger et al.

(2014) found three different clusters of behavior, differing in number of stops and duration at each stop. The majority of the participants preferred longer time at each stop over visiting many sights. The drawback of that study was that the sample was relatively small (N=68).

Studying the relation between built environment and cruise tourists' spatial movements in Catalonia, Domènech et al. (2020a) found that visibility of a tourist site and available economic activities there had higher impact on the behavior than urban morphology or physical attributes of the area. Differences in behavior were identified based on their expenditure rates. The group with high expenditure spent more time in the city center. Looking at sociodemographic and spatiotemporal variables, De Cantis et al. (2016) found great variability among the visitors: the middle-aged cruise passengers moved further than older and younger of the passengers. GPS tracking followed up by questionnaires to explain tourists' spatiotemporal behaviors is a common method, albeit still relatively novel within cruise tourism. Recently, Navarro-Ruiz et al. (2020) combined GPS trackers, questionnaires and diaries to capture the spatiotemporal behavior of cruise tourists. The tourists spent on average 4-5 hours on the shore even though the ships were on average 8.5 hours in the harbor.

To understand the experiences associated with the visit and the consumption of places, it is necessary to capture tourists' emotions. Capturing emotions in real time can indicate what visitors actually enjoy or like at a specific time and place, not only how long they stay in a place, or what they in retrospect state that they have enjoyed. Although emotions and feelings are essential for understanding behaviors and willingness to return, few studies have combined GPS tracking with capturing emotions. One that did so is Zakrisson and Zillinger (2012), through a survey they measured excitement factors defined as factors that were unexpected and thereby exceeded expectations. The risk of measuring emotions with surveys is that they measure individual's perceptions in retrospect, when the participant fills a survey not during but after their experience at the destination. We propose a method to measure the emotions using a GPS device with a click button to record emotions as they happen (for example asking the tourists to click when they see something they like). By combining the movement trajectories with what the tourists experience as positive in a spatiotemporal context gives insights into how they move and what they like at a specific place.

Methods

To understand the behavior of tourists visiting a rather unknown destination, hereafter called naïve tourist behavior, this research combines four different types of data: questionnaires, GPS tracks, geolocational characteristics, and specific points of interest noted by tourists. Through a combinative analysis, segmentation based on realized actual behavior is developed.

Choice of location

Small historic cities and islands that offer a clear entry and exit point facilitate the modelling of movements and the selection of potential participants (Shoval, Isaacson, & Chhetri, 2013). To analyze the behavior of naïve tourists, the Swedish island of Gotland was selected for this study. Gotland, situated approximately 100 kilometers from the mainland, is a traditional tourist destination for Swedes and foreign visitors and has long been a port of call for cruise ships. Until the beginning of the 2000s it received a relatively extensive number of cruise ships, with up to 150000 cruise tourists in 2008 (Besöksliv, 2018). With increasing ship size, the port layout became a limitation, being too narrow and shallow for larger ships. Following a decrease in number of visiting cruise ships, Gotland invested in a new large quay, adapted to receive the increasingly large cruise ships. After the inauguration of the new cruise quay in spring of 2018, it was the first year the island could receive a higher number of tourists. Thus, 2018 was selected as a starting point for data collection in this study[1]. The port is located in Visby, the main town on the island. The medieval part of Visby is on the UNESCO World heritage list since 1995. The city wall surrounding the town is nearly 800 years old, is an important landmark for Visby, and is typically portrayed when Gotland is marketed.

Figure 1. Visby

Photos by authors.
These images, devoid of people, were taken in February. Visby streets are bustling with people during the summer season, even during the pandemic.

[1] This study is not considering 2020 or later seasons due to the Covid-19 pandemic and its effects on tourism. It is expected that from summer 2023 Cruise tourism will more or less be returning to the pre-pandemic volumes.

Apart from the wall, Gotland is usually presented as an island whose nature resembles Mediterranean islands, with brochures informing the potential visitors that they can find similar things on Gotland as on Kos or Mallorca. Although the destination marketing deals with the whole of Gotland, it is clear that Visby is the major attraction (Ask and Ronström 2017). The marketing brochure images, devoid of pedestrians with houses resembling works of art, do not appear as from a living city. Such presentation makes the destination appear as quiet and malleable to the visitor's wishes (see for instance authors' images of Visby in Figure 1, similar to the brochures). However, during certain times in summer Visby is very crowded with Swedish and foreign visitors (especially during the Medieval Week or the Almedalen week dedicated to political debates). The new quay, built to accommodate significantly larger cruise ships than had been possible previously, is likely to add an increasing number of cruise tourists to the existing visitors. In the first year after inauguration, 75000 cruise tourists arrived to the island (Region Gotland 2018). By 2023, the goal for the destination is to double the number of arriving ships and reach the same number of cruise tourists as in 2008, i.e. in total 150000 cruise tourists per year (Besöksliv 2018). It is unclear how the coronavirus pandemic will affect long-term plans, but during the summers of 2021 and 2022 an increasing count of cruise ships continued to arrive to Gotland.

GPS loggers

We utilize GPS loggers to record detailed mobility trajectories. The chosen logger is small and easy to wear (size of a USB memory and worn using a cord around the neck). The logger has one button, and the visitors were instructed to click the button when they came to a location they appreciated or experienced something that interested them.

By associating these button clicks to specific locations with specific amenity profiles such as historical architecture, commercial activities, parks, not only a description of a place, but also of the tourists' stated preferences can be created. The data enables describing different groups of visitors, matching their behavior to specific geographical locations and to their own positive emotions experienced in what the tourists perceive as points of interest.

In total 288 unique GPS trajectories were recorded during the summer of 2018 by cruise tourists visiting Gotland who agreed to participate. The GPS loggers were turned on when handed out and turned off as the tourists returned to the pier. Out of 288 trajectories collected, 220 were used for this analysis; the excluded 68 visitors either participated in guided tours to other parts of Gotland (thus being outliers in the analysis) or did not show reliable trajectories due to faulty data or because the tourists accidentally shut off the loggers. On average, each tourist clicked 10.35 times, and in total, 2498 clicks were recorded.

Questionnaire design

Together with the GPS loggers, questionnaires in English and German were distributed to the cruise passengers at disembarking and collected upon return. The survey data was generated from 198 questionnaires to gather background information about the cruise tourists. Previous research (cf. DeCantis et al. 2016) has shown that age affects moving patterns, thus questions were asked about demographics such as age. The respondents were asked to estimate on a 7-point Likert scale their expectations (Field, Clark, and Koth 1985) regarding the visit to Gotland, previous knowledge about the destination, and satisfaction with the visit (cf. Duman and Mattila 2005). Complementing estimations of satisfaction and experiences, respondents were asked to state the attractions rendering the highest satisfaction. Intention of returning to the port of call was measured in line with Qu and Ping (1999) and Gabe et al. (2006). These questions captured if the participants knew about specific attractions on the island, what types of experiences they looked for and if the expectations were met or succeeded. In total 190 questionnaires were used for the analysis.

Data analysis

Of the visitors, almost none had previous knowledge about Gotland. Two individuals stated that they visited the island several decades ago, but the remainder had no previous experience and limited knowledge about Gotland and Visby from other sources. This is important since the core of the analysis relies on the naïve visitor's response to spatial distribution of amenities in Visby. Pre-knowledge might otherwise be associated with responses not only triggered by the visible opportunities, but also to an unknown extent by memories. In this case, the lack of prior knowledge or expectations confirms the assumption of a naïve visitor.

To analyze the like-click patterns of cruise tourists, we selected for analysis the geographical area containing all clicks in the town of Visby. The spatial extent of the touristic parts of Visby is relatively easy to define since the medieval wall, the surrounding parks, and the waterfront make up a natural boundary. Within this defined area we create a grid of 50m squares, with a point in the middle of each square representing a Point-of-Sight.

Points of Sight and Potential Points of Interest

The amenities, services or objects that are visible from each Point-of-Sight were recorded to represent Potential Points of Interest. Amenities, services and objects were categorized based on survey responses to reflect the things cruise tourists liked to do or see. The categories were the following:

- *Water* (most frequent is the sea view but also ponds);
- medieval *Wall*;

- planned *Green* space (including all park land but not forest or unmaintained green space);
- *Shops* (any category of stores);
- *Eateries* (cafés and restaurants);
- *Culture/History* (museums, ruins, medieval buildings - excluding the wall);
- and finally, *Picturesque* locations (after consulting with students, peers, and local guides, we mapped locations in which small houses, narrow streets, intricate woodworks on houses, town gardens, or similar, dominated the area).

From each Point-of-Sight, immediate surroundings were scanned using a combination of on-sight observations and photos from several sources, including the project team photos, Google Street View, Eniro Kartor (https://kartor.eniro.se), hitta.se (www.hitta.se), and social media images. Thus, the Potential Points of Interest values were based on what can be seen from each Point-of-Sight and 360 degrees around it. Occasionally the Point-of-Sight was located in a place with restricted or no access. In these cases, the observations were collected from the nearest location being accessible to pedestrians. In the medieval parts of the town (constituting the majority), the alternative locations where always in close proximity and well within each 50x50m grid unit. A few Points-of-Sight in the dock area close to the pier, were located in fenced or otherwise blocked units. These Points-of-Sight were given the likely values (water, and in two cases, planned green space) based on aerial imagery and proximal locations. None of these Points-of-Sight was like-clicked but they were still important as reference values in statistical analyses. In total 582 Points-of-Sight were created to cover the touristic parts of Visby.

Figure 2. Plan of Visby (left), gridded Potential Points of Interests (middle) and locations where tourists clicked “like” (right)

Objects from all categories were classified as Potential Points of Interest only if they were easy to spot from the Point-of-Sight. Hence, the abundant glimpses of water, wall, or planned greenery, were not categorized as a Potential Points of Interest. In Figure 2, the plan of the medieval town is illustrated in the left map (note that the outline of the town is the town wall), the middle map illustrates the spatial distribution of Points-of-Sight, and the rightmost map illustrates the observed like-click locations in Visby. The like-clicks are clearly clustered in specific parts of the town.

Recording tourists' Points of Interest

After importing the data from the GPS loggers, we merged the clicks from all loggers and saved as a shape file in a GIS software, keeping unique tourist ID and time stamps for each click. Click locations were spatially joined to the Potential Points of Interest categorization data, stored in each Point-of-Sight, thus assigning the categories to every click. The procedure rendered distances between clicks and Points-of-Sight, enabling us to validate that the join was kept local.

Clustering into segments

We segment the click behavior for segmenting groups of visitors by their attraction preferences. First, we describe both the general pattern of clicks and the local availability of Potential Points of Interests. This in order to generate a basic idea about the overall availability and spatial clustering of potential attractions in Visby, and the corresponding clustering of clicks. We used factor analysis to identify underlying factors that explain the correlation patterns between the co-location of amenities and click patterns.

Next, we employ a series of binary panel regressions (fixed effects logistic regressions) to predict the probability of clicking at different Potential Points of Interest, considering time (sequence order of clicks per tourist) and the heterogeneity of click behavior among the tourists. The predicted probabilities were subjected to the same kind of factor analysis as described above. The difference between the regression-based and the previous two factor analyses is discussed below in Results and Conclusions.

Limitations of the chosen method

We were, for ethical reasons, advised not to connect mobility and like-click behaviors to statistics on gender, age, etc. However, we know from the students who handed out the surveys and GPS-loggers that survey respondents and GPS recorders mostly were the same individuals, i.e. if they agreed to one they usually agreed to the other. Thus, general statistics about the visitors, collected from the surveys, can be used to understand the demographics of the GPS-trajectory visitors as well.

Results

The results are presented below in four steps.

Step 1 – Questionnaire survey

The average age of the respondents was 60.8 years. The majority of the visitors were from Europe with a considerable number of visitors from outside of Europe as well. Almost half of the respondents were from the UK. Other large groups consisted of Germans, North Americans and visitors from Australia.

Ranking the cruise-tourists' prior knowledge about Gotland on a scale between 1 and 7, the visitors' median score was 2 - somewhat lower than expected. Only 12 respondents stated that they had high or very high knowledge (6 or 7) about the destination. The respondents received the information about the destination during the cruise and not beforehand (Table 1). This suggests that the cruise tourists, on average, had limited knowledge about Visby, and that the information provided on board or at the pier made up an important base for the tourists' decisions on what to do in Visby. This also indicates that most of the tourists' choices were not planned in advance, but rather made spontaneously in response to the environment they encountered while walking around urban area. Most visitors identified history and architecture as what they expected to find and see, followed by nature, culture, food and shopping. The results were strikingly similar to the description of Visby and Gotland on the destination's websites and brochures. However, from the GPS data it seems that the list of activities was performed backwards, with tourists spending their first visits to streets with shopping and food.

Table 1. Descriptive statistics of the survey responses

Knowledge among cruise-tourists	Answers	Percent
Collection of information about Gotland and Visby	During cruise	83.3%
	Before cruise	16.7%
Expectations of sights on Gotland and Visby	History	85.9%
	Architecture	75.8%
	Nature	49.0%
	Culture	28.8%
	Local Food	27.3%
	Shopping	24.2%
	Something different	23.7%
	No expectation	2.5%
Likelihood to return	Unlikely (1-3) Indifferent (4) Likely (5-7)	39.3% 16.9% 43.7%
Recommend the destination to others	Unlikely (1-3) Indifferent (4) Likely (5-7)	4.4% 5.6% 90%

Although expectations were low, the majority of the visitors were highly satisfied with the visit, with a mean score of 6.2 (on a 7-point Likert scale where 1 is very unsatisfied and 7 is very satisfied). This was also reflected in intention to recommend the destination to others, where 90 percent would recommend it. Whereas likelihood to recommend Visby as a destination was high, the likelihood to return was lower, with only 43.7 percent stating that they would like to return. In the questionnaire comments, some respondents stated their age as a hinder to returning: "*Consider my age!!"* wrote an 80-year-old man from Australia. Those that stated that they would return commented on the experience as exceeding their expectations.

Step 2 - Potential Points of Interest

To create a baseline model of what Visby has to offer, we generated data describing the presence of Potential Points of Interest in 582 Points-of-Sight. These were used in both correlation and factor analyses to better understand the co-location of Potential Points of Interest. The factor analysis (Varimax rotation with Eigenvalue restriction of 1 in this and subsequent analyses) rendered four components (Table 2). We labelled the four components *L1_Medieval* (Eigenvalue of 1.582), *L2_Consumption* (1.227), *L3_Wall* walking (1.149) and *L4_Town* (1.002). Due to their loadings, the factor analysis picked up spatial co-location of the following elements:

- picturesque streets and historical environments in the *L1_Medieval* component;
- shops and restaurants in the *L2_Consumption* component;
- park landscape next to the medieval wall in the *L3_Wall* component;
- and finally, the co-location of picturesque, park-dense, and historical areas in the *L4_Town* component (see Pearson correlation in Table 2 right).

Table 2. What Visby has to offer, factor analysis - the baseline model (left) and correlation plot (right)

Factor analysis components from the baseline model					Correlation plot between included variables						
L1_Medieval	L2_Consume	L3_Wall	L4_Town		ich20_L	icwall_L	park_green_L	his_arc_cu_L	picturesq_L	eat_L	shop_L
-0.723	-0.250	-0.176	0.021	ich20_L	1	-0.048	0.102**	-0.075*	-0.269***	-0.066	-0.229***
0.102	-0.025	0.864	-0.121	icwall_L		1	0.148***	-0.138***	0.012	-0.091*	0.039
-0.318	-0.137	0.521	0.632	park_green_L			1	0.092*	-0.128**	-0.096*	-0.184***
0.252	0.034	-0.245	0.791	his_arc_cu_L				1	0.164***	0.044	-0.034
0.802	-0.121	-0.094	0.114	picturesq_L					1	0.054	-0.012
-0.044	0.778	-0.173	0.156	eat_L						1	0.268***
0.137	0.785	0.109	-0.202	shop_L							1
1.582	*1.227*	*1.149*	*1.002*	*Eigenvalue*	L = Locale*** is p<0.001, ** is p<0.01, * is p<0.05						

Step 3 - Points of Interest

Next, we used the recorded clicks that the cruise-tourists created during their visit to Visby (all clicks sorted into the 50m square grid of the Points-of-Sight). The click-based factor analysis results (Table 3) indicated that the spatial pattern of clicks at different Potential Points of Interest was dissimilar to the overall distribution of

Potential Points of Interests throughout Visby (Table 2). The cruise tourists' clicks rendered the two components labelled *C1_Consume* (Eigenvalue 2.067) that strongly favored locations with shops, eateries and picturesque streets, and *C2_Town* (1.329) that favored locations with concentration of parks, historical buildings/objects and picturesque streets (Table 3). The components indicate that Points of Interest are similar to the *L2_Consume* and *L4_Town* components of the baseline model, but the number of components has decreased from four to two.

Table 3. Factor analysis of the like-click model (left), and correlation plot between included variables (right)

Factor analysis components				Correlation plot between included variables					
C1_Consume	C2_Town		ich20_C	icwall_C	park_green_C	his_arc_cu_C	picturesq_C	eat_C	shop_C
-0.597	-0.232	ich20_C	1	0.071***	0.29***	-0.081***	-0.232***	-0.181***	-0.293***
-0.040	-0.679	icwall_C		1	0.055**	-0.254***	0.007	-0.065**	0.073***
-0.584	0.192	park_green_C			1	0.176***	-0.081***	-0.25***	-0.277***
-0.075	0.823	his_arc_cu_C				1	0.116***	-0.036*	-0.086***
0.489	0.278	picturesq_C					1	0.235***	0.226***
0.725	-0.014	eat_C						1	0.516***
0.773	-0.152	shop_C							1
2.067	*1.329*	*Eigenvalue*	C=click *** is p<0.001, ** is p<0.01, * is p<0.05						

Step 4 - Adjusted Points of Interest

We may assume that some tourists are clicking more than others are, and that their clicking behavior follows the constraints of their spatiotemporal mobility. When they first encounter a certain Point of Interest, they click. Later, on a repeat encounter, they would probably not click on the same attraction. Therefore, as they wander around the town, only new experiences (types of Potential Points of Interest) induce clicking. Some of these hypotheses were confirmed by descriptive statistics; with the minimum and maximum number of clicks were 1 and 59, with the median of 7 and standard deviation of 9.166 (i.e. there is difference between the tourists' click behavior). For instance, the visitors in Visby click in locations with a water view mostly in the beginning and the end of their visit (Table 4). This is a direct effect of the spatiotemporal distribution of events where the first click is close to the water (the cruise ship) and far from the medieval town center.

Table 4. Time sorting of click behaviour

	First click	Last click	Average observed click
Water	42%	45%	25%
Wall	21%	17%	26%
Park	23%	16%	26%
Histo	8%	12%	21%
Pict	13%	16%	30%
Eat	22%	19%	24%
Shop	20%	18%	24%

Overall, this suggests differences in click behavior among the tourists and among locations and dependent on the order of events. To control for biases related to these differences, we model the click probability using Fixed Effects logistic panel regressions on the observed clicks. The panel regression enables controlling for heterogeneity in click behavior among individuals, along with the time effect (here modelled as the sequence order of clicks, i.e. first to last for each individual). The individual-specific effects were correlated with the dependent variables, therefore fixed effects models rather than random effect models where used (the Durbin-Wu-Hausman test was conducted). The respective dependent variables for each of the seven regressions were the presence of water, wall, etc. at the locale. The independent variables contained the individual clicks for each of the amenities. The output can be interpreted as rendering the probability that an individual would like-click at a Point-of-Sight given presence of any of the seven amenities. The regressions results are available in the Appendix (Table A.1). By saving the probability for clicks derived from the regressions and subjecting the probability values to a factor analysis, three components were detected (Table 5). We labelled the three components *P1_Town* (Eigenvalue 3.23), *P2_Wall* (1.91), and *P3_Consume* (1.05). The factor analysis results in different components when the focus is shifted to the individual click-behavior rather than aggregate clicks.

Favored locations comprise the following components:

- *P1_Town* - near planned green areas, water, and in picturesque settings,
- *P2_Wall* - or in photogenic environments with the medieval wall, water and to some extent commercial activities,
- and finally, *P3_Consume* - in picturesque commercial parts of the town with historic buildings.

Table 5. Factor analysis results for the regression-based model (left), and correlation plot between the included variables (right)

Factor analysis components				Correlation plot between included variables						
P1_Town	P2_Wall	P3_Consume		ich20_P	icwall_P	park_green_P	his_arc_cu_P	picturesq_P	eat_P	shop_P
0.512	0.405	-0.699	ich20_P	1	0.47***	0.507***	-0.627***	-0.533***	-0.412***	-0.77***
0.080	0.972	-0.026	icwall_P		1	0.121***	-0.851***	-0.321***	-0.126***	0.093***
0.918	-0.007	-0.043	park_green_P			1	-0.004	0.156***	-0.599***	-0.574***
-0.048	-0.904	0.356	his_arc_cu_P				1	0.567***	0.228***	0.149***
0.237	-0.336	0.846	picturesq_P					1	-0.023	0.366***
-0.825	-0.147	0.037	eat_P						1	0.467***
-0.611	0.179	0.741	shop_P							1
3.231	*1.912*	*1.055*	*Eigenvalue*	P=probability to click *** is p<0.001, ** is p<0.01, * is p<0.05						

Step 5 - Developing the segments

To facilitate the interpretation of the factor analysis results, we correlated the coefficients for each variable (representing amenities like water, medieval wall, shops, etc.) to the four baseline components (row headers in Table 6), click-based components, and regression rendered components (column headers in Table 6). In

Table 6, the strongest positive (bold) and negative (underlined) correlations are listed for each row. The *L1_Medieval* baseline component (top row) correlates strongest with the regression rendered components, where the *P3_Consume* component shows a strong correlation between available (baseline) and liked locations. This indicates that the medieval town heritage, the picturesque streets and small-town shops constitute an attractive scenery that could be developed further. The *P2_Wall* regression-based component, describing interest in the wall and the waterfront, is the strongest negatively correlating component. *P2_Wall* indicates a group of tourists preferring the photogenic medieval wall and the water, is a different group of tourists compared to those who prefer the medieval center (the *P3_Consume*).

Table A.1. Logistic Fixed Effects regressions results

	ich20		**icwall**		**park_green**		**his_arc_cu**	
	ß (STD) Sig.	z	ß (STD) Sig.	z	ß (STD) Sig.	z	ß (STD) Sig.	z
ich20	1.192 (0.143)***	8.34	-1.089 (0.215)***	-5.05	-0.545 (0.158)**	-3.44	0.228 (0.198)	1.15
icwall	0.805 (0.142)***	5.68	4.585 (0.227)***	20.19	0.174 (0.157)	1.11	-1.405 (0.229)***	-6.14
park_green	0.687 (0.146)***	4.69	0.447 (0.199)	2.24	2.2 (0.152)***	14.5	-0.21 (0.177)	-1.18
his_arc_cu	-1.907 (0.204)***	-9.34	-1.342 (0.255)***	-5.26	-0.226 (0.161)	-1.4	2.587 (0.159)***	16.27
picturesq	-1.038 (0.156)***	-6.64	-1.749 (0.208)***	-8.43	0.142 (0.15)	0.95	0.945 (0.158)***	6
eat	-0.354 (0.185)**	-1.91	0.934 (0.203)***	4.6	0.283 (0.215)	1.32	0.437 (0.208)	2.1
shop	-1.387 (0.217)***	-6.4	-0.512 (0.223)**	-2.3	-3.125 (0.432)***	-7.23	-0.289 (0.217)	-1.33
log likelihood	-700.58		-457.77		-636.82		-531.77	
N obs	2174		2223		2012		1967	
N groups	176		182		156		155	
LR chi2(7)	555.81		1189.54		478.71		591.46	
Prob > chi2	0.000		0.000		0.000		0.000	
*** is p<0.001, ** is p<0.01, * is p<0.05								
	picturesq		**eat**		**shop**			
	ß (STD) Sig.	z	ß (STD) Sig.	z	ß (STD) Sig.	z		
ich20	-0.973 (0.184)***	-5.28	-0.076 (0.217)	-0.35	-1.601 (0.363)***	-4.41		
icwall	0.313 (0.147)	2.12	-0.237 (0.188)	-1.26	1.089 (0.179)***	6.08		
park_green	-0.661 (0.157)***	-4.2	-1.242 (0.244)***	-5.09	-0.827 (0.257)**	-3.22		
his_arc_cu	1.566 (0.139)***	11.29	0.206 (0.19)	1.08	1.622 (0.187)***	8.68		
picturesq	1.265 (0.123)***	10.27	-0.357 (0.175)**	-2.04	-0.389 (0.169)**	-2.29		
eat	-0.528 (0.179)**	-2.96	1.518 (0.174)***	8.73	0.575 (0.179)	3.21		
shop	-1.094 (0.179)***	-6.12	-0.464 (0.195)**	-2.38	1.156 (0.174)***	6.66		
log likelihood	-757.52		-494.73		-474.31			
N obs	2089		1699		1895			
N groups	163		131		139			
LR chi2(7)	377.59		157.08		278.69			
Prob > chi2	0.000		0.000		0.000			

The baseline component *L2_Consume* is strongly positively correlated with the corresponding consumption-oriented components (C1_Consume from aggregated clicks, P3_Consume from FE panel regression). However, the baseline component *L2_Consume* is strongly negatively correlated with the *P1_Town* component representing preference for water, picturesque streets, and planned greenery. It is likely that this group of visitors spends less time and money at local shops and eateries. The baseline component *L3_Wall* is strongly correlated with the regression-based component *P2_Wall*, but it is strongly negatively correlated with the click-based *C2_Town* component (oriented towards history and culture parts of the town). Finally, the baseline component *L4_Town* is positively correlated with both the click-based *C2_Town* and the regression-based *P1_Town* components. Since all these correlated components are characterized by few like-clicks in locations with eateries and shops, finding out how these tourist groups could be attracted to the commercial parts of the town could be a tourist management priority in terms of encouraging tourists' consumption of local businesses.

Conclusions

This article contributes to research by developing a mixed method approach to analyze spatiotemporal behavior; presents a method to predict behavior among naïve consumers in general by focusing on cruise tourists specifically; and finally develops geolocation-specific segments. Contributing to the findings by Shoval et al. (2020), this article broadens the understanding of revealed behaviors by combining geolocation analysis with what tourists actually see and like. This article presents a systematic five-step method. In this conclusion, the relevance from a Covid-19 perspective is also addressed.

The method provides insights into tourists' perceptions of a specific location, which is especially important when the tourists' prior knowledge of a destination is low or next to none, as they were in the case of cruise tourists visiting Gotland where the average knowledge of the destination was 2 out of 7 on the Likert scale. With the low expectations and knowledge of the destination, one can expect that the level of satisfaction is rather high. This was also confirmed as the visitors stated very high levels of satisfaction with their visit. Explanations for the low level of expectations were given as "Visby was a stop on the way to other more famous destinations".

In order to better understand what the cruise tourists did during their stay and what they liked, the data analysis of the GPS tracks provided more insights. Researchers utilized mobile phone network detail records to understand tourism-related mobility. However, the spatial resolution of such data was insufficient in the medieval town, characterized by narrow, meandering, and irregular streets in combination with a low number of GSM antennas. Thus, GPS-based location data was used. The five-step method, developed in this article, combines GPS tracking devices, where the technology allows for participants to register what they like, with more traditional questionnaires. This method reveals geolocation-specific movements used to explain behavioral patterns of the destination-naïve tourists. The limited knowledge they possessed, indicated that history, architecture and nature were the three dominant expectations. Thus, the cruise tourists could be defined as consumers of the destination. The next step was to derive possible attractions, Points-of-Sight. The amenities sighted from each of these Points-of-Sight were identified using a number of different sources, representing the Potential Points of Interest. Through factor and correlation plot analyses, four different types of offers were identified: *L1_medieval, L2_consume, L3_wall,* and *L4_town*. Thereafter, the emotions were analyzed by focusing on where the cruise tourists clicked at sights they liked (so called like-clicks). Through this step in the analysis, the revealed perception of the location was captured. The fourth step controlled for individual-specific click patterns and the order of the clicks. Hence, the analyses did not only consider what the cruise tourists liked but also the order in which the like-clicks took place on an individual level. The final analysis provided the probability for what an individual would like-click.

Developing segments based on revealed behavior

Previous research has found differences between first-time and repeat visitors. Whereas repeat visitors exploit selective sites and are interested in shopping and dining, first-time visitors instead explore the place and visit as many attractions as possible (Kemperman et al. 2004; Grinberg et al. 2014; McKercher et al. 2012). The analysis of the revealed behaviors in Visby/Gotland, with a majority being first-time visitors, shows that the cruise tourists follow the patterns of both first time and repeat visitors. The tourists both explore, in ways that are associated with first-time visitors in previous research, and enjoy going to restaurants and shopping areas, just as repeat visitors. Since almost all tourists were first-time visitors, their visiting history cannot explain these behavior patterns. By dividing the tourists into segments based on the probability to click in relation to the specific amenities, another pattern emerges.

Through the analysis, three segments (*P1_Town, P2_Wall*, and *P3_Consume)* were developed. The *P1_Town* cruise tourists preferred to see green park areas and water where picturesque buildings added to the positive experience. This category of cruise tourists did not spend their money on food or shopping as that did not fit within their objectives of visiting Gotland. The behavior of *P1_Town* is on one hand similar to the explorers, who like to stroll on their own and as first-time visitors as they do not like the shopping areas or restaurants. This segment seems to like to explore the historical areas of the town. We can call this segment explorers or 'historians', as they are exploring the city and seem to seek out historically interesting amenities. The *P2_Wall* on the other hand prefers the sceneries of the wall and is more likely to be emotionally inspired when there is water close by. To shop is not what was primarily being sought after, but shopping added to the experience. An explanation could be that a souvenir can remind them of the wall and sceneries. This segment, with preference to walk along the wall, shows similarities to samplers but would not quite fit the characteristic of the segment defined by Hayllar and Griffin (2009) as the samplers seek out known tourist areas. Recalling that the tourists visiting Visby had little prior knowledge of the destination, they did not really know about specific attractions. They also seemed to explore, but focused on a single attraction - the wall. This segment could also be called the romantic segment as they were looking for beautiful sites. The last segment, here called *P3_Consume*, did not experience anything positive in seeing the water. Rather, they were interested in the picturesque town and its shops. This segment was more likely to spend money than the other two, and was less interested in the specifics of the town (such as the wall). This segment enjoyed the streets where the history is surrounding the atmospheric houses and shops. To an extent, this segment resembles the pattern of the repeat visitors (McKercher et al. 2012; Grinberger et al. 2014) despite being first-time visitors. As they like dining and shopping areas, we choose to call them spenders.

Although the segments developed in the paper are specific for the destination, the five-step method can be generalized as it takes the experiences on site, comparing it to what is potentially offered at the destination and to the movement pattern, including the visual characteristics and the experienced positive emotions. This combination of data shows revealed behavior and can be used to predict cruise tourists' preferences based on a destination’s specific geolocational characteristics. This article adds to previous research using GPS tracking technology (De Cantis et al. 2016; Ferrante, De Cantis, and Shoval 2018; Domènech et al. 2020b) by analyzing spatiotemporal behaviors based on movement, emotions and visual attractions. Through the 5-step method, the article adds to the understanding of factors affecting actual behavior of destination-naïve cruise-tourists embarking at ports-of-call that are not the main attraction on the cruise tour.

Practical implications

The combination of different data and the provided method for analysis can offer important insights into tourists’ behavior that are specific to the destination’s geographical characteristics. For destination management organizations the results give a number of important implications, both for when tourists start returning to destinations and for the future to identify potential areas where there is a risk of crowds. To be able to formulate a visitor strategy, the destination management organizations can use the different steps in the method to identify what the destination has to offer, what the tourists actually like and which combinations of sights the choose at what time. Potential Points of Interest (PPOI) can both provide insights to marketers who can choose to promote those PPOI to pre-defined segments when there is existing knowledge about what this group of tourists are looking for. A second implication is when there is low knowledge of destination, the strategy for the destination managers can be to continuously track behaviors to identify the sights that evoke positive emotions, and through this create the information that would appeal to the revealed behavior-based segments would be attracted to. Based on the data, storeowners can identify which type of tourists is most likely to visit their shops and what attracts them. This can thus provide useful information on the assortment on offer. A third implication relates to the current COVID-19 pandemic related situation: if the individuals searching for safer destinations could identify potential risks for crowds in real-time. Based on the movement patterns, the destination managers can place sensors in places they have identified as exposed for crowds. These sensors can then provide real-time information for tourists and other visitors on when there is a crowd and when the place is "safe" to visit.

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ONO ŠTO VIDITE JE ONO GDE IDETE: PROSTORNO PONAŠANJE TURISTA SA KRSTARENJA NA TURISTIČKIM DESTINACIJAMA

Apstrakt: Korišćenje tehnologija praćenja za merenje otkrivenih preferencija može pomoći da se otkriju lokacije sa potencijalom za dalje širenje ili sa rizicima od prevelikog porasta turizma i posledičnim eksternalijama. Razumevanje ponašanja potrošača u prostorno-vremenskim dimenzijama može otkriti koji kontekstualni faktori utiču na posetu destinacije. Ovaj rad ima za cilj da doprinese znanju o segmentaciji zasnovanoj na ponašanju dezagregacijom prostornog ponašanja turista u kontekstu unutar destinacije. Ponašanje je istraženo fokusirajući se na turiste sa krstarenja u Visbiju koristeći GPS logere i skup podataka o iskustvu posmatranja sa mrežom. Da bi identifikovali tačke interesovanja, turisti su naznačili da im se sviđaju koristeći GPS registratore klikova. Rezultati su upoređeni sa prostornom distribucijom vidljivih sadržaja i metodom koraka izvedeni su segmenti zasnovani na ponašanju, zasnovani na pokretima i pozitivnim emocijama. Rad doprinosi prethodnim istraživanjima intradestinacijske turističke mobilnosti razvijanjem metode za identifikaciju otkrivenog ponašanja i razvojem segmenata koji se mogu koristiti za usklađivanje interesa turista sa distribucijom pogodnosti. Metoda ima za cilj da zainteresovanim stranama pruži alate koji im mogu olakšati strategojsko upravljanje i marketing destinacije.

Ključne reči: turizam; segmentacija zasnovana na ponašanju; GPS; pogodnosti

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Marina Toger specialises in spatial analysis and modelling urban dynamic processes. Her latest research comprises empirical studies on human spatial mobility and spatial distribution of inequity. GIS, Geosimulation, agent-based modelling, spatial and network analyses are the main methods that Marina implements in her research. Her PhD related to urban open-space connectivity, network morphology and dynamics resulting from urban expansion and interaction between urban environment and wildlife.

John Östh, originally trained as a teacher and geographer (PhD, and Professor in Human Geography) has joined OsloMet in September 2021 to do research and to teach in GIS, spatial analytics and computer aided geo-techniques. He has long experience of microdata research, data creation in GIS, Spatial Big Data studies (primarely using Mobile phone data) as well as development of geo-software. His most widespread software is EquiPop which currently is used in 28 countries**.**

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