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Tracking cruise passengers' consumption: An analysis of the relationships between onshore mobility and expenditure

Caterina Sciortino [a], Mauro Ferrante [b], Stefano De Cantis [a], Szilvia Gyimóthy [c,*]

[a] Department of Economics, Business and Statistics, University of Palermo, Viale delle Scienze e Ed. 13, 90128 Palermo, Italy
[b] Department of Culture and Society, University of Palermo, Viale delle Scienze e Ed. 15, 90128 Palermo, Italy
[c] Department of Marketing, Copenhagen Business School, Solbjerg Plads 3, 2000 Frederiksberg, Denmark

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ABSTRACT

This paper analyzes the relationships between the spatial behaviour and destination expenditures of cruise tourists by integrating customer surveys and GPS tracking technology. Based on data collated in 2018 and 2019 in Copenhagen, cruise passenger expenditure was modelled via logistic regression, using socio-demographic characteristics and mobility-related variables. In order to map the spatial behaviour and the key characteristics of the itinerary followed, tracking data were synthesized into meaningful mobility variables. An analysis of stops was performed to identify locations with the potential highest expenditure density. The results indicated that spatial movement and, in particular, stop activities are relevant in explaining expenditure behaviour. The implications of the proposed methodology are discussed with regards to further research, and destination management.

1. Introduction

Prior to the COVID-19 pandemic, urban coastal destinations witnessed a rapid and unsustainable rise in cruise arrivals, with an excess of daily peaks in visitor volumes in already congested city centers. Indeed, many consider that cruise tourism often epitomizes overtourism, as reported by the media and in debates regarding the tourism pressures on local communities (Holland, Mazzarol, Soutar, Tapsall, & Elliott, 2021; Holtegaard-Kasler, 2019). Despite claims that cruise tourists constitute an affluent visitor segment, some critics argue that their negligible onshore expenditure during short term or transit visits does not offset the social and environmental costs of destinations hosting large vessels (Larsen, Wolff, Marnburg, & Øgaard, 2013). This asymmetric distribution of benefits and impacts, which is attributable to cruise tourism, poses a challenge to destination managers in assessing and managing short-term visitor flows.

Bearing in mind the aforementioned critical challenges of mass visitation, the COVID-19-related break in cruise tourism provides us with an opportunity to reflect on visitor management at port destinations. This requires a comprehensive view of visitor flows and the spatiotemporal consumption in port-of-calls, which will also include greater clarification regarding the determinants of cruise passenger spending at their destination. The scope of short-term (transit) destination consumption can be demonstrated in economic and geographical terms, whilst assessing onsite expenditure (monetary consumption) and spatiotemporal behaviour (consumption of destination space). However, these strands deriving from the literature have not yet been fully synthesized. Despite the availability of new tracking technologies and recent studies in Mediterranean cruise destinations (Casado-Díaz, Navarro-Ruiz, Nicolau, & Ivars-Baidal, 2021; Domènech, Gutiérrez, & Anton Clavé, 2020; Domènech, Gutiérrez, & Clavé, 2020), the relationships between tourist mobility and spending behaviour merits further attention. The overall objective of this article is, therefore, to analyze spending patterns in the urban destination space, and to explore the relationship between transit (<24 h) cruise passengers' onshore spending behaviour and mobility-related variables. Accordingly, the objectives of the research are threefold:

- to analyze cruise visitor expenditure as a function of mobility behaviour
- to characterize the spending propensity of cruise visitors and analyze its distribution in geographic space and
- to highlight variations in expenditure level, which are based on distinct mobility characteristics

* Corresponding author.
E-mail addresses: caterina.sciortino@unipa.it (C. Sciortino), mauro.ferrante@unipa.it (M. Ferrante), stefano.decantis@unipa.it (S. De Cantis), sgy.marktg@cbs.dk (S. Gyimóthy).

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These objectives were formulated into three specific research questions (RQ):

- RQ 1. How do mobility characteristics (e.g., tour duration, tour length, stop activities) explain the scope and composition of visitor expenditure?
- RQ 2. How are mobility differences reflected in spending propensity and expenditure levels (high vs. low spenders)?
- RQ 3. Do socio-demographic characteristics explain the scope and components of visitor expenditure?

The paper is organized as follows: Section 2 discusses the existing literature relating to cruise passenger expenditure relating to tourist mobility and the linkage between spatial behaviour and expenditure. Section 3 presents the data and methods used for the analysis, illustrating the survey methodology and the main important information, which has been derived from GPS tracking data. Section 4 reports and discusses the results obtained from the city of Copenhagen. And Section 5 discusses the main implications of the study in concluding the paper.

2. Literature review

In order to explain cruise visitor consumption, this literature review has compiled publications from the past twenty years, whilst considering tourism consumption by addressing three main themes:

- cruise passenger expenditure (monetary consumption behaviour)
- tourism mobility (spatiotemporal behaviour and movement patterns) and
- spatiotemporal consumption (studies combining expenditure and mobility behaviour).

Each section below in the literature review identifies key focus areas, approaches and contributions, also highlighting uncharted research questions informing the design of this present study.

2.1. The onshore expenditure of cruise passengers

With the rapid growth of cruise tourism, the number of academic papers on this topic has increased significantly in the past twenty years. An extensive review of the literature (Papathanassis & Beckmann, 2011) has identified passenger expenditure studies as a key theme among several research interests. High environmental and social costs, which are associated with crowding in ports, have prompted researchers and destination managers to explore patterns of cruise passenger spending (Henthorpe, 2000). Based on evidence from different empirical contexts, scholars have begun to question shore visitors' contribution to local economies and tourism businesses during their brief time span (Andriotis & Agiomirgianakis, 2010; Brida, Bukstein, Garrido, & Tealde, 2012; Gouveia & Eusébio, 2019; Larsen et al., 2013; Penco & Di Vaio, 2014; Thurau, Seekamp, Carver, & Lee, 2015).

The initial studies conducted on cruise passenger expenditure were mainly descriptive and they focused on the general characteristics of expenditure (Brida & Zapata, 2010; Douglas & Douglas, 2004; Gabe, Lynch, & McConnon, 2003; Henthorpe, 2000); later publications attempted to define the key drivers of onshore spending actors. Researchers observed that contextual (time, weather) and individual factors (sociodemographic characteristics, previous experiences) determined variations in expenditure patterns. Henthorpe's study regarding passenger expenditure in the Caribbean (Henthorpe, 2000) demonstrated that the amount of time spent in port can have a substantial impact on the amount of money spent therein. In Adriatic and Mediterranean ports, namely Koper (Marksel, Tominc, & Božičnik, 2017) and Piraeus (Papadopoulou, Sambracos, & Xesfingi, 2017), the expenditure of cruise passengers was found to correlate with: gender, nationality, destination familiarity, age, and number of previous cruises.

The analysis of the literature relating to cruise passenger expenditure highlights a high degree of variability. The lowest values of average per-capita expenditure, of approximately 25–35€, have been reported for various Mediterranean (Casado-Díaz et al., 2021; Domènech & Gutiérrez, 2020; Domènech, Gutiérrez, & Anton Clavé, 2020), Scandinavian (Larsen & Wolff, 2016), and Latin American destinations (Brida et al., 2012; Brida, Lanzilotta, Moreno, & Santiñaque, 2018; Seidl, Guiliano, & Pratt, 2007). Other studies (Pino & Tovar, 2019) have reported slightly higher values (45 to 75€), whereas many visitors to Caribbean, North American and Australian ports can spend up to €200/visit (Dwyer & Forsyth, 1998). The following factors were found to be significant regarding socio-demographic determinants of passenger expenditure: *income* (Brida et al., 2012; Brida & Risso, 2010; Parola, Satta, Penco, & Persico, 2014), *age* (Brida et al., 2012, 2018; Brida, Bukstein, & Tealde, 2015; Casado-Díaz et al., 2021; Domènech, Gutiérrez, & Anton Clavé, 2020; Henthorpe, 2000; Parola et al., 2014; Papadopoulou et al., 2017; Gargano and Grasso, 2016), *passenger's educational level* (Parola et al., 2014), and *nationality* (Brida et al., 2012; Marksel et al., 2017; Parola et al., 2014). And, of the trip-related characteristics, *Length of stay* was found to be positively associated with expenditure levels (Brida & Risso, 2010; Brida et al., 2012; Casado-Díaz et al., 2021; Domènech, Gutiérrez, & Anton Clavé, 2020; Henthorpe, 2000; Parola et al., 2014; Gargano & Grasso, 2019).

Douglas and Douglas (2004) have analyzed categories relating to cruise passenger expenditure for two cruises visiting seven Pacific island ports of call. Their results demonstrated that age and weather determined variations in expenditure categories patterns for each port: older people displayed a greater propensity to seek out food and beverage options ashore, and purchase more duty-free perfume and alcoholic beverages. Moreover, all-inclusive cruise packages are designed in such a way so as to retain the largest share of wallet. This means that cruise tourists will spend significantly lower on other categories. For instance, as meals are included in the price of the cruise, cruise passengers tend to return to the ship for their meals (Gouveia & Eusébio, 2019). In addition, passengers often chose shore excursions offered by cruise companies (despite premium prices), owing to passenger unfamiliarity and convenience (Douglas & Douglas, 2004).

A comprehensive review of methodical approaches of onshore expenditures has revealed that the majority of studies are based on data collected, which have been collected from face-to-face interviews and surveys conducted with embarking passengers, and ad hoc questionnaires (Di Vaio, Lepore, & Varriale, 2018; Gargano & Grasso, 2016; Henthorpe, 2000; Gabe et al., 2003; Marksel et al., 2017; Parola et al., 2014). Pino and Tovar (2019) have found evidence of studies drawing on other types of data, for instance, credit card statements or other data sources (Brida & Risso, 2010; Brida, Bukstein and Tealde, 2015, Brida et al., 2015, Brida et al., 2018). Neither of these approaches are flawless, and, as other scholars have noted, particularly recall bias remains a fundamental weakness in the research rigour (Hardy, Birenboim, & Wells, 2020; Shoval & Isaacson, 2007).

2.2. Tourist mobility at a destination

The analysis and prediction of tourists' spatiotemporal movements and interactions in a destination is a challenging task from methodological and managerial (planner) perspectives (Hall, 2015; McKercher & Lew, 2004). Tourist movements can be considered as the set of spatial choices within the destination (Caldeira & Kastenholz, 2020; Lau & McKercher, 2006). The understanding of spatial behaviour of tourist activities in tourism studies was for long a purely conceptual endeavour. A limited number of works in the 1990s focused on the analysis and modelling of tourist routes and movement patterns (Oppermann, 1995). In the cruise context, Jaakson's observation study regarding the port of Zihuatanejo, Mexico (Jaakson, 2004) was the first to conceptualize onshore movement patterns. Based on qualitative and quantitative approaches, this study introduced the notion of the tourist bubble, noting

that the majority of cruise visitor spending occurs within a very limited geographical scope.

Owing to the rapid development of GPS-tracking technologies in recent decades, the number of empirical studies tracking tourist movements has increased rapidly (Caldeira & Kastenholz, 2020; Shoval & Ahas, 2016). Early contributions to this field were purely exploratory and they focused on understanding intra-destination mobility and factors influencing spatiotemporal choices. And, in these early days, the most widely used methods were simple, descriptive itinerary maps or travel diaries, in which planned destinations and stopovers were listed (McKercher & Lew, 2004). These methods produced heuristic typologies, resting on the assumption that distance and familiarity may be key factors in explaining variations in tourist flows. For instance, Lew and McKercher (2006) have proposed a crude territorial model of the patterns of tourist destination movement, differentiating between four types. These are: *zero movement*, *convenience based* (when the tourist remains in the proximity of their accommodation), *concentric exploration* (identified as a *confused tourist*, with insufficient information about the destination) and, finally, the *wide movement* (with useful knowledge about the destination (Lew & McKercher, 2006)).

While such models can offer various conceptual guidelines for the analysis of tourist itineraries at destinations, the applied methods are fraught with structural weaknesses, mapping inaccuracies and insignificant detail. For example, these approaches do not account for individual characteristics, despite the acknowledgement that socio-economic characteristics and lifestyle plays an important role in tourist choices and spatial behaviour. Whilst acknowledging the significance of spatial models, several studies have attempted to map the concentration of consumption activities around particular attraction sites (Zoltan & McKercher, 2015) and destination space (Xiao-Ting & Bi-Hu, 2012); however, they have to date failed to identify a universally explanatory model. These approaches are based on the assumption that patterns of tourist movement closely correlate with the location of attractions (identified as either *nodal, linear* or *area*), and crowd densities will follow the rule of distance decay (McKercher, 2018). However, the center-periphery dispersion theory has been refuted by Timothy & Boyd (2015) and Domènech, Gutiérrez, and Clavé (2020). These two groups of researchers have demonstrated more nuanced relationships between the characteristics of the built-up environment and the spatial behaviour of cruise passengers. Whilst the spatial syntax (configuration of street networks) explained the uneven distribution of visitors in the port of Tarragona, Domènech and his colleagues (2020b) observed that the visibility of areas frequented by tourists and ambient factors (e.g., shaded side of the streets) were major determinants of destination mobility.

More recently, Hardy and colleagues (Hardy et al., 2020; Hardy, Vorobjovas-Pinta, Wells, Grimmer, & Grimmer, 2021) have contributed to this research with an empirically substantiated model in explaining variations in tourist intensity and dispersal. They also introduced meaningful metrics to illustrate the dispersal of tourists in Euclidean space. With a bespoke mobile application, *The Tourism Tracker App*, they were able to follow and model: the movement patterns of wine tourists (Lewis, Hardy, Wells, & Kerslake, 2021), multi-day visitors (Hardy et al., 2020), and cruise tourists disembarking from the port of Sydney (Hardy et al., 2021). This latter study has also demonstrated significant differences in the dispersal patterns between passengers of local, domestic and international provenances. They observed that international passengers travel the shortest distances and primarily visit recreational, culture and nature spots.

2.3. Studies combining mobility and expenditure behaviour

Despite their limitations of scope, there are a few notable studies linking tourist movement and spending choices. For instance, an extensive observational study by Jaakson (2004) produced an inductive typology, in which variations in the patterns of cruise visitor spatial activity was depicted. Three groups dominated the study: each group remained in the tourist bubble at the port, however, demonstrating distinct consumption characteristics. As the following segments indicate, the *Shopping Browsers* and the *Café Crowd* looked for retailing vs. food & beverage experiences. The so-called *Pack* segment referred to passengers with limited or no spending power, and they remained close together as a group after disembarkment. Jaakson (2004) also identified a smaller group of individualistic *Explorers*, who wandered off the beaten track and beyond the tourist shopping zones. However, this heuristic typology was not corroborated by means of robust geolocational approaches.

Still later, McKercher and his colleagues initiated mixed method approaches (combining data streams from interviews, GPS-tracking, GIS analysis and/or diaries) with which to enhance the precision of locating expenditure estimates. McKercher and Lew (2004) studied the spatio-economic dispersion of tourism consumption by considering two aspects of tourist movement: *territoriality* and the *intensity of spending*. And McKercher, Hardy & Arial (2019) have identified major differences in movement patterns and duration among three visitor segments to a historic tourist shopping village in Tasmania.

In the past five years, Sicilian, Catalan and Tasmanian tourism researchers have made notable advances in analyzing the spatial determinants of cruise tourist expenditure. De Cantis, Ferrante, Kahani, and Shoval (2016) were the first to corroborate a multi-method approach, combining GPS-tracking and traditional survey methods in analyzing cruise passenger behaviour at their destination. Domènech, Gutiérrez, and Anton Clavé (2020) have applied a similar methodology to the analysis of cruise passenger behaviour, confirming the importance of the length of stay on passenger expenditure, as mentioned above. Their study also provided empirical evidence of the aforementioned *Explorer* patterns; it confirmed that respondents with the highest per capita spending visited fewer tourist sites, preferring to spend more time in areas with mixed (commercial and recreational) functions. Casado-Díaz et al. (2021) have identified that patterns of cruise visitor spatial mobility (regarding routes, stops frequency) and onshore choices (independent vs. group visit) are significant factors affecting destination spending levels. Based on a state-level study in Tasmania, Hardy et al. (2020) established three factors determining the spatial dispersion of tourists: length of stay, familiarity of destination and transport choices. They also drew attention to the role of gateways (entry/exit points) regarding consumption intensity. These studies suggest a considerable potential in identifying the association between *stop activity* and *expenditure behaviour*, calling for a robust method with which to derive and summarize stop locations from GPS tracking data.

3. Data and methods

3.1. Study site

The Danish capital Copenhagen is a popular port-of-call on Baltic Sea cruises, being located on the Oresound Strait, dividing Denmark and Sweden. It is the most populated city in Denmark but the host community of 794,128 inhabitants (2020) is dwarfed by the 10 million annual tourist arrivals. Prior to the pandemic, cruise tourism had seen an unprecedented boom in Copenhagen, which led to fierce public debates regarding overtourism in the 2017–2019 period. Critical voices complained of the problem of increasing congestion in the Inner City, and low consumption levels despite high visitor volumes. As Bent Lohman, chair of the Inner City Local Committee noted in the summer of 2019:

> *"On a busy summer day, 300 tourist buses travel around the Inner City. After all, the city is like a zoo where the buses pass through. [But] the tourists are not even here for a day. They don't spend a lot of money in the city, because it's typically just a lunch they eat here, and then they have to move on"* (Holtegaard-Kasler, 2019).

Copenhagen's congestion problems can be related to the its particular topographical features and tourist landscape. The city is built on a flat terrain along the waterfront, and all the main sights and attractions are concentrated in the city center, which borders on a medieval canal moat system. The most popular nodal tourist sights have been identified from two sources, listing the top attractions of the Danish capital (*VisitCopenhagen* and *TripAdvisor*). Fig. 1 below also depicts the main pedestrian streets. These linear attractions feature a high density of retail centers, restaurants, and tourist sights. And, from a tourist point of view, the concentration of shopping facilities and the high degree of walkability (main attractions and city center located in walking distance from the port) makes Copenhagen a very attractive and easily negotiable day trip destination. However, the sweet spot of tourist activities covers an area with a radius not exceeding 2–3 km, and the narrow medieval street plan may further increase perceptions of crowding.

The City of Copenhagen and Wonderful Copenhagen's cruise department, Copenhagen Cruise Network, have evinced great interest in testing GPS tracking technologies to map the consumption behaviour of short-term (transit) cruise tourists. And, in collaboration with tourism researchers from different universities, they have agreed to launch a larger data collection at the Langelinie pier, which hosts most transit calls during the summer season.

3.2. Data collection procedures

Data on cruise passenger onshore behaviour in Copenhagen was collected during early autumn 2018 and summer 2019. The two periods were selected according to the total number of cruise passengers, as made available by the Copenhagen port authority. Data collection was via an integrated approach of combining GPS technology with a traditional, questionnaire-based consumer survey. The present approach is similar to that proposed by Ferrante, De Cantis, and Shoval (2018), and adopted in other European contexts,: Palermo (De Cantis et al., 2016; Ferrante et al., 2018; Shoval, Kahani, De Cantis, & Ferrante, 2020), Dubrovnik (Ferrante et al., 2018); Tarragona (Domènech, Gutiérrez, & Anton Clavé, 2020; Domènech, Gutiérrez, & Clavé, 2020) and Valencia (Casado-Díaz et al., 2021; Navarro-Ruiz, Casado-Díaz, & Ivars-Baidal, 2020). The research team obtained a privileged position in proximity of the disembarkation point, which permitted the efficient management of interviews. Guests were asked to bring a GPS logger with them during their visit, in addition to completing two brief, assisted questionnaires when disembarking and when returning to the shop (these questionnaires can be located in Appendix A).

In adopting a pseudo-systematic approach, the research team selected approximately one in every 20 passengers. The questionnaires were administered through face-to-face interview, the aim of which was to collect socio-demographic information, in addition to other pre- and post-visit information, including: party size, previous visit to the destination, expenditure levels and categories (following Mak, Moncur, & Yonamine, 1977; Breen, Bull, & Walo, 2001; Frechtling, 2006). The collation of information relating to expenditure at the termination of the visit encourages a reduction in recall bias (Hardy et al., 2021; Rylander, Propst, & McMurtry, 1995); this also avoid the risks of influencing expenditure patterns, compared to other data recording processes, such as the use of a diary (Faulkner & Raybould, 1995). Excluding total expenditure, the respondents were also asked to recall spending according to the following six categories: *Expenses of an organized tour*; *Food and beverages*; *Ticket entry to museums and attractions*; *Transportation services*; *Shopping* and *Souvenirs*. The reported currencies were subsequently converted into euros.

Spatial tracking was conducted with the Conrad GT730FL GPS Data Logger, and the recording interval of coordinate points was set at every 10 s. This type of logger is a small device, which is worn around the neck, with the battery lasting for the duration of the visit at their destination. The logger was provided to every cruise interviewed passenger prior to administering the initial questionnaire. At the termination of the visit, every cruise passenger returned the GPS data logger and they completed the conclusive questionnaire.

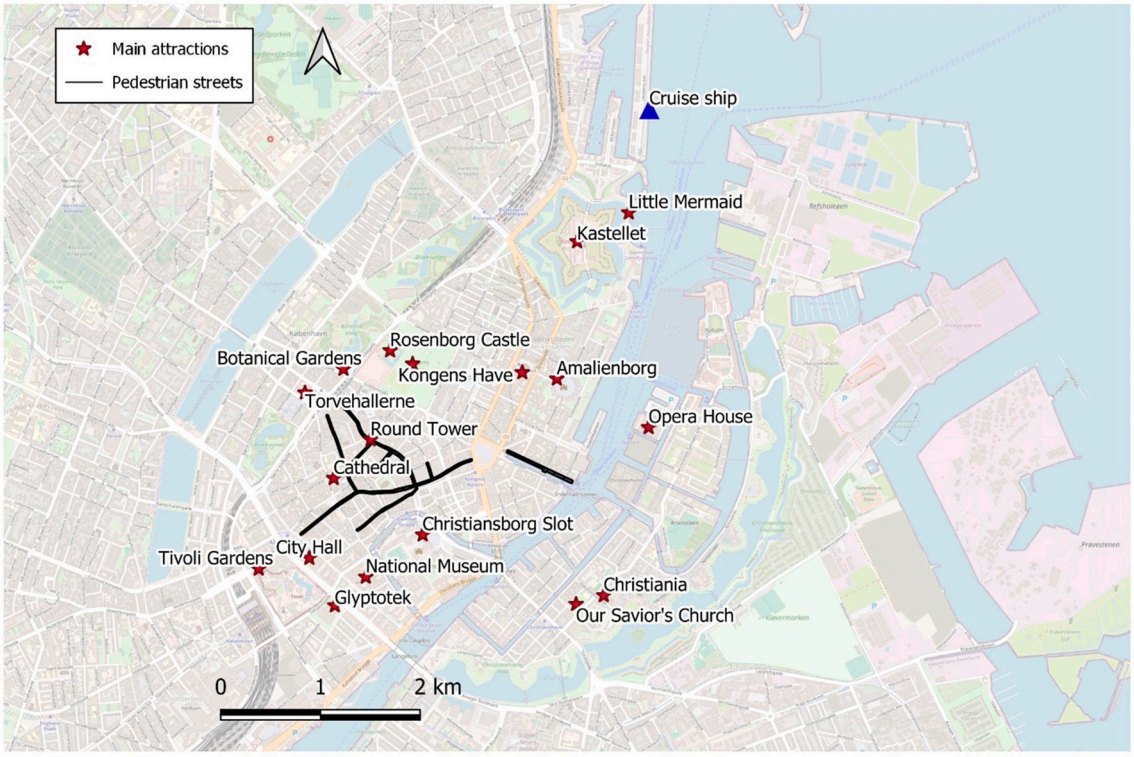

Fig. 1. Main attractions, pedestrian streets and cruise ship dock location in the city of Copenhagen (Base Map: OpenStreetMaps).

3.3. Methods

3.3.1. Processing GPS tracking data

The initial step in the analysis of GPS tracking data involves the pre-processing of the information, the aim of which is to reduce data anomalies (such as outlier observations and missing values), in addition to obtaining important information from the data through a procedure of reformatting (Abbruzzo, Ferrante, & De Cantis, 2021; Stopher, Fitz-Gerald, & Zhang, 2008). The authors of this paper have used an approach to outlier detection, which is based on *jumps in speed* and *signal loss*. Having observed systematic outlier observations after signal loss, these five subsequent points after signal loss were deleted from the series. Such a choice was determined by a visual inspection of individual tracking data and bearing in mind the time required by the GPS tracking device to realign the signal to the correct location. However, the specific model of device used, in addition to the frequency of the recording interval chosen, may have influenced the selection of this parameter. Jumps in speed were identified by comparing the original series with a smoothed series, the latter which was obtained by computing a centered, two-minute moving average of the coordinates. Those points which exceeded a threshold value of the distance between the smoothed and the original series were deleted from the analysis. Thereafter, these deleted points were replaced by a linear interpolation of the last and first valid data point, thus assuming a linear trajectory with a constant value of speed between the missing data points.

Having pre-processed the GPS tracking data and having derived information relating to the time interval, distance and speed between consecutive points, a set of six concise variables were computed for each cruise passenger (De Cantis et al., 2016). These included: *total length of tour* (in km, provided by the sum of distances between all the pairs of consecutive points), *total duration of tour* (in minutes), *maximum distance from the port location*, *maximum speed*, *average speed*, and *90th percentile of speed*. This latter indicator was used to determine whether the cruise passengers used a transportation mode or not. It was assumed that all cruise passengers, whose 90th percentile of speed exceeded 5 km/h, used a transportation mode (for at least 10% of the duration of their itinerary).

3.3.2. Definition of stop locations

The final step in the extraction of useful information from GPS tracking data involved the identification of stop locations, which may indicate important locations or points of interest for cruise passengers. Various approaches have been proposed for the identification of stops in GPS tracking data (Abbruzzo et al., 2021; Grinberger & Shoval, 2019). For example, Gong, Sato, Yamamoto, Miwa, and Morikawa (2015) have proposed a classification of methods according to five groups, namely: centroid-based methods, speed-based methods, duration-based methods, density-based methods, and hybrid methods. Each of the first four categories can be said to have various limitations, and these have been fully reviewed by Gong et al. (2015). The latter authors concluded that hybrid methods might improve the accuracy of stop identification by combining some of the criteria of the other methods (such as *speed* or *density*, and *duration*). Based on these considerations, the authors of this paper have used a hybrid method, based on *speed* and *duration* criteria. Specifically, this approach initially considers a smoothed series of data points for every *i*-th cruise passenger, based on a space-time centered moving average of 10 min, as follows:

$$(\widetilde{x}_t, \widetilde{y}_t) = \left(\frac{x_{t-300} + \sum_{k=1}^{590} x_{t-300+k} + x_{t+300}}{60}, \frac{y_{t-300} + \sum_{k=1}^{590} y_{t-300+k} + y_{t+300}}{60} \right)$$

in which it is assumed that every point is collected every 10 s. Nonetheless, the `proc. sql` function implemented in SAS® software, allows for irregular time intervals between point coordinates to be considered, by ensuring a constant time interval in the calculation of moving averages. This step permits 'noise points', which may determine small jumps in speed, to be averaged with other neighbourhood points, thereby ensuring a more stable measure of the speed variable. Having derived the smoothed series, and computing a new speed variable (based on averaged consecutive data points), a threshold of speed of 20 m per minutes (1.2 km/h) was set to identify a stop.

Consecutive time intervals, corresponding to values of speed below this threshold value, were aggregated, and a stop was defined when the duration of aggregate time intervals exceeded a threshold of 2 min. Conclusively, if two stops were observed at a time interval of a distance <5 min from each other, they were considered as a *single stop*. The stop coordinates were then fixed as the centroid of the data points pertaining to that stop.

In order to graphically illustrate how the proposed algorithm functions, two subsets of points pertaining to two cruise passengers are reported in Figs. 2a.1 and 2b.1. Both patterns suggest the presence of a stop where several points are concentrated. Having implemented the space-time moving averages, the proposed algorithm correctly identifies a stop, as displayed in Fig. 2a.2. However and in the case of the second sequence, the concentrated points were derived from two very different moments of the tour: a set of points was recorded at the beginning of the visit (shown in blue in Fig. 2b.2), and the other set of points refers to movements occurring at the end of the visit, as shown in red in Fig. 2b.2. Thus, it can be stated that any algorithm which does not consider the sequence of points in stop identification (e.g. DBSCAN algorithm) may incorrectly identify such situations as a *stop*.

Having identified all the stops made by cruise passengers during their visit at their destination, further information regarding stop activities could be obtained. This included: the *total number of stops*, the *total duration of stops*, and the *average duration of stops*. A binary variable was also added to indicate the *maximum stop duration,* assuming a value equal to 1 if a cruise passenger made a stop lasting for >40 min; if not, this value was 0.

3.3.3. Analysis of expenditure behaviour at the passenger destination

A two-step procedure was implemented to analyze cruise passenger expenditure behaviour at their destination, in relation to individual characteristics and spatial behaviour. The first step analyzed differences among spenders and non-spenders in order to explore the role of socio-demographic characteristics and mobility information. And the second step divided expenditure levels at the destination into two categories: *high* and *low* spenders (above and below €50 respectively, €50 representing the median value of expenditure among spenders). This permitted an analysis of the impact of socio-demographic characteristics and spatially-related information on the level of expenditure. The degree of association between socio-demographic characteristics and spatially-related information with expenditure propensity (spenders vs. non-spenders) and the level of expenditure (high vs. low Spenders) was first explored through the analysis of contingency tables and the Pearson's Chi-squared test of independence among categorical variables. Variables showing significant ($p < 0.05$) associations with expenditure were selected for their inclusion in a multiple regression model, which was subsequently implemented through binomial logistic regression. Specifically, two-logit models were estimated: the first considered a dichotomous variable according to spenders and non-spenders, as follows:

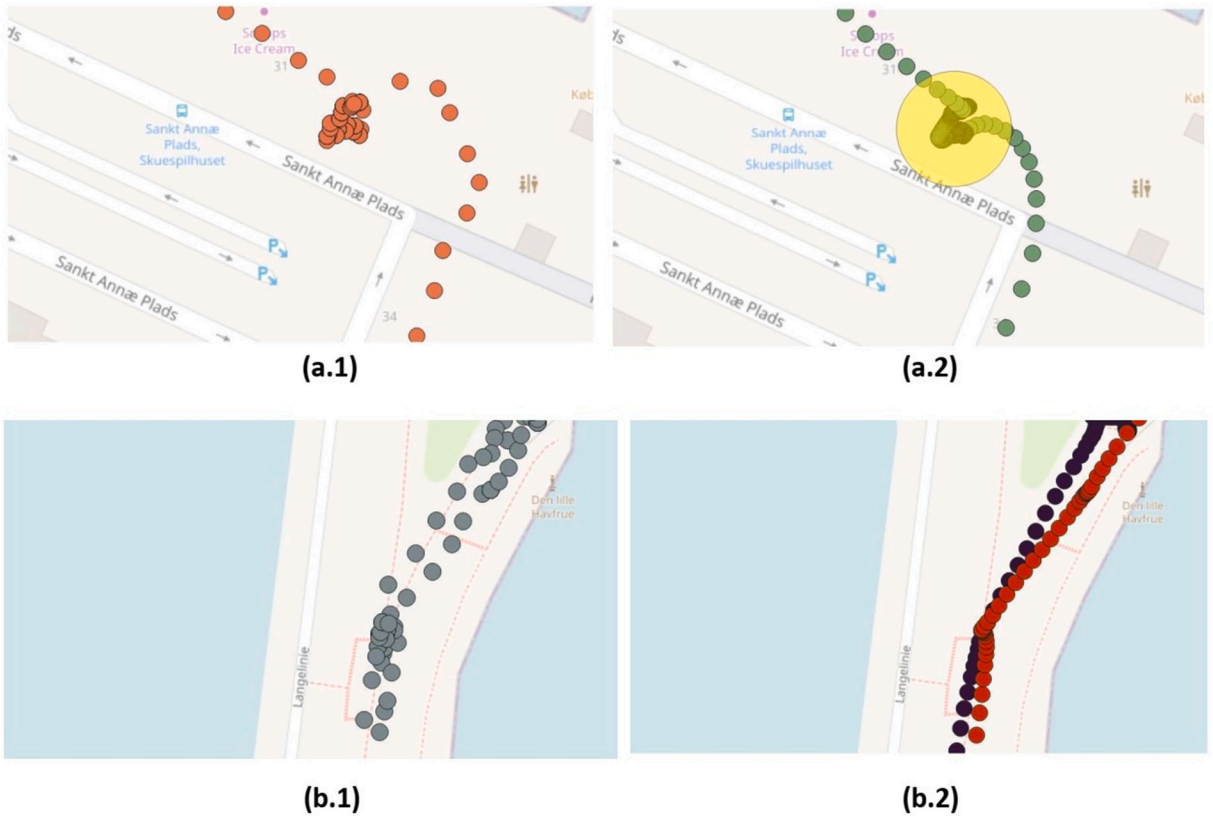

Fig. 2. Graphical illustration of stop identification algorithm (Base Map: OpenStreetMaps).
Figure a.1 and b.1 show a raw subset of tracks relating to two cruise passengers. Figure a.2 and b.2 are the same subset of points after the implementation of space-time moving averages. In the former, a stop is correctly identified, based on speed criterion; in the latter, no stops are identified since the points refer to two different periods of the visit: at the beginning (in blue) and at the end (in red).

$$log\frac{\pi_i}{1-\pi_i} = \beta_0 + \beta_1 PLAN_i + \beta_2 SIZE_i + \beta_3 TOURTIME_i + \beta_4 TOURLENGHT_i + \beta_5 MAXDIST_i + \\ + \beta_6 MAXSTOPDUR_i + \beta_7 TRANSPORT$$

where π_i represents the probability of being a spender, *PLAN* is a binary variable which indicates whether the passengers planned their excursion in advance, *SIZE* refers to party size, *TOURTIME* indicates the total time spent at the destination, *TOURLENGTH* represents the total length of tour, *MAXDIST* is the maximum distance from the port location, and *MAXSTOPDUR* indicates the maximum duration of the stop made by the considered cruise passenger. Departing from the inclusion of all these variables, the final model was estimated by implementing a forward selection criterion in order to identify the most parsimonious model.

Similarly, a second model - the level of expenditure (high vs. low) - was modelled, by considering only the sub-sample of cruise passengers who spent at the destination, as follows:

$$log\frac{\pi_i^{'}}{1-\pi_i^{'}} = \beta_0^{'} + \beta_1^{'} TOURTIME_i + \beta_2^{'} MAXSTOPDUR_i + \beta_3^{'} TRANSPORT_i$$

where $\pi_i^{'}$ represents the probability of being a *high-spender*, and *TOURTIME*, *MAXSTOPDUR* and *TRANSPORT* refer to the same variables, which have been defined above. None of the socio-demographic characteristics was included in this model, due to the absence of a significant association with expenditure level; a forward selection criterion was also implemented in this case. Finally, expenditure composition by category was analyzed, to accurately describe the characteristics of cruise passenger expenditure at their destination and to explore the main determinants of various expenditure categories. In this final step, visual projections of the stop patterns of spenders and non-spenders, and of the stop pattern of high vs. low spenders, was performed to highlight areas of the city in which stops are mainly concentrated, thereby demonstrating potential passenger expenditure.

4. Results

4.1. Data description

A total of 183 valid interviews was collected during the two survey periods, each containing a set of fully-completed questionnaires and valid GPS tracks. Based on the distribution and meaningfulness of variables, the number of value categories was reduced into binary sets. For example, when considering the frequencies of the *age* variable, respondents were divided into two categories, namely *18–65* and *66+*. The authors of this paper consider that this division makes practical sense as urban port destinations currently receive a steadily growing volume of senior visitors, and it is, therefore, appropriate to identify their specific needs and onshore behaviour. Similar dichotomous reductions were made in relation to the variables of *income*, *education*, *country of*

Table 1
Socio-demographic characteristics of cruise passengers, interviewed in the City of Copenhagen.

Variables	Categories	Freq.	%
First time visitor?	yes	103	43.70
	no	80	56.30
Age category	18–65	82	44.80
	66+	101	55.20
Country of residence	Europe (EU)	113	61.70
	non-Europe (non-EU)	70	38.30
Education (missing = 7)	secondary or lower	59	33.50
	tertiary/ +	117	66.50
Net annual income (missing = 7)	less than €40,000	70	39.80
	more than €40,001	106	60.20
Planned details for CPH visit	no	105	57.40
	yes	78	42.60
Purchased shore excursion	no	160	87.40
	yes	23	12.60
Planned visit attractions	no	77	42.10
	yes	106	57.90
Alone	no	175	96.20
(missing = 1)	yes	7	3.80
Spouse/partner	no	27	14.80
(missing = 1)	yes	155	85.20
Children/relatives	no	157	85.80
	yes	26	14.20
Friend(s)	no	156	85.20
	yes	27	14.80
Party size	1 or 2	141	77.00
	2+	42	23.00

residence, *party size* and *visiting history*. Table 1 illustrates the complete socio-demographic profile of the cruise respondents.

The descriptive statistics above revealed that more than half of the sample (55%) had already visited Copenhagen on at least one occasion. Approximately 55% of the sampled cruise passengers were 66+ years old and an estimated 60% was European. 65 + % of cruise passengers had a tertiary/+ level of education, whereas approximately 60% declared an annual income of €40,000+. The majority of interviewed passengers (about 87%) had not purchased an excursion, unlike 13% of organized cruise passengers who had purchased an excursion. The party size composition comprised mainly one or two passengers (77%), with a spouse or partner (85%). 14% of the parties included children or friends.

Participants in the survey were requested to indicate the amount of money they had spent in the six expenditure categories. Summary statistics for total expenditure and by category are reported in Table 2 below. It shows that the average expenditure per capita is €56, with the median expenditure being considerably lower, that is, approximately €28. This difference can be attributed in terms of maximum expenditure to the share of non-spenders (22% of total passengers interviewed) and to the presence of various outliers. Nonetheless, the third quartile of total expenditure is approximately €75, which is in agreement with previous studies on Scandinavian countries (Larsen et al., 2013). Expenditure categories also resonate with Jaakson's (2004) observations of activities concentrating on shopping and café visits. The *Food and beverages* and *Shopping* categories displayed the highest concentration of expenditure, with about €18 and €19 of average expenditure (32% and about 35% of total expenditure) respectively. Expenditure for guided tours accounted for 12% of total expenses, being approximately €7 on average; spending on *Museum and attractions, (*an average of €5; 8.7%), and *Souvenirs* (€3.4; 6.5%) was even lower than the aforementioned categories. Only 5.9% of total expenses accounted for *Transportation services* (€3), which might be explained by the central location of Langelinie and the walkability of the city.

The exploratory analysis of the data determined the threshold value for the categorization of total expenditure levels, which was based on its median value among spenders. The final set of information was derived from GPS tracking data, and it permitted the summarizing of cruise passenger spatial mobility at their destination as other potential determinants for a deeper understanding of expenditure dynamics. Table 3 below reports the summary statistics for mobility-related variables.

Cruise passengers spent an average of about 4 h in Copenhagen, undertaking a tour of approximately 12 km in length; these passengers also remained in the vicinity of the port with 75% of them travelling less than about 3 km. This confirms a convenience-based (Lew and McKercher, 2006) mobility pattern, which also documented an average speed of 5 km/h and the absence of a high proportion (75%) of cruise passengers using any kind of transportation mode. Cruise passengers made stops accounting for about 1 h and 40 min on average during their tour, with an average duration of stop of about 20 min. Finally, the average number of stops (as deployed in this research) was 5.5, and every passenger stopped at least once (>2 min). Such stopping patterns are reminiscent of a grazing pattern, which was first described by Jaakson (2004) and characterized by slow speed and impulsive browsing in the urban landscape. As will be demonstrated below, this spatial activity can facilitate, but it does not necessarily stimulate, monetary expenditure.

4.2. Determinants of cruise passenger expenditure

In order to analyze the main determinants of cruise passenger expenditure, socio-demographic variables and spatial mobility characteristics were considered. Table 4 below details bivariate distributions of the variables under consideration for spenders and non-spenders. And, to evaluate the degree of association between these categorical variables and expenditure behaviour, the Pearson's Chi-squared test of independence was used. This analysis revealed little or no influence of socio-demographic characteristics (such as age, education, or income) on expenditure behaviour, and is anomalous with much of the aforementioned literature. Only *Party size* and *tour planning* (*Planned detail)* were slightly associated with expenditure. That is, those who planned the details of their visit in advance and those passengers in larger groups were more likely to spend money at their destination. A similar result was also observed in Brida et al. (2015) and Casado-Díaz et al. (2021).

RQ1. How do mobility characteristics (e.g., tour duration, tour length, stop activities) explain the scope and composition of visitor expenditure?

The results in Table 4 demonstrate that all the variables derived from cruise passenger spatial behaviour at their destination were significantly associated with expenditure. Specifically, respondents, who embarked

Table 2
Summary statistics of expenditure at destination by category, collected through a questionnaire-based survey of cruise passengers, interviewed in the city of Copenhagen (values in €).

Expenditure		Total	Tour	Food & Beverages	Museum & Attraction	Transport services	Shopping	Souvenirs
mean		56.19	6.80	18.12	4.91	3.29	19.42	3.64
median		28.00	0.00	12.00	0.00	0.00	0.00	0.00
St. Dev.		85.47	23.8	23.78	19.49	10.11	66.03	10.34
max		799.0	171.00	180.00	179	70	732	80.3
quantiles	25	5.20	0.00	0.00	0.00	0.00	0.00	0.00
	75	74.20	0.00	25	0.00	0.00	7.00	0.00
Expenditure composition		100%	12.11%	32.24%	8.74%	5.85%	34.57%	6.48%

Table 3
Concise information (per cruise passenger) on the itinerary undertaken, derived from GPS tracking data (n = 183) in the City of Copenhagen.

Variables	Mean	St. Dev.	Quartiles			Min	Max
			25	50	75		
Total duration of tour (hour)	4.18	1.66	2.92	4.13	5.47	0.63	8.00
Total length of tour (km)	12.32	9.26	7.59	10.91	15.09	1.36	99.99
Maximum distance from the port (km)	2.79	2.24	2.07	2.77	3.18	0.31	28.18
Total stop duration (hour)	1.68	1.07	0.81	1.54	2.32	0.04	4.98
Mean speed (km/h)	2.54	1.19	1.91	2.34	2.83	0.59	11.24
90° percentile of the speed (km/h)	5.30	3.47	3.90	4.30	4.77	1.62	33.42
Maximum duration of stop (minutes)	47.83	33.42	20.81	42.83	66.71	2.58	172.70
Average stop duration (minutes)	20.51	17.98	9.82	16.11	24.18	2.58	137.74
Average number of stops	5.49	2.56	4.00	5.00	7.00	1.00	15.00

on a longer tour (in terms of span and duration) and those who wandered further from the port, were more inclined to spend money. Those who stopped for 40 min at least once were likely to spend more when compared to those who stopped briefly. Similar observations were made for those using transport. Evidently, opportunities to spend money whilst travelling (e.g. bus sightseeing tours) were minimal, if not altogether absent.

RQ2. How are mobility differences reflected in spending propensity and expenditure levels (high vs. low spenders)?

Having ascertained an association between spatial mobility variables and expenditure propensity, the relationship between the same set of variables and the level of expenditure was analyzed. Table 5 below regards the bivariate distributions of spatial variables for low and high spenders (defined as those with a total expenditure below or above €50 respectively), together with a summary of the Pearson's Chi-squared test. Non-spenders were excluded from this analysis. An analysis of this data confirms that expenditure levels are equally associated with mobility behaviour, the only exception being the total tour length. As previously reported, (Brida & Risso, 2010; Brida et al., 2012; Casado-Díaz et al., 2021; Domènech, Gutiérrez, & Anton Clavé, 2020; Henthorpe, 2000; Parola et al., 2014; Gargano & Grasso, 2019), those passengers who spent >3.5 h at their destination tended to spend more than those who spent less time at their destination. These results are also consistent with earlier findings (Gouveia & Eusébio, 2019; Larsen et al., 2013), suggesting that shorter stays may indicate passengers returning to the ship for meals. This explorative, wider movement type of pattern of visitation (Jaakson, 2004; Lew & McKercher, 2006) was characterized by furthest maximum distance from the port and higher spending. Similar to the results reported in Table 4, also in this case a stop of at least 40 min is significantly associated with a higher level of expenditure, in addition to using any kind of transportation mode. In contrast, different expenditure levels were not explained by any of the socio-demographic characteristics under consideration.

RQ3. Do socio-demographic characteristics explain the scope and composition of visitor expenditure?

Table 4
Distribution of socio-demographic and trip-related characteristics, according to cruise passenger expenditure (yes/no) in the City of Copenhagen (row percentages), and summary of the Pearson's Chi-squared test of independence among categorical variables.

Variables	Categories	Spenders		Pearson Chi-Squared	
		No	Yes	Chi-squared	*p*-value
First time visitor?	no (*n* = 80)	27.5%	72.5%	2.123	0.145
	yes (n = 103)	18.4%	81.6%		
Age category	18–65 (*n* = 83)	19.3%	80.7%	0.854	0.355
	66-more (*n* = 100)	25.0%	75.0%		
Country of residence	EU (*n* = 113)	23.9%	76.1%	0.377	0.539
	non-EU (*n* = 70)	20.0%	80.0%		
Education	secondary or lower (*n* = 59)	28.8%	71.2%	3.245	0.072
	tertiary/+ (*n* = 117)	17.1%	82.9%		
Net annual income	less than €40,000 (n = 70)	24.3%	75.7%	0.745	0.388
	more than €40,000 (*n* = 106)	18.9%	81.1%		
Planned details	no (*n* = 105)	27.6%	72.4%	3.853	0.050
	yes (*n* = 78)	15.4%	84.6%		
Purchased excursion	no (*n* = 160)	24.4%	75.6%	2.844	0.092
	yes (*n* = 23)	8.7%	91.3%		
Party size	2 or less (*n* = 141)	28.4%	71.6%	12.572	0.000
	>2 (*n* = 42)	2.4%	97.6%		
Tour time	<3.5 h (*n* = 69)	43.5%	56.5%	28.295	0.000
	>3.5 h (*n* = 114)	9.6%	90.4%		
Tour length	<9.5 km (*n* = 72)	38.9%	61.1%	18.554	0.000
	>9.5 km (*n* = 111)	11.7%	88.3%		
Max distance from the port	<2.5 km (n = 72)	40.3%	59.7%	21.812	0.000
	>2.5 km (n = 111)	10.8%	89.2%		
Maximum stop duration	<40 min (*n* = 86)	43.0%	57.0%	39.677	0.000
	>40 min (*n* = 97)	4.1%	95.9%		
Use of any transportation mode	No (*n* = 147)	25.9%	74.1%	5.104	0.024
	Yes (*n* = 36)	8.3%	91.7%		

In order to answer the third research question, a regression modelling approach was adopted to quantify the combined effects of socio-demographic and mobility characteristics on expenditure behaviour. Tables 6 and 7 below present the results of the two estimated logit models: the former describes spenders/non-spenders, and the latter regards the level of expenditure (*high* vs. *low*). Variables demonstrating significant associations in bivariate analysis, with a *p*-value ≤0.05, were included in the model selection algorithm, and a forward selection criterion was used in identifying the most parsimonious model.

The results reported in Table 6 demonstrate that there is a higher probability of spending when the party size exceeds two people, they travel 2.5+ km from the port with a maximum stop duration in excess of 40 min. These latter results can be considered as intriguing as there is a retail row, located on Langelinie quay, which targets disembarking cruise visitors. However, the retail units only offer standard souvenir items whilst more diverse and less tourist-targeted shopping opportunities are located beyond a radius of 3 km from the pier. The high values for the odds ratio indicate a substantial degree of association between these variables and expenditure propensity. In addition, the association among some of the spatial mobility variables determines the inclusion of only some of them in the final model.

Table 5
Distribution of socio-demographic and trip-related characteristics, according to cruise passenger expenditure level (low/high) in the City of Copenhagen (row percentages), and summary of the Pearson's Chi-squared test of independence among categorical variables.

Variables	Categories	Level of expenditure		Pearson Chi-Squared	
		Low	High	Chi-squared	p-value
First time visitor?	no ($n = 58$)	55.2%	44.8%	1.355	0.244
	yes ($n = 84$)	45.2%	54.8%		
Age category	18–45 ($n = 67$)	49.3%	50.7%	0.000	0.992
	66-more ($n = 75$)	49.3%	50.7%		
Country of residence	EU (n = 86)	54.7%	45.3%	2.502	0.114
	non-EU ($n = 56$)	41.1%	58.9%		
Education	secondary or lower (n = 42)	45.2%	54.8%	0.327	0.568
	tertiary/+ (n = 97)	50.5%	49.5%		
Net annual income	less than €40,000 ($n = 53$)	50.9%	49.1%	0.140	0.708
	more than €40,000 (n = 86)	47.7%	52.3%		
Planned details	no ($n = 76$)	48.7%	51.3%	0.024	0.876
	yes ($n = 66$)	50.0%	50.0%		
Purchased excursion	no ($n = 121$)	51.2%	48.8%	1.237	0.266
	yes ($n = 21$)	38.1%	61.9%		
Spending group size	2 or less ($n = 115$)	49.6%	50.4%	0.018	0.895
	>2 ($n = 27$)	48.1%	51.9%		
Tour time	<3.5 h ($n = 39$)	64.1%	35.9%	4.716	0.030
	>3.5 h ($n = 103$)	43.7%	56.3%		
Tour length	<9.5 km ($n = 44$)	56.8%	43.2%	1.443	0.230
	>9.5 km ($n = 98$)	45.9%	54.1%		
Max distance from the port	<2.5 km ($n = 43$)	58.1%	41.9%	8.342	0.004
	>2.5 km ($n = 99$)	45.5%	54.5%		
Maximum stop duration	<40 min ($n = 49$)	63.3%	36.7%	5.841	0.016
	>40 min ($n = 93$)	41.9%	58.1%		
Use of any transportation mode	no ($n = 109$)	56.0%	44.0%	8.342	0.004
	yes ($n = 33$)	27.3%	72.7%		

Table 6
Results of the logit model relating to passenger expenditure propensity at their destination (spenders vs. non-spenders), according to socio-demographic and mobility-related variables (n = 183).

	Beta	Std. err.	Wald	p-value	Exp (Beta)
Party size = 2+	2.411	1.075	5.032	0.025	11.141
Max distance from the port = 2.5+ km	1.546	0.454	11.579	0.001	4.693
Maximum stop duration = 40+ minutes	2.843	0.583	23.794	0.000	17.166
Constant	−7.532	1.531	24.207	0.000	0.001

Hosmer and Lemeshow's goodness-of-fit test p-value = 0.908

By analyzing the results of the model in which the level of expenditure was used as a response variable (Table 7), the presence of a stop in excess of 40 min is also confirmed to be significantly associated with the level of expenditure. And the probability of spending more than €50 among those who made such a stop is >2.5 times higher than for those who made briefer stops. The other variable included in the final model is related to the use of any kind of transportation mode, which is also positively associated with the level of expenditure.

Table 7
Results of the logit model of passenger expenditure level (high vs. low expenditure) at their destination, according to socio-demographic and mobility-related variables (only for spenders n = 142).

	Beta	Std. err.	Wald	p-value	exp (Beta)
Use of any transportation mode = yes	1.308	0.450	8.436	0.004	3.698
Maximum stop duration = 40+ minutes	0.959	0.380	6.359	0.012	2.610
Constant	−1.376	0.436	9.946	0.002	0.253

Hosmer and Lemeshow's goodness-of-fit test p-value = 0.130

4.3. Cruise passenger expenditure by category

In concluding the analysis, the pattern of passenger expenditure composition was considered (Table 8). Being a first-time visitor in Copenhagen determines a higher propensity to spend more on guided tours and souvenirs; non-European cruise passengers are more likely to purchase a guided tour, compared to Europeans. Those passengers with a higher level of education are more likely to spend more on transportation services, whereas there appears to be a loose association between a planned visit and expenditure for museum and attractions (p-value = 0.053). Having performed an excursion is clearly associated with expenditure on guided tours, but also with expenditure for food and beverages.

Group size appears to be only significantly associated with expenditure on transportation, an assertion supported by the presence of children or senior citizens with special mobility needs; economies of scale could be attained with transport solutions, including the use of taxis. In contrast, age characteristics do not appear to be associated with any of the expenditure categories. By examining mobility-related variables, it can be stated that the time spent at destination is significantly associated with expenditure on food and beverages, but loosely associated with the expenditure on souvenirs. These results may indicate that those longer stops (>40 min) in the aforementioned analysis may be attributed to café and restaurant visits. Tour length and maximum distance from the port are associated with expenditure for transportation services. Finally, maximum stop duration is associated with expenditure on food and beverages and for museums and attractions. Higher speed levels, indicating the use of transportation (derived from the GPS tracking data), were also associated with expenditure on guided tours (e.g. canal boats or sightseeing buses), food and beverages and, of course, transportation services.

4.4. Analysis of cruise passenger stop locations in Copenhagen

A careful analysis of stop behaviour and stop locations highlighted the relevance of mobility characteristics on spending behaviour. Table 9 below summarizes the distribution of cruise passengers according to the number of stops and expenditure behaviour. The final column on the right confirms that all cruise passengers made at least one stop at their destination but only 8 (4.37%) cruise passengers made >9 stops (for a minimum of 2 min). The average number of stops for the whole sample exceeds five stops, with a standard deviation of approximately 2.6. And examining the distribution of the number of stops according to expenditure behaviour in Table 9, it appears that spenders have a higher propensity to make a stop, compared to non-spenders, with an average of 5.57 stops (compared to 4.56 for non-spenders). In addition, slight differences appear among spenders: the average number of stops is relatively higher for high spenders, compared to low spenders (5.78 and 5.36 respectively).

However, the number of stops per passenger may be influenced by

Table 8
Summary of the Pearson's Chi-squared test of independence of cruise passenger socio-demographic and trip-related characteristics by expenditure category.

Variables	Purchased guided tour?		Food and Beverages		Museum and Attractions		Transport		Shopping		Souvenirs	
	χ^2	*p*-value	χ^2	*p*-value	χ^2	*p*-value	χ^2	*p*-value	χ^2	*p*-value	χ^2	*p*-value
First time visitor?	7.977	**0.005**	0.035	0.851	0.125	0.724	0.075	0.784	0.085	0.771	5.144	**0.023**
Age category	2.466	0.116	0.873	0.350	0.946	0.331	0.023	0.879	1.866	0.172	0.362	0.547
Country of residence	6.383	**0.012**	0.000	0.985	0.150	0.699	0.104	0.747	0.286	0.593	1.016	0.314
Educational level	0.468	0.494	1.284	0.257	0.484	0.487	5.671	**0.017**	1.482	0.224	0.104	0.747
Net annual income	0.086	0.770	1.358	0.244	1.326	0.250	0.118	0.731	0.326	0.568	0.193	0.661
Planned trip?	0.681	0.409	0.705	0.401	3.744	***0.053***	0.028	0.868	0.171	0.680	0.499	0.480
Purchased excursion	25.613	**0.000**	8.335	**0.004**	0.187	0.665	0.057	0.812	0.960	0.327	0.876	0.349
Spending group size	1.665	0.197	0.506	0.477	0.179	0.672	4.517	**0.034**	0.234	0.629	0.576	0.448
Tour time	0.000	0.982	11.932	**0.001**	0.849	0.357	0.475	0.491	1.350	0.245	3.264	**0.071**
Tour length	0.168	0.682	0.022	0.883	1.712	0.191	4.093	**0.043**	0.977	0.323	2.534	0.111
Max. distance from the port	0.704	0.402	0.488	0.485	0.075	0.784	10.667	**0.001**	2.698	0.100	0.803	0.370
Max. stop duration	1.598	0.206	10.599	**0.001**	4.598	**0.032**	0.089	0.766	2.504	0.114	0.372	0.542
Use of any transportation mode	18.758	**0.000**	5.034	**0.025**	0.385	0.535	17.897	**0.000**	0.769	0.380	0.001	0.977

Table 9
Distribution of cruise passengers according to the number of stops made and expenditure behaviour.

Number of stops	Non-spenders	%	Spenders						Total	%
			Low	*%*	*High*	*%*	*Total*	*%*		
1	1	2.44	5	7.14	3	4.17	8	5.63	6	3.28
2	4	9.76	7	10.00	7	9.72	14	9.86	18	9.84
3	7	17.07	4	5.71	6	8.33	10	7.04	17	9.29
4	10	24.39	5	7.14	10	13.89	15	10.56	25	13.66
5	9	21.95	13	18.57	11	15.28	24	16.90	33	18.03
6	3	7.32	13	18.57	9	12.50	22	15.49	25	13.66
7	3	7.32	11	15.71	8	11.11	19	13.38	22	12.02
8	3	7.32	6	8.57	3	4.17	9	6.34	12	6.56
9	1	2.44	5	7.14	11	15.28	16	11.27	17	9.29
10–15	0	0.00	1	1.43	4	5.56	5	3.52	8	4.37
Total	41	100.00	70	100.00	72	100.00	142.00	100.00	183	100.00
Mean	4.56		5.36		5.78		5.57		5.49	
Std. dev.	1.87		2.35		2.98		2.69		2.56	

Table 10
Distribution of stops according to their duration by cruise passenger expenditure category.

Stop duration	Non-spenders	%	Spenders						Total	%
			Low	*%*	*High*	*%*	*Total*	*%*		
2–10	126	67.38	210	53.44	199	46.82	409	50.00	535	53.23
10–30	51	27.27	110	27.99	119	28.00	229	28.00	280	27.86
30–60	9	4.81	51	12.98	70	16.47	121	14.79	130	12.94
60–100	1	0.53	18	4.58	24	5.65	42	5.13	43	4.28
100–180	0	0.00	4	1.02	13	3.06	17	2.08	17	1.69
Total no. of stops	187	100.00	393	100.00	425	100.00	818	100.00	1005	100.00
Median	6.42		8.92		11.42		9.97		9.17	
Mean	9.97		17.84		22.47		20.24		18.33	
Std. Dev.	9.61		21.88		27.06		24.82		23.12	

the choice of algorithm used to identify the stops, in addition to tuning parameters (e.g., minimum stop duration, threshold speed value, etc.). On the other hand, stop duration may be a more reliable indicator, which is likely to be less influenced by the selected algorithm.

The distribution of the 1005 stops, which were made by the 183 interviewed cruise passengers, is reported in Table 10 below. Taking into consideration the whole sample, the average stop duration last for approximately 18 min. There were significant differences between spending and non-spending passengers, with the former displaying an average stop duration in excess of 20 min, compared to the latter, who did not exceed an average stop duration of 10 min. The average stop duration was also significantly higher for high-spending passengers, compared to low-spending passengers (22.47 vs. 17.84 respectively); similar differences may be observed between non-spenders and spenders. Only 33% of stops made by non-spenders lasted in excess of 10 min, compared to approximately 54% for high spenders. Only one non-spender stop lasted for >60 min (corresponding to 0.53% of the total number of stops made by non-spenders); approximately 7% of spender stops continued for more than one hour. These results suggest that it is possible to conceptually differentiate mooring vs. grazing behaviour, as characterized by specific stopping characteristics.

As a final step in the analysis of cruise passenger behaviour onshore, visual projections were created in order to capture the observed differences in stop activity and expenditure behaviour. Fig. 3a and b below illustrate the distribution of non-spending passenger and spending-passenger stops respectively; circular radii correspond to the duration of each. As confirmed by Table 10, non-spenders seem to move in more hectic patterns. None of non-spenders made stops lasting in excess of 100 min, and only one passenger made a stop of more than one hour. In terms of stop locations, non-spenders were concentrated around the Langelinie quay, visiting the free attractions in the proximity of the port: Amalienborg, Kastellet and the Marble Church. Only a few passengers

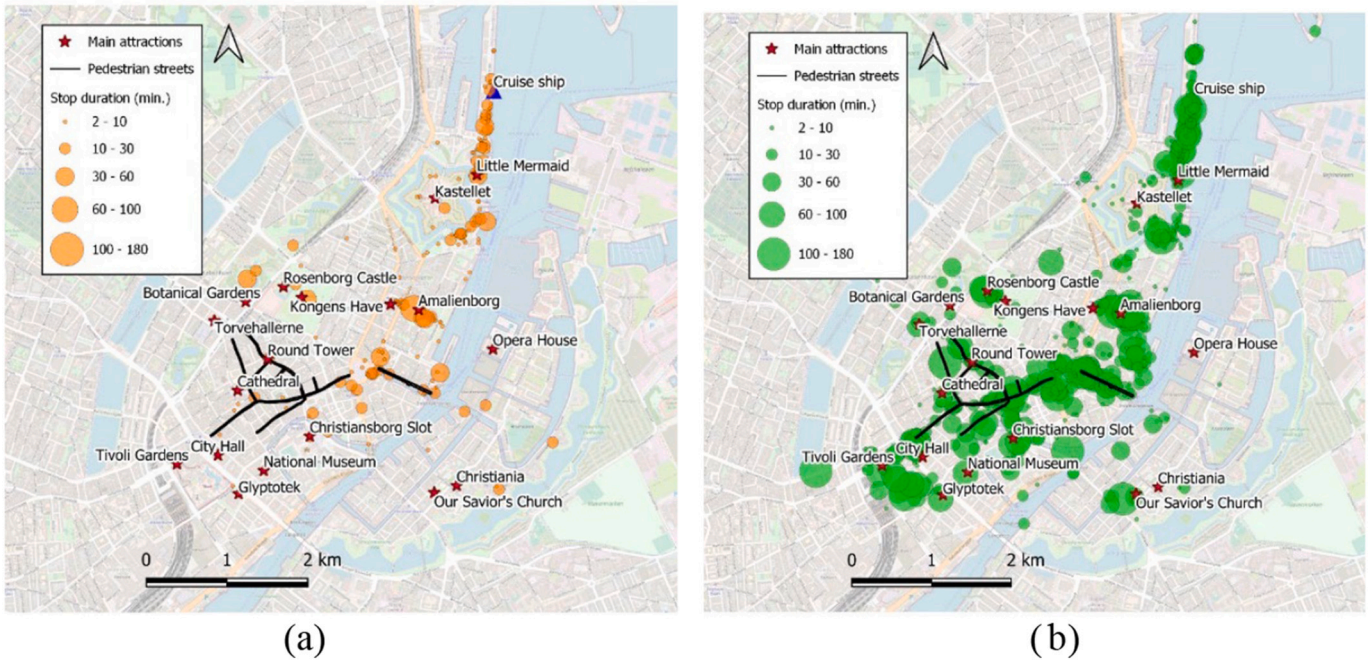

Fig. 3. Spatial distribution of stop locations for non-spending (3a) and spending (3b) cruise passengers (Base Map: OpenStreetMaps).

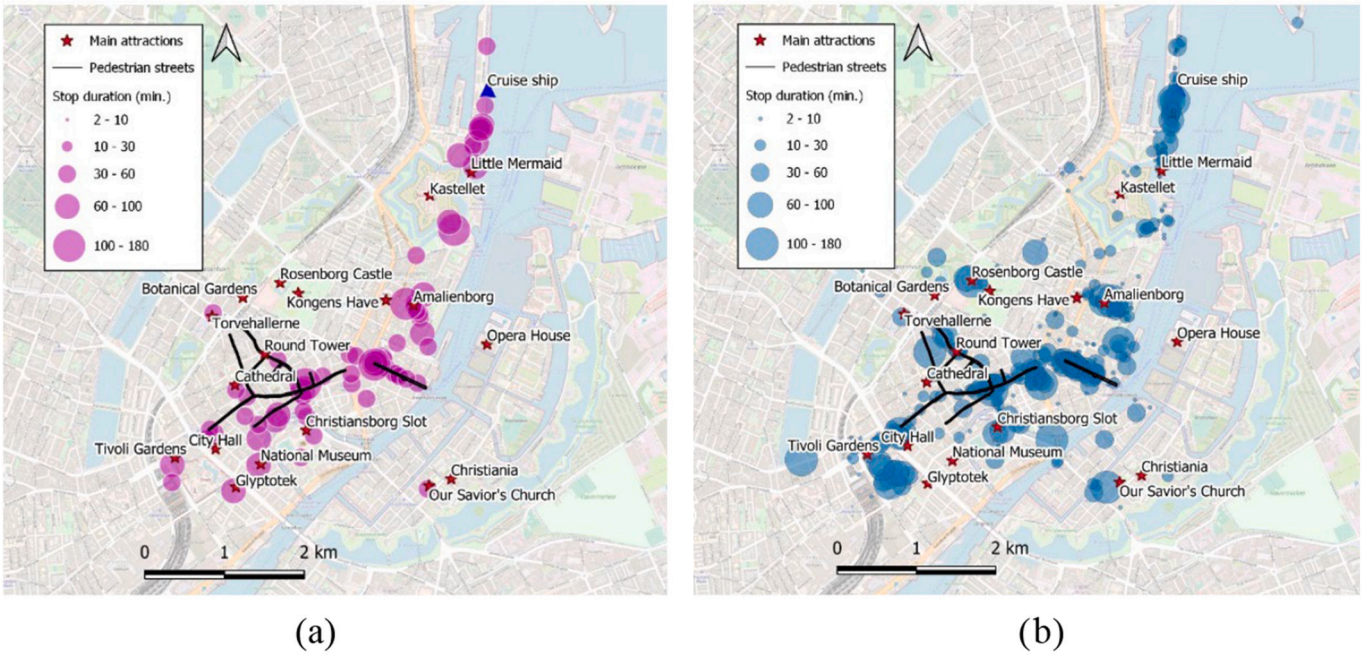

Fig. 4. Spatial distribution of stop locations for low-spending (<50€) and high-spending (>50€) cruise passengers (4a and 4b, respectively). (Base Map: OpenStreetMaps).

visited pedestrianized areas, and the stops made were brief.

A more varied pattern emerged from the analysis of spender stop locations, as confirmed in Fig. 3b. The stops are more widely scattered and distributed across the various attractions of the city (excluding the Opera House). Spenders spent more time onshore, with their stops generally being longer. All the pedestrianized areas were densely filled by stops made by spenders, who also visited attractions further from the port: for example, the Tivoli Gardens and the Glyptotek Museum).

The analytical differences in terms of spatial activity among low-spending and high- spending passengers which emerged are also visible by examining the stop locations for the two segments, that is, spending vs. non-spending passengers, and high- and low-spending passengers (Fig. 4a and b). Indeed, the intensity of stop activity is heightened for high-spending compared to low-spending passengers, and the distance of the stop location from the port is greater for high spenders. These results seem to confirm the specific findings of Domènech, Gutiérrez, and Anton Clavé (2020), namely that, high spenders spent more time in mixed activity (recreational and commercial) areas, instead of visiting the main tourist sites.

High-spending cruise passengers spent more time in the pedestrianized areas, in the proximity of the Cathedral and city hall with its ample shopping opportunities; this finding is supports the propositions

of McKercher (2018) with regards to the impact of distance on tourism mobility. It is of interest to note that, in contrast with low spenders, none of the high-spending passengers visited the National Museum or Kastellet citadel. As entrance to these attractions is free of charge, they may be particularly appealing to more frugal tourists.

5. Conclusion

The authors of this study hope that it will make a contribution in enhancing our understanding of the spatiotemporal consumption of cruise visitors. It is to be hoped that the extensive empirical material has demonstrated how tourism spending is located in geographical space, thereby indicating significant relationships between mobility and expenditure behaviour. Despite the small sample size, it was possible to establish that spending propensity is associated with spatial movement. While selected socio-demographic characteristics were found to be insufficient in explaining the scope and composition of visitor expenditure, distinct mobility characteristics (such as: distance travelled, tour and stop duration, and the use of transport) have highlighted substantial variations in expenditure levels and composition. These findings resonate well with the empirical studies, which were conducted in the ports of Tarragona (Domènech, Gutiérrez, & Anton Clavé, 2020), Valencia (Casado-Díaz et al., 2021), Hobart (Hardy et al., 2020) and Sydney (Hardy et al., 2021). Furthermore, the dispersion of stops in the destination space confirms the generic assumption that territorial characteristics and consumption are related to each other (McKercher & Lew, 2004).

5.1. Contributions and further avenues of research

This paper demonstrates the utility of geolocational analytical methods in tourism studies. It supplements the pioneering work of Hardy and colleagues, who introduced innovative indicators to illustrate the spatial dispersion of consumption on a larger regional scale. In contrast, our study offers micro-scale metrics in order to express tourist movement in terms of meaningful temporal and spatial variables. Specifically, a reliable method with which to derive stop locations and related characteristics from GPS-data has been presented. This permits the identification of hotspot locations with the highest density of spending in city destinations. The proposed analysis has also been supported by graphic visual projections of stop patterns, which have indicated distinct differences among the mobility patterns of various passenger segments (spending vs. non-spending passengers, and high- and low-spending passengers).

Nonetheless, it has not been easy to identify a causal link between stopping and spending activities. A propensity to higher expenditure may determine a greater propensity to reach more distant attractions, in addition to stops for shopping, food and beverage consumption and other activities, all of which may imply additional expense. On the other hand, the presence of consumption opportunities (shopping, catering or other attractions) may have an influence on the tourist's choice of stopping at these places and possibly spending money. However, the acknowledgement of links between expenditure and mobility suggests segmenting cruise passengers appropriately (where possible), according to spatiotemporal consumption behaviour.

Based on the substantial mobility/spending differences in the sample presented in this paper, its authors would like to suggest a simple typology, which is defined by spatial and expenditure behaviour patterns, rather than sociodemographic characteristics alone. Fig. 5 below illustrates a potential framework with four ideal-typical consumption forms, which have been derived by juxtaposing stop intensity (frequent vs. few stops) and economic yield (high vs. low spending). *Swarming* is determined by high stopping intensity and zero or low expenditure levels, where stops would most likely indicate photo stops or a fleeting glance of tourist sites. *Grazing* entails frequent stops of a short duration, which are combined with considerable total expenditure (e.g. on an organized sightseeing tour). Jaakson's (2004) "pack" and "shopping browsers" would probably follow a swarming or grazing pattern. In contrast, *mooring* and *savoring* segments demarcate mobility patterns with few longer stops, where the latter is usually associated with higher levels of spending. Such a spatiotemporal consumption style would well describe "explorers" and the "café crowd" (Jaakson, 2004), while the *mooring* behaviour describes a new segment, which could easily be observed in recreational areas (parks and benches) in urban destinations.

Future research could further delve into operationalizing and testing the four ideal-typical spatiotemporal forms, which are offered by the model in different empirical settings. In order to test this model, future studies could combine geolocational data with the sensory metrics of emotional variables (Shoval, Schvimer, & Tamir, 2018a, 2018b). External factors (e.g. time constraints, unfamiliar environments) and personal characteristics (neophilic or allocentric personality, age, physical conditions) may condition affective responses, such as stress,

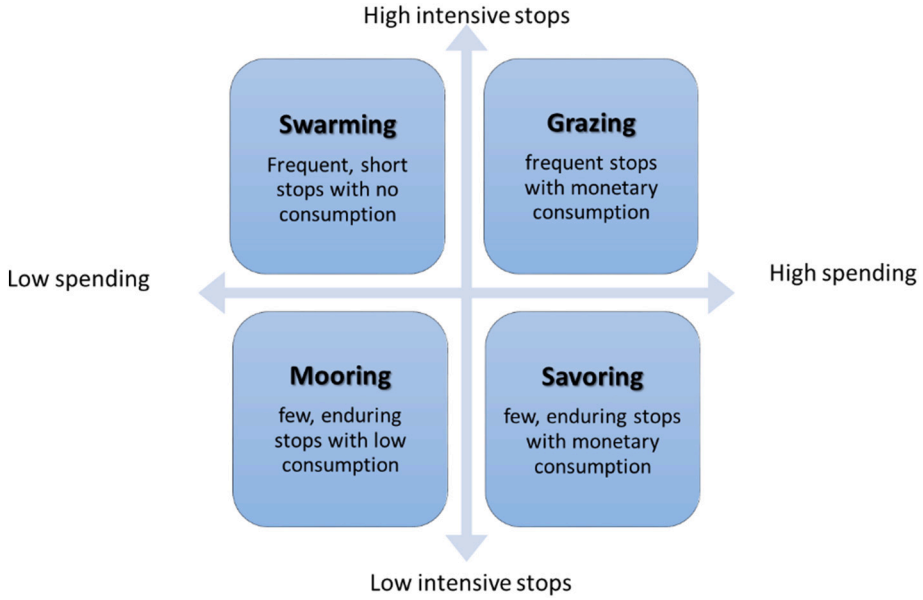

Fig. 5. Towards a typology of spatiotemporal consumption forms.

anxiety and excitement. It is likely that the arousal levels and types will differ between high and low intensity segments.

5.2. Implications for practitioners

The results presented in this paper have clearly established an association between cruise passenger mobility and expenditure behaviour. Three insights are of interest to destination marketers and planners, whose aim is to make cruise tourism more sustainable after the COVID-19 pandemic. Firstly, it has been verified that cruise passenger expenditure increases with more intense mobility characteristics (in terms of a greater distance from the port, tour length and duration), and this resonates well with the findings of De Cantis et al. (2016) and Hardy et al. (2021). Secondly, stop intensity is also associated with expenditure, and higher-spending passengers stopped more frequently and for a longer time than non-spending and low-spending passengers. Thirdly, a visual mapping of stop locations indirectly highlights where most expenses are likely to be concentrated in the urban landscape, also in terms of expenditure category. Mapping stops may assist in the identifying bottlenecks of crowd concentrations and areas flocked by tourists, in addition to highlighting less visited attractions and shadow areas. Combining new insights into mobility intensity and stop locations may also contribute to redefining the tourist landscape and smoothen the beaten track corridors in urban destinations.

The associations thus far identified in this paper between walking behaviour, stops and expenditure in the city of Copenhagen suggest that the presence of more varied expenditure opportunities (not only souvenirs) in the vicinity of the port may increase the visitor duration of onshore visits and spending propensity. Drawing on the observations of Domènech, Gutiérrez, and Clavé (2020) regarding the role of the built-up environment, improved the signposting to nearby attractions and shopping streets in the residential neighbourhood of Østerbro could alleviate the pressure of tourist traffic in the congested areas and balance spatial consumption patterns. Finally, the authors of this paper would like to propose that planners facilitate the introduction of accessible onshore experiences in the form of bookable activities; this would also increase the economic benefits of cruise tourism to local businesses. Innovative initiatives (involving encounters with the local community), personalised guided tours, targeting small groups, or thematic retail experiences could offer competitive alternatives to existing standard packages.

5.3. Limitations

Reflecting on the limitations of this study and future research, an inherent difficulty relates to the collation of data relating to tourist expenditure. Whilst its collating at the termination of a passenger's onshore visit may reduce recall bias, and, therefore, avoid the risks of modifying the expenditure patterns, compared to diary reporting (Faulkner & Raybould, 1995; Shoval & Isaacson, 2007), the presence of errors due to omissions (under reporting) and telescoping (over reporting) are difficult to avoid (Breen et al., 2001). With this in mind, the use of Citycards (prepaid or discount cards with chips) or mobile devices afford many new opportunities with which to enhance the data collection relating to tourist expenditure. And this is notwithstanding the current paucity of evidence of effective ways for integrating these new technologies into survey data collection (Jäckle, Burton, Couper, & Lessof, 2019). A second limitation regards the choice of metrics used for summarizing passenger mobility at their destination, as obtained with GPS tracking data. A set of significant indicators has been used in this paper but much more information could be derived from raw GPS data, the selection of which depends on the research aims. Similar considerations may also be made regarding the algorithm used for stop identification, in addition to the values used for tuning parameters. Such considerations, regarding the use of the total number of stops, herald a note of caution in favour of more reliable information, as derived from a categorization of stop duration. It has not been possible in this study to link stop location information with the type of expenditure effected. Indeed, there is a need for comparative studies, focusing on linking observations to cruise passenger stop activity and related expenditure at different destinations. The development of algorithms, which are capable of linking the most probable places to be visited by cruise passengers and based on stop location coordinates, could provide information regarding the exact locations in which expenditure was made, thereby signalling future avenues of research.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.annale.2022.100059.

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Caterina Sciortino, PhD-student in behavioral economics and tourism at the Department of Business, Economics and Statistics, University of Palermo.

Mauro Ferrante, Assistant Professor in Social Statistics, University of Palermo. His research focus on GIS applications in tourism.

Stefano De Cantis, Associate Professor in Social Statistics, University of Palermo. His expertise lies in quantitative, multidimensional methods in tourism.

Szilvia Gyimóthy, Associate Professor in Marketing, Copenhagen Business School. She specializes in cultural aspects of tourism flows.