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FULL LENGTH ARTICLE

Measuring reactions to congestion in the digital era

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A B S T R A C T

Cities are experiencing accelerated growth in visitor numbers to the point of overcrowding, raising concerns about negative effects on both destinations and residents. Academic discourse on overtourism primarily addresses environmental damage, infrastructure overload, and resident dissatisfaction, often overlooking how tourists experience overcrowding. When examined, tourist experiences have predominantly been measured using subjective self-report tools such as questionnaires and surveys.

This study addresses this gap by introducing an objective, real-time, multi-method framework that integrates spatiotemporal tracking, wearable physiological sensors, and mobile eye-tracking to assess visitors' emotional and visual responses to various conditions of density and congestion outside the laboratory. Although the pilot experiment was conducted with local participants due to international travel restrictions during the COVID-19 pandemic, the methodology developed is relevant for broader application to tourist populations.

Results show that high visitor numbers affect visitors' emotional states and visual attention. Furthermore, the study proposes that the aforementioned methodology can be applied not only for the dependent variable, that is, emotional arousal, but for the independent variable, density and congestion, as well. By presenting the tourist gaze as a dynamic metric to measure density and congestion, the study advances theory and offers tourism destination managers and urban planners' tools to cope with overcrowding and enhance the tourist experience.

Introduction

Academic research on density and tourist congestion has a long history, especially since tourism has become a mass phenomenon (Cohen, 1972). Research includes classic models that describe the change in local populations' responses (Doxey, 1975); the changed life cycle of the tourist destination (Butler, 1980) as dependent on the destination's number of visitors; and the use of tools and methods for estimating visitor flow to heritage cities in order to moderate it (Van der Borg et al., 1996). In the past decade, the discussion of density, crowding and congestion at tourist destinations has returned to the fore and has been reframed using the term “overtourism” (Capocchi et al., 2020; Dodds & Butler, 2019), but this discussion has primarily focused on the destination's perspective and the phenomenon's effect on the local population (Yu & Egger, 2021). How tourists experience and perceive acute congestion has received relatively little attention (Neuts & Nijkamp, 2012).

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Though we tend to relate to the two as synonymous, "density" and "crowding" are distinct. While the former is purely objective and quantitative, presenting the relationship between the number of people and a specific area, the latter includes the individual's subjective understanding of objective conditions and attributes negative dimensions of pressure to it (Stockdale, 1978; Stokols, 1972). To enhance the tourist experience, researchers aim to measure visitors' emotional responses concerning density and congestion conditions, commonly referred to as crowding or perceived crowding. These assessments typically rely on subjective measures of visitor satisfaction and behavioral intentions, including willingness to revisit or recommend the destination (Kohlhardt et al., 2018; Popp, 2012). However, empirical studies have struggled to confirm the link between perceived crowding and satisfaction, with coping mechanisms often used to explain these gaps (Li et al., 2017).

The integration of physiological and objective measures monitoring individuals' unconscious emotional arousal with methods identifying movement patterns in time and space can help bridge the methodological gap and expand researchers' and tourism destination managers' understanding of the tourist experience in conditions of density and congestion. The tourist experience has been studied through various disciplinary perspectives, leading to the development of models, typologies, and dimensions within the tourism field (Scott & Dung Le, 2017). Larsen (2007) has suggested examining it from a psychological perspective using a time-based distinction between expectations (feelings before the visit), perceptions (feelings during the visit/event), and memories (feelings after the visit).

Renewed interest in the emotional dimension of the tourist experience is tied, inter alia, to technological developments in the field of cognition and psychophysiology; over the past decade, these have begun to be applied to tourism research as well (Kim & Fesenmaier, 2015; Li et al., 2015; Reif & Schmücker, 2021; Shoval, Schvimer, Tamir, 2018a; Shoval, Schvimer, Tamir, 2018b). These developments make it possible to supplement subjective affective measurements—which depend, for the most part, on verbal surveys, questionnaires, and interviews (Li et al., 2015)—with objective, quantitative measures that monitor the visitor's unconscious arousal at the destination. Despite the recent increase in physiological measurement in tourism research and the opportunities it affords us for wireless measuring, most research applying this type of assessment has been conducted in static and controlled laboratory setting (Walters et al., 2023).

Recently, scholars have proposed integrating advanced tracking technologies in tourism demand measurement (Mashkov & Shoval, 2023). Their more continuous, precise, and sensitive presentation successfully addresses the central pitfalls of traditional density and intensity metrics. However, such measures do not reveal the meaning of different levels of densities for the individual, nor do they provide information about the individual's perception of crowding (Stockdale, 1978). To preserve visitors' objectivity, on one hand, and to include their perspective, on the other, this study has uniquely employed embodied physiological research methods to examine the impact of density and congestion on the emotional experience of tourists. While traditionally, emotional responses were assessed subjectively, we propose an integrated methodology for objectively evaluating density and congestion, emotional arousal, and the connection between the two.

Alongside the spatial and temporal information, physiological data about electrodermal activity were collected in real-world conditions to measure the dependent variable: objective emotional response. Additionally, eye-tracking methods were applied to measure the independent variable: density and congestion (see Fig. 1). Two central research questions guided this study: (1) How does density affect the emotional tourist experience? (2) Can density and visitors' emotional response to it be measured in an objective and continuous manner, and if so, how?

By integrating spatial, temporal, physiological, and behavioral data, this study aims to enhance the objectivity of measuring density, congestion, and the emotional responses they evoke. While the methodology was designed with tourist settings in mind, the

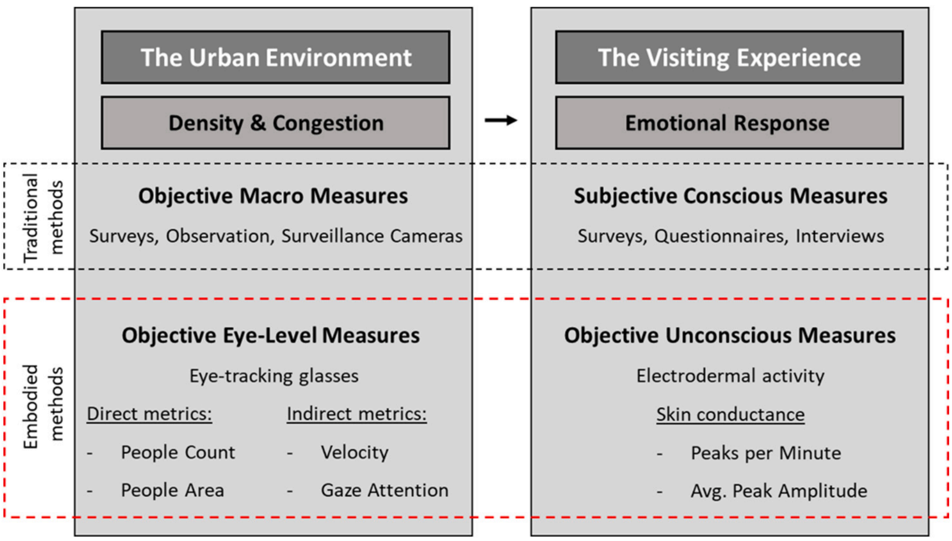

Fig. 1. Conceptual model.

study was conducted with local participants due to travel restrictions at the time. This pilot enables the methodological framework to be tested in real-world urban environments, laying the groundwork for future research with actual tourist populations.

Literature review

The emotional aspect of the tourist experience

The tourist experience is a central topic in tourism research, with discourse dating back to the late 1960s (Uriely, 2005). Early studies examining the tourist experience as one unit of analysis, synonymous with the entire trip. Thus, the motivation for a visit was studied more generally, primarily focusing on the destination's external features (Scott & Dung Le, 2017), while the tourist's personal and emotional characteristics were almost nonexistent (Scott & Dung Le, 2017; Uriely, 2005). Cohen (1972) challenged this view, introducing five experience modes—the recreational, the diversionary, the experiential, the experimental, and the existential—reflecting the meaning of the experience for the visitor, especially in the context of the tourist's relationship to local society and desire to interact with it.

In the 1990s, more researchers began to use experience-based approaches in an effort to better understand the dynamic, varied, and tailor-made nature of the tourist product (Cutler & Carmichael, 2010). Within the range of definitions for the tourist experience (see Cutler & Carmichael, 2010; Scott & Dung Le, 2017), we focus on Page et al.'s (2001) definition: "a complex combination of factors that shape the tourist's feeling and attitude towards his or her visit."

Larsen (2007) views the tourist experience as a psychological process shaped by expectations before the trip, emotional perception during the core experience, and memory afterward, influencing overall evaluation and future travel intentions. From a spatial-geographical perspective, the core experience has occupied many scholars who wished to document the visitor's spatial and temporal activity in a destination, based on the assumption that visitors' movement patterns and spatial consumption form the basis for evaluating the tourist experience (Hardy, 2020; McKercher & Lau, 2008; Shoval & Isaacson, 2009). Moreover, understanding how tourists move in time and space and the factors that influence their movement have important implications for the development of the tourist product as well as the planning and management of a destination (Lew & McKercher, 2006).

Three central methods exist for documenting visitors' spatial and temporal activity in a destination: methods based on observation, methods based on surveys and interviews (for elaboration see: Shoval & Isaacson, 2007; Shoval & Ahas, 2016; Hardy et al., 2017; Hardy, 2020). Digital tracking methods have been adopted over the past two decades thanks to their ability to collect plentiful and precise data passively and without bias (Hardy, 2020; Shoval & Ahas, 2016). Recently, researchers have proposed integrating these methods with tourism demand measures for the first time, creating a tool for assessing and dealing with extreme conditions such as tourist saturation and overtourism. The proposed intensity-density index facilitates high-resolution and less biased reporting than was common in the past (Mashkov & Shoval, 2023).

Physiological methods for monitoring emotional responses have begun to be applied in parallel to the digital methods described above. These have three significant advantages: the physiological data present objective, unbiased responses; they capture unconscious responses; and they are collected in real time, continuously, with no need to rely on memory (Walters et al., 2023). Common physiological methods include eye-tracking, the skin's electrodermal activity, the brain's electrical activity, heart rate, and facial recognition. Some of the proposed methods use ambulatory, wearable sensors, making monitoring changes in mental state possible even outside of laboratory conditions in the real world (Birenboim et al., 2019).

Walters et al. (2023) reviewed 83 articles in tourism research that applied various physiological methods (2011−2023); Li et al. (2022) surveyed 25 articles in a similar period (2012−2021), but focused on the skin's electrodermal activity; and Savin et al. (2021) surveyed 70 eye-tracking studies (2007–2020). These review articles illustrate the growing popularity of physiological methods in tourism over the past decade. Nonetheless, sample sizes are relatively small, attesting to obstacles in cost and expertise. Most of the studies that have used eye-tracking, it appears, did so in laboratory conditions and with static stimuli. Wearable sensors have made the use of electrodermal activity more accessible in relation to other physiological measures outside of the laboratory and in real-world conditions.

The impact of density and congestion on the tourist experience

Density and crowding have a bidirectional contribution to the tourist industry. On the one hand, they signify the destination's popularity and demand (Petr, 2009); on the other hand, exceeding capacity can detract from the destination's attractiveness, impact residents' quality of life, and degrade tourists' experiences (Gabe, 2021). Density is a quantitative measure related to the number of items or units that inhabit it (Stockdale, 1978). In the social sciences, "social density" refers to the ratio of people to a geographical setting (Papadopoulou et al., 2023). This objective definition has made it a popular metric across fields. However, it is often critiqued for not fully capturing the human experience or accounting for varying density levels (Stockdale, 1978).

From a psychological perspective, it is important to distinguish between density, a measure that is neutral emotionally and defined based on spatial parameters alone, and crowding, which describes the individual's subjective experience concerning physical conditions. Crowding is a product of spatial, personal, and social limitations and is typically associated with negative affective responses, such as stress (Papadopoulou et al., 2023; Stockdale, 1978; Stokols, 1972).

Two central psychological theories explain these negative responses: The Social Interference Theory and the Stimulus Overload Theory. The Social Interference Theory posits that crowding is perceived negatively when physical restrictions in space interfere with the individual's freedom of movement and choice. The Stimulus Overload Theory focuses on the cognitive burden resulting from stimulus overload, perceiving crowding negatively when it exceeds individual tolerance (Kalisch, 2012; Li et al., 2017; Stockdale, 1978).

The term overcrowding assumes a maximum threshold for mental carrying capacity. In contrast, congestion, primarily from traffic and transport fields, describes a state of usage load that exceeds a street's capacity (Jia et al., 2022). Interpersonal space—defined as a protective boundary between individuals—is used as an additional metric to measure social density. Physical proximity and infiltration of personal space can elicit negative feelings such as anxiety, lack of control, and fear (Gabe, 2021; Jacobson et al., 2019).

Fruin (1970) introduced a method for calculating pedestrian densities using a Level of Service metric based on pedestrian flow rate, walking velocity, and density. This method confirmed the classic hypothesis of a negative correlation between density and walking velocity—higher pedestrian volumes lead to decreased spacing and slower walking speed. However, it did not capture pedestrians' dynamic behavior (Jia et al., 2022).

Five decades later, technological advances allow for more precise, continuous density measurement. Jia et al. (2022) proposed a local density method using Peri-Personal Space to measure variability in pedestrian personal space through above-ground video. Their method identified a low-density, low-velocity phenomenon, where slow walking velocity corresponded with low local density. In the tourism context, people count is a key metric for assessing not only density and congestion but also overall tourist flows and tourism demand (Buitrago & Yñiguez, 2021). Recently, alongside traditional tourism surveys, researchers have been integrating advanced technologies, including image analysis of surveillance cameras (Li, 2020) and technological sensors to detect wireless signal traces (Santos et al., 2024).

One of the key ways to examine the impact of crowding on tourists' emotional response is through satisfaction level. While the classic hypothesis suggests a direct correlation between social density, perceived crowding, and visitor satisfaction, empirical studies show inconsistent results (Kalisch, 2012; Kohlhardt et al., 2018; Li et al., 2017; Yu & Egger, 2021). The variability in findings can be attributed to methodological limitations, including how perceived crowding is defined and measured (Cheng et al., 2021; Neuts & Nijkamp, 2012; Pons et al., 2014; Yu & Egger, 2021) and the almost exclusive use of satisfaction as an assessment tool (Kohlhardt et al., 2018; Li et al., 2017; Papadopoulou et al., 2023).

Moreover, studies highlight psychological-behavioral coping mechanisms tourists use to mitigate interference with their experience in crowded settings. These mechanisms include behavioral methods such as displacement and changes in usage patterns as well as psychological strategies such as rationalizing and perceptual-cognitive defense to reduce stress and dissatisfaction (Jacobson et al., 2019; Li et al., 2017; Pons et al., 2014; Kohlhardt et al., 2018; Papadopoulou et al., 2023). These strategies underscore the need for a multidimensional approach that considers space, time, affect, and gaze to better capture and understand the tourist experience in

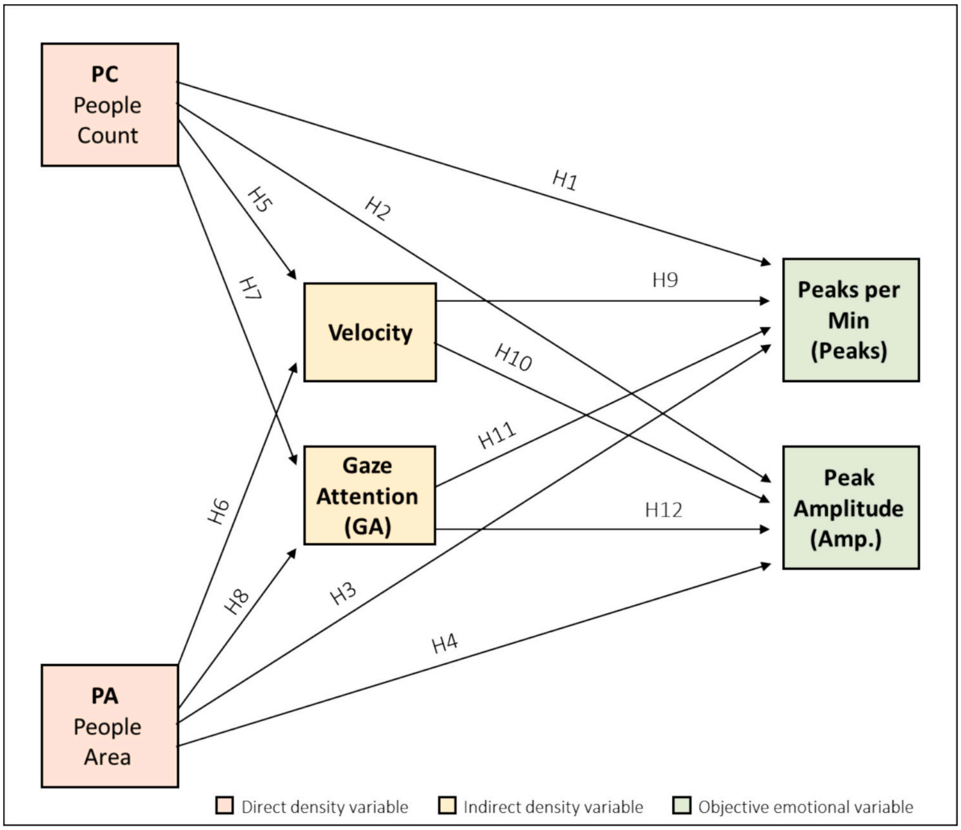

Fig. 2. Diagram of hypotheses.

crowded urban destinations.

Hypotheses development

Three sets of hypotheses were developed concerning the first research question.

The first examines the correlation between direct density variables and objective emotional arousal, positing that as direct density rises, so will emotional arousal ($H_{1–4}$). Previous research has shown mixed results with regard to the influence of crowding on tourists' emotional experience (Kohlhardt et al., 2018; Neuts & Nijkamp, 2012). We posit that objective measurement of emotional arousal will minimize coping mechanisms and display significant, strong correlations. Moreover, it is hypothesized that the direct density measure "People Area", which represents the proximity between visitors, will show the highest correlation with objective emotional measures ($H_{3–4}$), in contrast with the "People Count" measure (H_{1-2}). This hypothesis corresponds with the academic literature that distinguishes between density and local density (Aguayo et al., 2023; Jia et al., 2022); when the latter is violated and there is high level of invasion of the individual's personal space, emotional arousal is expected to be high and negative (Christou et al., 2015; Jacobsen et al., 2019). Similarly, while "People Area" will maintain a high positive correlation with emotion, "People Count" may also display a high number of people at a distance, in which case, emotional arousal levels will be lower.

To confirm the use of indirect density variables, a second set of hypotheses explores their correlation with the direct density variables. It is hypothesized that a strong negative correlation will be found between direct variables and walking speed; as the number of people in a frame and the area taken up by people in a frame grows, walking speed will fall ($H_{5–6}$). This corresponds to Fruin's pedestrian Level of Service model (Fruin, 1970), which posited that congestion translates into slow walking (Gabe, 2021). Moreover, a strong positive correlation is expected between direct density measures and the rate of the gaze's focus on people; as the number of people in a frame and the area of people in a frame rise, the gaze focused on people will grow ($H_{7–8}$).

Finally, the third set of hypotheses investigates the correlation between the indirect density variables and the objective emotional measures. It predicts that a strong correlation will be found between indirect density variables and objective emotional arousal. That is, as the speed of walking falls, the objective emotional arousal will rise (H_{11-12}). Fig. 2 presents the diagram of hypotheses related to this research question.

With regard to the second research question, it is hypothesized that the proposed methodology—which integrates space-time monitoring, emotional arousal, and gaze—can be used as a tool, not only to measure density and congestion but also to gauge visitors' emotional responses to them. Technology that was not available in the past makes it possible for researchers and policy-makers to collect unique, credible, continuous data and, at the same time, to expand their knowledge about the tourists' emotional experience in urban spaces, specifically as it relates to different levels of density. Aside from the theoretical contribution, these findings have the power to improve the visiting experience in urban destinations and make it more efficient in relation to other urban features as well.

Methodology

Methods and instruments

A multidimensional methodology was applied to address the research questions and examine the effect of density and crowding on visitors' affective responses. This methodology integrated physiological sensors with digital tracking in real-life conditions. Visitors' movement patterns in the destination were recorded using a GPS smartphone application, capturing both movements (linear paths between locations) and stays (duration at specific points), the two components of tourist flow (McKercher & Lew, 2004). Objective affective response was monitored using a Shimmer3 GSR+ wearable physiological sensor that documents electrodermal activity. Electrodermal activity is also known as galvanic skin response. It defines autonomous changes in the skin's electric characteristics using dependent variables such as *Peaks per Minute* and *Average Peak Amplitude* (for more details about this method, see Boucsein, 2012; Braithwaite et al., 2013, and Aqajari et al., 2020).

A third research tool used was TobiiPro 2 eye-tracking glasses (https://Tobii.com). As the name suggests, the method tracks observers' eye movements in relation to given scenes—what and where they looked, for how long, the route their eyes took, and so on. Eye-tracking furnishes an opportunity to assess visual attention and even hint at how people perceive their environment (Duchowski & Duchowski, 2017).

Using eye-tracking glasses, visual and temporal data were collected; crowding and density measures were calculated objectively,

Table 1
Summary of instruments, measurements, and metrics.

Metrics	Measurement	Instrument
Duration Passage	Temporal and spatial flow	GPS Smartphone app
People Count People Area	Direct density and congestion	TobiiPro 2 Eye Tracking Glasses
Gaze Attention Velocity	Indirect density and congestion	
Electrodermal activity (Peak per Min) Electrodermal activity (Avg. Peak Amp)	Physiological, emotional response	Shimmer3 GSR+

and from the visitors' point of view. Four quantitative metrics were extracted: two direct and two indirect. The direct density measures—*People Count* and *People Area*— reflect social density, focusing on the number and proximity of individuals in time and space. The indirect metrics—*Velocity* and *Gaze Attention*—serve as objective proxies for visitors' perceptions of crowding, capturing motor and visual behaviors, such as walking pace, and rate of gaze focus on people as a function of the level of congestion in the space. This research method collected quantitative data for the two research questions.

Table 1 summarizes all methods, instruments, and metrics used in the research.

Research design

Site and research population

The research was conducted at Machane Yehuda, western Jerusalem's central food market. The market is located near the city's central business district and is bounded by Agrippas Street and Jaffa Street, one of Jerusalem's primary thoroughfares, which stretches from the city's entrance to the Old City gateway (see Fig. 3).

Over the past fifteen years, the market has undergone retail gentrification and touristification, becoming a popular destination among locals and tourists (Mashkov & Shoval, 2020). The expansion of its functions to include recreation and leisure has created high visitor flow, characterized by fairly consistent peak and low hours. This characteristic facilitates the study of density and crowding in urban tourism spaces.

Spatially, the experiment focused on Etz Haim Street. Its relatively narrow width (roughly 2 m), the food stands along both sides, the light roofing, and the well-defined entry and exit points bounded the experiment space naturally, making it possible to recreate the visiting experience for different participants as optimally as possible outside a laboratory setting, and even increased the perceived crowding.

Twenty-five participants were recruited for the experiment, all Jerusalem-based students. The vast majority were undergraduate students in their twenties (average age 26), with an almost equal gender division (52 % women and 48 % men). The relatively small research population resulted from a desire to examine the feasibility of the multidimensional methodology. Efforts were made to keep the research population as homogenous as possible to minimize variance between participants. It should be noted that the group was not meant to represent the tourist population but rather to demonstrate the proposed methodology. In addition, participants were selected in accordance with the limitations of the tracking devices; they did not wear glasses or contact lenses, and their health was satisfactory (confirmed via recruitment questionnaire, including sufficient physical fitness to walk comfortably for approximately 30 min).

The experiment

A within-subjects experiment was designed, in which participants performed a repeated walking task under two varying density conditions. Each participant walked twice along a predetermined route in the market (see Fig. 3). Data collection was conducted over three weeks (Aug 23–Sept 14, 2021), with daily maximum temperatures ranging between 28 °C and 32 °C. This design helps minimize the effect of physiological differences between individuals (Boucsein, 2012) and increases the statistical power. The experiment included five stages: briefing and consent, a preliminary questionnaire, the first walk, the second walk, and a summary questionnaire. In the first stage, participants received an explanation about the experiment, its procedures, the tracking devices they would carry, and the optimal way to carry them. This stage also included signing a consent form. In the next stage, participants completed a preliminary questionnaire online (see Appendix 1.A) that included general questions for characterizing the participant, consumer habits, and prior perceptions of crowding.

In the third and fourth stages, participants undergo a short walking task along a fixed 220-m route on Etz Haim Street (mostly flat). Equipment, instructions, and tasks were identical in both sessions, differing only by time: morning and early afternoon. The morning walks took place first between 7:00 and 9:00 a.m. (or 7:00 to 8:00 a.m. on Fridays), during the market's quiet hours as it was just opening and free of visitors (off-peak). The afternoon walks took place second between 12:00 and 3:00 p.m. (or 10:00 a.m. to 3:00 p.m. on Fridays), during the market's busiest hours when it was crowded with visitors (peak hours). Walking times were defined in accordance with visitors' flows at the market. While no official pedestrian flow statistics were available for this specific setting, our classification aligns with daily market rhythms, validated through observational assessments and vendor interviews.

During each walk, participants wore various monitoring devices adapted and calibrated for each. The route itself was divided into five standing points, where participants were instructed to stop for 2 min to experience the space (see Fig. 3). The first and fifth standing points—located outside of the market—served as “baseline” and “relaxing” points. The remaining standing points—second, third, and fourth—were located at the entrance to Etz Haim Street (from Agrippas Street), the center, and the exit (towards Jaffa Street), respectively. After each stop, participants completed a short, repetitive online questionnaire (see Appendix 1.B) on arousal level, affective valence, and sense of security. At the end of the walk and after they were disconnected from the devices, participants completed an additional online questionnaire (see Appendix 1.C) asking them to detail their feelings during the walk inside the market.

In the fifth and final stage, participants completed a concluding questionnaire (see Appendix 1.D) comparing the two walking experiences and questions related to the COVID-19 pandemic and its effect on perceived crowding. Participants who completed both experiment sessions received monetary compensation (~$20 US).

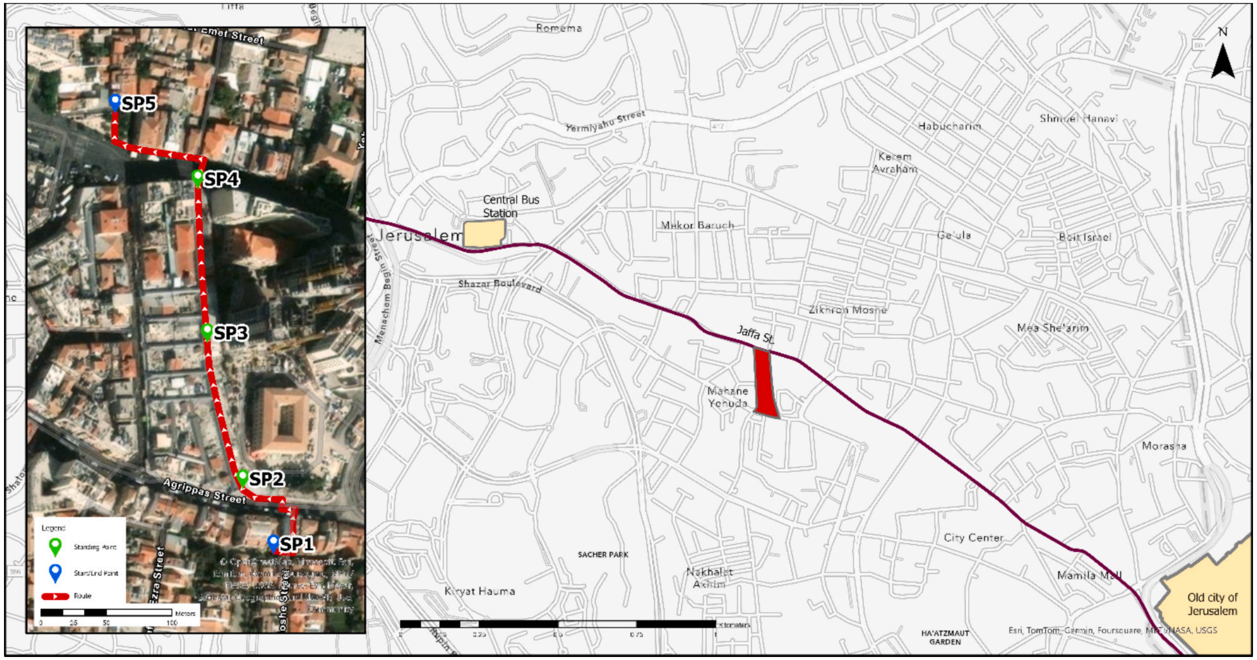

Fig. 3. Location of the market and walking route.

Research data

Spatial-temporal data

Spatial and temporal data were collected by a GPS application on the participants' smartphones, which was used to answer online surveys. As the experiment was conducted on a street with light roofing, the GPS data were not always continuous. In such cases, data were supplemented using video output from the eye-tracking glasses, making it possible to find each participant's spatial location at a given point in time. The duration measure was adjusted using the street's length to define Velocity (see next section). The passage measure was unnecessary in the given case, as the experiment was designed with fixed standing points in both location and time. However, future experiments, with participants who move spontaneously, may find that this measure holds great significance (see Section 5.2).

Density and congestion data

Direct and indirect density measures were collected using eye-tracking glasses. Participants wore TobiiPro Glasses 2, equipped with five cameras: a high-definition scene video camera positioned on the forehead on the external part of the glasses captures a wide-angle view of everything the participant sees, and four eye-tracking sensors—two per each lens—positioned on the internal part of the glasses to record eye orientation (see Fig. 4). Data from the glasses were recorded using iMotions software (https://imotions.com), enabling synchronized collection from multiple physiological sensors.

Preliminary manual processing used the iMotions software to identify and annotate key sequences. For each walk, six annotations were identified: five two-minute sequences representing the duration of each standing point and a sixth sequence representing the duration of the total walk (morning or afternoon walk). The sequence's duration varied in the walks in accordance with walking speed. Given the temporal character of the marked sequences using digital tracking by GPS, it was possible to calculate walking speed by dividing the length of Etz Haim Street (approximately 220 m) by the overall walk duration minus the cumulative time spent at the three standing points:

$$\frac{Distance\ (meter)}{Total\ Walk\ time\ \ (min) - Standing\ Point\ time\ (min)}$$

Walking speed is influenced to a great degree by visitor congestion, creating a physical limitation in space; it was therefore defined as an indirect crowding variable (Velocity, or V).

Additional processing took place using artificial intelligence. A Python script was developed (see Appendix 2) to extract the two direct density metrics: People Count and People Area. The script applied a deep learning-based approach and used the OpenCV library that provides a comprehensive set of algorithms for computer vision tasks, including detection and recognition.

The script included the following steps:

First, frames from the original videos were extracted systematically, every 300 frames, that is, 10-s intervals for videos recorded at a frame rate of 30 frames per second. In accordance with the sequences defined, between 60 and 94 frames were received for each walking route.

Second, each extracted frame underwent automated analysis to identify and count the human objects (the certainty percentage was defined at 70 %). The number of detected individuals was recorded as the “People Count” measure and is presented in absolute numbers. The script then calculated the overall area covered by human bodies. A bounding box describing each human object's spatial location in the frame was used for this calculation. The “People Area” measure was calculated by dividing the total area occupied by the detected objects (subtracting overlapping areas) by the total area of the frame; it was presented in percentage. Fig. 5 compares these two direct crowding measures for participant no. 8's two walks.

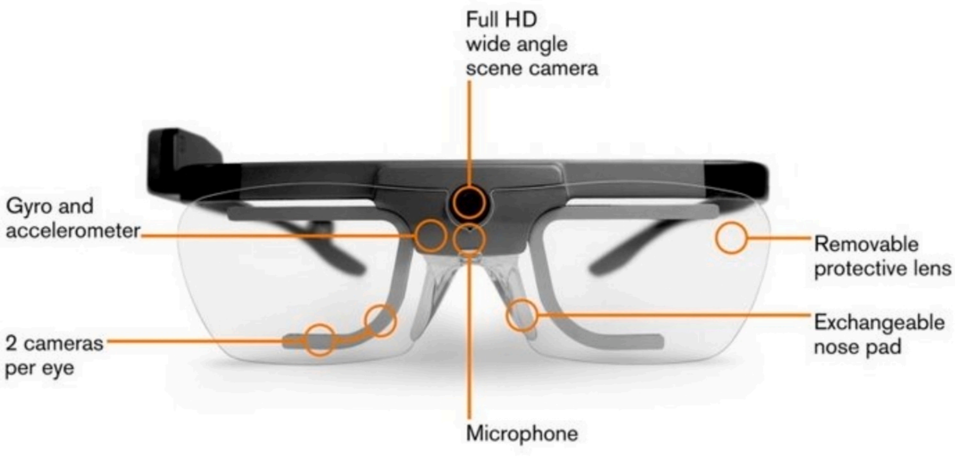

Fig. 4. Head-unit scheme of TobiiPro 2 eye-tracking glasses (from https://Tobii.com).

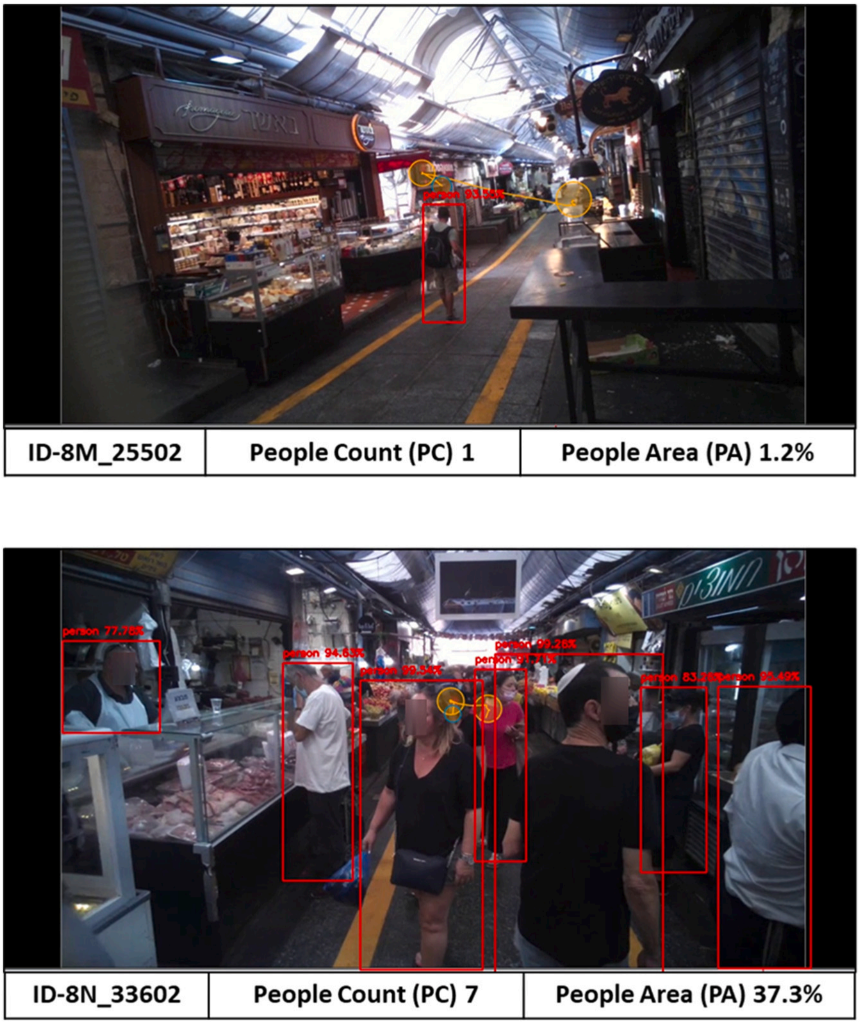

Fig. 5. Participant No. 8's walks in the Machane Yehuda market, with two varying density levels (top: morning walk; bottom: afternoon).

Finally, each extracted frame was classified in relation to the visitor's visual attention, that is, the central element in the space that captured his eye. This was possible thanks to the original video output's report of the gaze itself. For this purpose, five types of "gaze target" were defined: *structural gaze*, such as floors and ceilings; *consumer gaze*, for marketplace products; *human gaze*; *digital gaze*, for

Fig. 6. Examples of the five classifications of visual attention, each marked with a blue circle; from left to right: structural gaze, consumer gaze, human gaze, digital gaze, and external gaze. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

cellphones; and *external gaze*, for gazes outside the market. Fig. 6 illustrates the five different types, with the blue circle in each picture noting the participant's gaze target at a given point in time. This analysis made it possible to calculate the Gaze Attention measure, both as a categorical variable (average gazes for each category) and as a continuous variable presenting the rate of human gaze within all of the gaze targets (in percentages).

Emotional arousal data

Objective affective responses were monitored using the Shimmer3 GSR+ for biosensing, which measures Galvanic Skin Response). The Shimmer3 GSR+ is a wearable physiological sensor that facilitates the continuous and mobile evaluation of emotional arousal in real-world conditions (Trull & Ebner-Priemer, 2013). By transmitting a low electric flow between two skin contact points and measuring the difference between the two, electrodermal activity is recorded. A pair of electrodes were attached to the hand's inner proximal phalanges on the index and middle fingers (see Fig. 7).

The raw Electrodermal Activity signals collected included two metrics: Skin Conductance and Skin Resistance. The data from the Shimmer3 GSR+ were sampled at 1024 Hz and transmitted to the iMotions software using Bluetooth (in parallel to the visual data from the eye-tracking glasses). Although participants carried a laptop for data streaming on their backs, some 8 % of all data collected by the Shimmer3 GSR+ was incomplete (see Appendix 3). Moreover, irregular observations were removed using statistical calculations of the interquartile range.

The phasic component was extracted from the tonic one to identify peaks. Data processing included several phases. Ledalab software, a free software based on MATLAB, was employed for the processing and analysis of Skin Conductance data (http://www.ledalab.de). To simplify processing and analysis, a much lower sampling rate than the original one can be used without affecting the data (Aqajari et al., 2020). The first stage, therefore, was comprised of downscaling the sampling rate to 16 Hz and cleaning and correcting the Galvanic Skin Response data for visual artifacts identified in the sequence; these might have been caused by participants' movements and/or the movement of electrodes from their place (Xia et al., 2015). The next important step was the decomposition of Electrodermal Activity to its components (tonic and phasic). The decomposition was carried out according to the threshold value recommended in the research literature for peak detection of SC data—0.05 micro-siemens (μS)—and was based on Continuous Decomposition Analysis) (Benedek & Kaernbach, 2010).

Fig. 7. Wearing the monitoring devices: TobiiPro 2 and Shimmer3 GSR+ (photo credit: authors; consent obtained from participant).

Metrics for evaluating level of affective arousal include Average Peak Amplitude (measured in micro-siemens [uS]) and Peak Count (Aqajari et al., 2020). These were calculated for the annotated standing points in iMotions. Average Peak Amplitude represents the participants' average amplitude in each standing point. The comparative metric of Peaks per Minute is generated using the Peak Count in each segment and its division by segment duration.

Findings and discussion

Regressions results

To address the first research question—the link between density and congestion, on the one hand, and objective emotional arousal, on the other—a Pearson correlation coefficient was calculated. The objective emotional variables (Avg. Peak Amplitude and Peaks per Minute) were defined as dependent variables; the direct density variables (People Count and People Area) and the indirect density variables (Velocity and Gaze Attention) were defined as independent variables whose influence we wished to examine. Below is a breakdown of the analysis's results for each set of hypotheses. It must be noted that this analysis captures only linear correlations and does not relate to other potential factors that might influence its execution. Fig. 8 presents the results on the hypotheses diagram.

Regarding the first set of hypotheses, $H_{1\text{–}4}$, that state that as the direct density variables rise, objective emotional arousal will increase, the results partially confirm H_1, H_2, and H_4, and reject H_3:

H1. An examination of the linear correlation between number of people (People Count) and Average Peaks per Minute found a moderate positive correlation, $r = 0.322$, $p < 0.05$.

H2. An examination of the linear correlation between number of people (People Count) and Average Peak Amplitude found a moderate positive correlation, $r = 0.446$, $p < 0.01$.

H3. An examination of the linear correlation between People Area and Average Peaks per Minute found a weak positive correlation that was not significant, $r = 0.149$, $p > 0.05$.

H4. An examination of the linear correlation between People Area and Average Peak Amplitude found a moderate positive correlation, $r = 0.396$, $p < 0.01$.

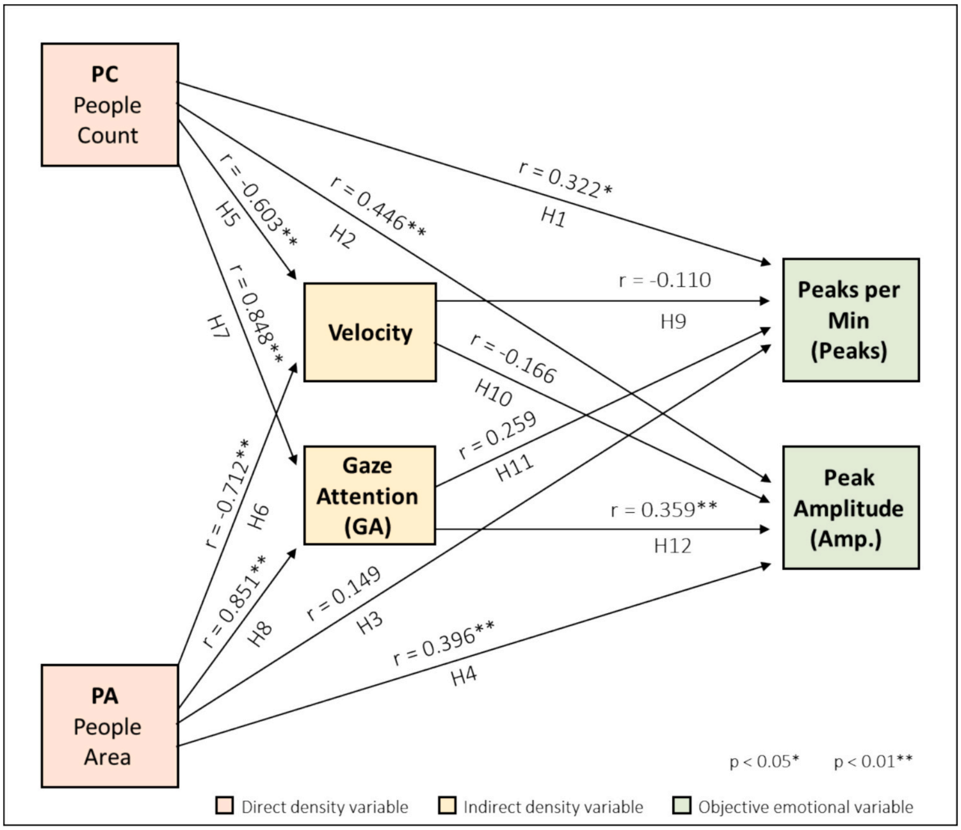

Fig. 8. Results of Pearson correlation coefficients.

These findings indicate that the direct density measures better predict the objective emotional measure of Peak Amplitude than Peaks per Minute. Similarly—and in contrast with the hypothesis—of the direct density measures, a stronger link was found between People Count and Peak Amplitude.

With regard to the second set of hypotheses, $H_{5–8}$, a strong correlation was expected between the direct and indirect density variables. This link was confirmed:

H5. An examination of the linear correlation between People Count and Velocity found a strong negative correlation, $r = -0.603$, $p < 0.01$.

H6. An examination of the linear correlation between People Area and Velocity found a strong negative correlation, $r = -0.712$, $p < 0.01$.

H7. An examination of the linear correlation between People Count and rate of Gaze Attention on people found a very strong positive correlation, $r = 0.848$, $p < 0.01$.

H8. An examination of the linear correlation between People Area and rate of Gaze Attention on people found a very strong positive correlation, $r = 0.851$, $p < 0.01$.

Fig. 9. Illustration of the coping mechanism of gaze displacement in conditions of congestion and density (top: Gaze Attention on the outside of the market; bottom: Gaze Attention on food products).

These findings indicate that the direct density measures are very good predictors of indirect density measures. Of the two indirect measures, Gaze Attention displayed a stronger correlation.

With regard to the third set of hypotheses, $H_{9–12}$, an expected strong correlation between the indirect density variables and objective emotional arousal, the findings confirmed H_{12} but rejected hypotheses $H_{9–11}$.

H9. An examination of the linear correlation between Velocity and Average Peaks per Minute found a weak negative correlation, $r = -0.110$, $p > 0.05$.

H10. An examination of the linear correlation between Velocity and Average Peak Amplitude found a weak negative correlation, $r = -0.166$, $p > 0.05$.

H11. An examination of the linear correlation between rate of Gaze Attention on people and Average Peaks per Minute found a weak positive correlation, $r = 0.259$, $p > 0.05$.

H12. An examination of the linear correlation between rate of Gaze Attention on people and Average Peak Amplitude found a significant moderate positive correlation, $r = 0.359$, $p > 0.05$.

These findings indicate that the indirect density measures do not predict objective emotional arousal well. The only correlation found to be moderate and significant was between Gaze Attention and Peak Amplitude.

Visitors as sensors?

This study employed an integrated and multidimensional methodology to examine the influence of density on emotional arousal. Moreover, it proposed reexamining not only how emotional metrics are collected in tourism research but also the measurement of crowding and density and the connection between the two. The first research question examined the correlations between the different variables measured empirically. The results indicate a strong linear connection between the direct density measures and the indirect ones; this result confirms the hypothesis regarding the use of walking speed (Velocity) and Gaze Attention as measures of crowding and density. It was further found that of the four density measures (direct and indirect), the three gaze-based ones (People Count, People Area, and Gaze Attention) were able to predict objective emotional arousal well, specifically Peak Amplitude, which serves as the most common indicator for evaluating Skin Conductance response magnitude (Boucsein, 2012).

At the same time, the direct density measures displayed better results (a stronger correlation) than the indirect density measure of Gaze Attention, as this variable reflects not only the expected environment but also the individual's visual behavior in relation to the environment. Earlier studies focusing on psychological behavioral dimensions (Jacobsen et al., 2019; Kohlhardt et al., 2018) identified a number of coping mechanisms, such as tourists' physical, emotional, or social displacement, whose goal is to enhance the tourist experience. The current study expands this insight into visual coping mechanisms. To minimize the negative experience that stems from crowding during the market visit, it is evident that some visitors activated the coping mechanism of visual displacement, which was manifested in an unconscious diversion of the gaze. In many cases, it was found that, despite the high crowding conditions of the market, the gaze targets documented were not necessarily human. Visitors displaced their gaze from what was perceived as a disturbance (human gaze targets) to structural, consumer, or external gaze targets (see Fig. 9).

The second indirect density measure, walking speed (Velocity), showed no linear connection with any crowding variables, in contrast with the hypothesis. Two explanations can be given for this. The first explanation, a methodological one, is tied to the way in which the measure is calculated and the sample size: walking speed was calculated as a correlation between the length of the route and the general duration of walking (one measure for each walk). Whereas the rest of the measures (crowding and objective emotional) were measured continuously, in higher resolution, and averaged for each standing point (see Section 3.3). When examining the correlation between walking speed and objective emotional measures, the latter were averaged an additional time to present one value for each walk. This double averaging may have led to an elimination of variability in emotion.

The second explanation is rooted in walking speed's nature as a motor behavioral metric, which can be influenced by personality dimensions and diverse sensory stimuli—not solely by spatial constraints such as crowding and density. The morning walk, for some participants, was documented as slower than the afternoon walks, despite the fact that the latter was characterized by greater crowding. This illustrates the influence of other interfering stimuli on pedestrians' walking speed. While previous research on pedestrian density used walking speed to assess the level of crowding, relying on Fruin's (1970) "Level of Service," the current study indicates a difficulty with this metric and a need for a renewed examination of its use for pedestrian crowding. This aligns with Jia et al. (2022), who called this phenomenon *low density low velocity*.

Furthermore, this finding corroborates the conclusions of earlier studies that determined that quantitative, objective analyses must be supplemented with subjective reports (Li, 2021; Mashkov & Shoval, 2024; Shoval, Schvimer, Tamir, 2018a; Uysal & Sirgy, 2019). Objective and subjective metrics must be compared in order to interpret the results and expose new dimensions regarding the crowding experience, in particular in cases in which there is no congruence between the two. The present study was primarily concerned with the feasibility of the multi-dimensional methodology, and thus, a comparative analysis is beyond its scope.

The second research question asked if and how density and visitors' emotional reactions to it could be objectively and continuously measured. Findings indicate that direct density measures made it possible not only to present the phenomenon continuously and in high resolution, but also to offer a new classification for changing conditions of crowding and density at a destination from the visitor's perspective. Three states can be identified (see Fig. 10). In the first, *no overcrowding*, both direct measures of density are very low (People Area under 10 % and People Count under 2; see lower left-hand quadrant). In the second, *mild overcrowding*, People Area is low

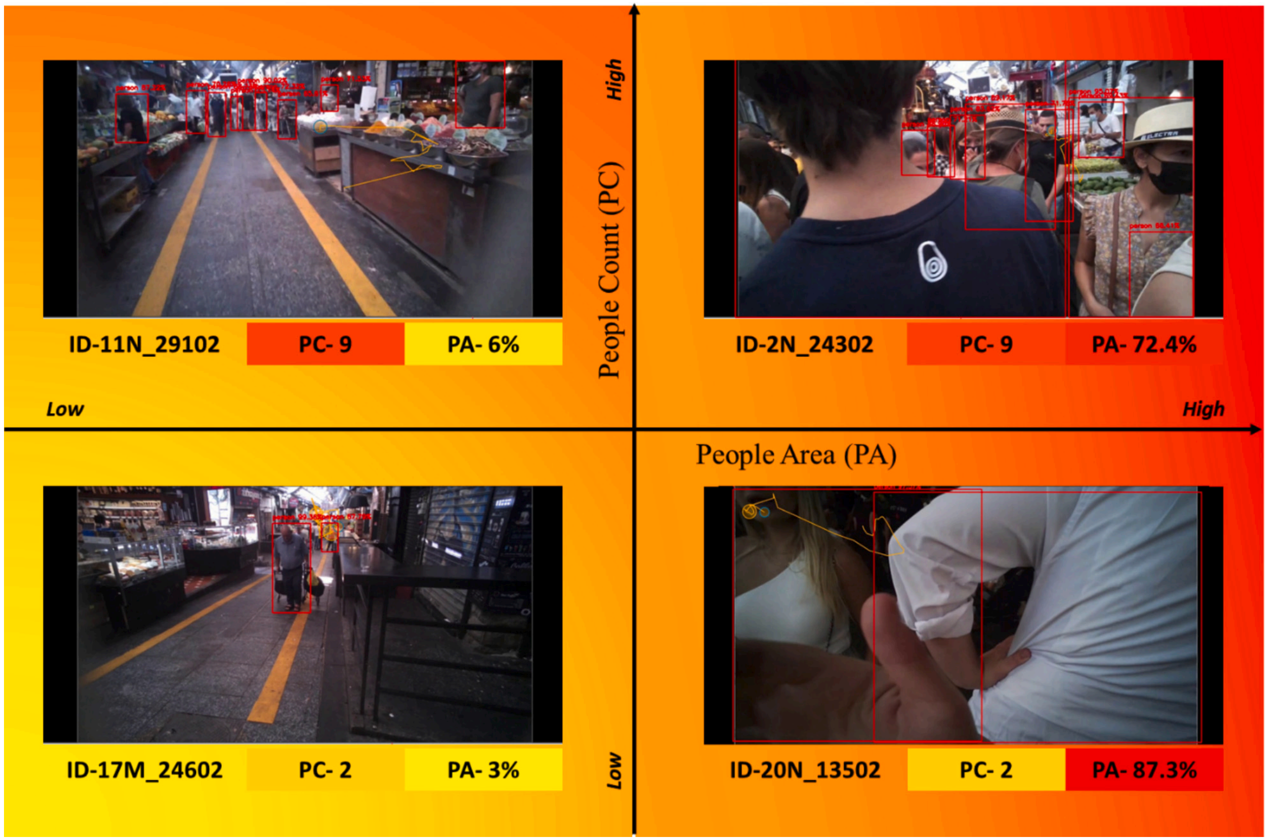

Fig. 10. Classification of overcrowding (bottom left: low People Count and People Area; top left: high People Count and low People Area; bottom right: low People Count and high People Area; top right: high People Count and People Area).

but People Count is high (People Area under 10 % and People Count over 6; see upper left-hand quadrant). Finally, *overcrowding* occurs when People Area values are very high (over 70 %; see right-hand quadrants). This follows what was noted in the previous paragraph: when density is examined from the visitor's perspective, high People Area values will necessarily attest to a state of overcrowding.

Conclusion

Contributions and implications

This study used technological tools innovatively in order to examine the effect of crowding on emotion. In addition, it proposed reexamining the measurement of the way in which emotion is measured in tourism research; the way crowding and density are measured; and the relationship between the two. Unlike earlier studies that attempted to examine the correlations between emotion and crowding using subjective emotional measures and generic crowding measures, the current study applies a multi-dimensional methodology that includes objective emotional and gaze-based measures alongside temporal and spatial data. Gaze is the central sense through which tourists experience destinations (Urry, 1990). Technological advances make it possible to expand research regarding the tourist gaze beyond the theoretical framework as an applied tool that uses the visitors as sensors to evaluate the tourist experience under varying crowding conditions.

To capture the emotional dimension, physiological sensors were used to monitor unconscious emotional arousal. Moreover, two innovative measures for the continuous, precise evaluation of crowding from the visitor's perspective using eye-tracking glasses were presented. Direct density was based on two accepted measures: density and local density (Ji et al., 2022), also known as proximity (Stockdale, 1978). In contrast with traditional measures, this study approach combines the need for objective, unbiased measurement of the phenomenon and the need to take the visitor's perspective into consideration as well, and this is its advantage.

Existing density measures are typically based on visual information collected either actively by surveyors, observers, or passively via fixed or mobile cameras or sensors. Active methods often suffer from a lack of continuity and precision, and are susceptible to bias, while passive methods using cameras generally use a bird's-eye perspective or a vertical view. The current research is the first to propose a "human's-eye perspective," also known as a first-person view, from a horizontal perspective (Fröhlich et al., 2008). This was done not only concerning a binary temporal classification of off-peak and peak hours as has been done in the past (Mashkov & Shoval, 2024) but also continuously, in a moment-to-moment evaluation.

One of the current study's central contributions lies in its innovative approach to measuring crowding and density in urban tourist destinations. In order to better capture the essence of the measures and their unique characteristics as they are extracted from the gaze data, we propose the following names: *Gaze-based Density* and *Gaze-based Proximity*. The two metrics relate to the concentration of people in a specific scene as measured using eye-tracking data. They quantify the intensity of human presence in a defined area based on the place to which people direct their gaze. *Gaze-based Density* counts the human objects in each frame; throughout the article, we referred to it in its simpler form as "People Count". In contrast, *Gaze-based Proximity* measures human presence by calculating the relative area taken up by human objects in each frame, and, accordingly, we called it "People Area".

Understanding tourist experiences and movement patterns is critical for effective tourism management, destination planning, and the overall sustainability of urban tourism. This study provides significant contributions to the tourism sector by offering a multidimensional approach to assessing visitor congestion, density, and experiential quality using physiological sensors and spatial data. While the experiment was conducted on locals rather than tourists, the findings remain highly relevant to tourism studies, as they offer a methodology to gain insights into how individuals navigate and experience urban environments. This methodology also has practical implications for the tourism industry. It informs urban planners and destination managers on how to enhance visitor satisfaction, reduce overcrowding, and improve the design of public spaces to create a more engaging and stress-free experience.

The continuous monitoring of negative emotional responses caused by human crowding can assist destination managers in finding short and long-term solutions. Real-time monitoring can make it possible to manage visitor flows and moderate congestion. In the long term, understanding tourists' spatial, visual, and emotional behavior, both the conscious and unconscious, can benefit a site's management by creating alternate routes adapted to personal preferences, modifying timing, and amending activities to minimize density and crowding. The Gaze Attention measure can also help with the design and development of public areas, improving the quality of the tourist experience quality and residents' lives by identifying the effects of visual stimuli on the emotional experience.

Limitations and future directions

First, methodologically, a key limitation of this study is its reliance on local participants rather than tourists, which may influence results due to differences in familiarity, navigation patterns, and emotional responses to urban environments. The selection of a student population was due to international movement restrictions at the time (the beginning of the fourth wave of COVID-19 in Israel) and was not meant to represent a tourist population but rather to demonstrate the method's feasibility. As both groups share public spaces, the study still provides valuable insights into urban congestion and spatial experiences. The methodology is transferable to tourist experiences, providing a template for assessing visitor interactions in real-world urban settings.

Second, the experiment included only 25 participants and a total of 50 walks. The relatively small number of participants is non-representative, which raises difficulties in concluding about the general population. Future research with tourist populations is necessary to validate and refine the methodology for tourism applications.

Third, each of the three research tools has built-in limitations that must be considered. The GPS used for digital location in space and time is built to receive signals in open areas and is less effective in-built environments (Shoval & Isaacson, 2009). The market route had a light roof, which caused occasional GPS disconnections. We used a fixed route and supplemented the GPS data with gaze-tracking data to minimize data loss. Electrodermal Activity may be considered a leading method for documenting unconscious emotional arousal (Boucsein, 2012). However, other methods—such as body temperature, heart rate, breathing rate, and pupil size—also exist. Future research would do well to integrate several objective emotional measures so that they can validate one another and create a deeper understanding of emotional states (Parikh et al., 2021).

Fourth, the use of physiological sensors and GPS tracking in research raises an ethical question regarding participants' rights, privacy, and protection of personal data collected per the instructions of institutional ethics committees. The study received the necessary ethical approval. All respondents received detailed information about the study and provided their consent to participate by signing a consent form. In the context of gaze-tracking, the privacy of those pictured must also be considered. To address this, a masking process was performed to protect the privacy of individuals captured in images during human detection analysis. The process of gathering information may be passive, but the knowledge that the participant is being tracked, particularly when he or she must wear significant amounts of equipment, may influence his or her emotional and spatial behavior.

Finally, future studies should include the performance of an additional task in which the spatial variable (route) is not fixed but rather free, allowing for spontaneous movement in space. The integration of Social Interference Theory in the experiment, as proposed by Li et al. (2017), can expose additional and new information not only about the effects of overcrowding on emotional arousal but also on visitors' coping mechanisms (e.g., spatial displacement) and the trade-offs they are willing to make for the sake of the overall planned experience.

This study demonstrated how a multidimensional, innovative methodology can be applied to answer questions related to visitors' behavioral patterns at crowded urban destinations. This methodology expands the understanding of the tourists' experience in destinations that suffer from density and crowding, facilitating a study not only of where visitors are and when but also of what they are looking at and hearing and what their affective reaction is to the stimuli around them. We believe that in the not-too-distant future, the "visitor as sensor" methodology will become more available both financially and professionally. Its accessibility will facilitate the broader use of such methodologies in terms of sample size and research scope.

CRediT authorship contribution statement

Rotem Mashkov: Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Noam Shoval:** Writing – review & editing, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Brian Isaac Rizowy:** Software, Methodology. **Uriel Shavin:** Investigation, Formal analysis, Data curation. **Hagar Srulovitch:** Investigation, Formal analysis, Data curation. **Assaf Shwartz:** Writing – review & editing, Software, Resources, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.annals.2025.103976.

Data availability

Data will be made available on request.

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