WHERE IS EMOTION? COMPARING EMOTION MAPPING TECHNOLOGIES

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Understanding how experiences unfold requires measuring participants' emotions, especially as they move from location to location. Measuring and mapping emotions over space is technically challenging, however. While a number of technologies to record and spatially resolve emotion data exist, they have not been systematically compared. We present emotion data collected at a natural and military heritage site in the Netherlands using three different methods, namely retrospective self report, experience reconstruction, and physiology. These data are applied to three corresponding mapping methods. The resulting maps lead to divergent findings, demonstrating that spatial mapping of emotion data accentuates differences between distinct dimensions of emotions.

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1 Introduction

Experiences are a key construct in understanding how people use and value space. *Spaces* become *places* when imbued with social meanings (Tuan, 1977), and such meanings arise from individuals' experiences. Experiences are defined differently by fields such as philosophy and neuroscience, but a common thread in existing definitions is that an experience comprises the conscious content of a person's mind. In this paper we follow the Bastiaansen et al. (2019) theory of experience as a process, in which sensory inputs are filtered through mental models, creating a stream of consciousness in a person's mind. According to Bastiaansen et al. (2019), emotions are crucial in the process of experiencing. Emotions translate the inputs of experience into both memory and behavior. An experiential episode only changes a person's behavior, and is only remembered, if it makes a person emotional. Thus, measuring emotions is crucial to designing and managing experiences.

In recent years, scholars have asserted that experiences should be managed based on measuring participants' emotions, and that emotion data should be spatially visualized in 'emotion maps' to inform management decisions (Mitas, Cuenen, et al., 2020; Mitas, Mitasova, et al., 2020). This paper explores three emotion mapping methods: 1) experience reconstruction maps; 2) emotion physiology maps, and; 3) emotion effectiveness maps. Importantly, no single study has applied all three of these methods to the same context. Thus, little information currently exists to help researchers choose an optimal emotion mapping method to address spatial management demands. The objective of this paper is to **compare and contrast the affordances and caveats of each of these methods of emotion mapping.** Extending previous research, we apply all three emotion mapping methods to the same location for the first time, a Napoleonic fort in the Netherlands which offers visitors both natural and built heritage settings. We acknowledge that this is a primarily methodological objective, with potential theoretical and practical implications playing a secondary role.

2 Background

Measuring experiences with useful spatial resolution is technically challenging. Emotions arise and fade in the mind quickly and unpredictably. Memory and recollection of emotions is biased (Bastiaansen et al., 2019). Therefore, technologies to measure emotion all have limitations. These limitations must also be kept in mind when applying spatial resolution to emotion data.

Bastiaansen et al. (2019) propose the use of emotion measurement technologies from psychology and neuroscience. Their approach enables real-time tracking of emotional reactions through EEG, heart rate, facial expressions, and skin conductance. These may be complemented using more traditional methods of retrospective self report.

2.1 Emotion measuring technologies

2.1.1 Retrospective self-report

Many studies rely on self-reports to measure experiences, whether through post-experience questionnaires and interviews or experience sampling. It is difficult to fully capture emotional ebb and flow with self-report methods. First, they measure memory of the experience rather than the experience itself, which can lead to distortions due to aggregation processes and temporal bias (Tonetto & Desmet, 2016). Second, time resolution by experience sampling, although seen by some as 'real time' measurement, in fact disrupts the natural flow of an experience, particularly in short or immersive settings. Third, self-reports are susceptible to social desirability bias and coping strategies (Larsen & Fredrickson, 1999), while fourth, they fail to capture unconscious emotional processes that play a crucial role in forming memorable experiences (Winkielman & Berridge, 2004). Therefore, existing methods should be complemented with modern research tools from psychology and neuroscience, enabling more precise and comprehensive measurement of emotions throughout experiential episodes (Bastiaansen et al., 2019).

2.1.2 Experience reconstruction self-report

Kahneman et al. (2004) developed the 'day reconstruction method,' a narrative interview at the end of the day that segmented the narrative into several experience episodes, and elicited emotion ratings for each episode. Because the process of narrative interviewing and segmenting is laborious, Strijbosch et al. (2021) developed the experience reconstruction method one step further, identifying obvious episodes (scenes) in a structured experience (a musical) *a priori* and using photos and descriptions to represent these in a questionnaire, eliciting self-report emotion ratings of each.

Experience reconstruction has several important advantages. If limited in scope, it is convenient and fairly low-burden for participants, fitting easily into a post-experience exit questionnaire. It can accommodate a variety of self-report emotion items and formats. If the episodes of the experience represent locations rather than moments in time, it also can produce data with moderate spatial resolution. The method carries limitations as well, however. First, it is still susceptible to social desirability and recall biases, just like retrospective self-report (Bastiaansen et al., 2019) though perhaps less so (Kahneman et al., 2004). Second, it depends greatly on participants understanding and recalling episode or location the researcher is referring to. Third, there is a tradeoff between resolution and participant burden. If more than (approximately) 10 episodes or locations are asked about, there is a real risk of participants getting irritated or bored with the questionnaire, to the extent that the validity of their responses declines.

2.1.3 Physiology

Emotions affect the processes of the human body. Thus, measurement technologies have been under development since the 1960's to capture emotions' physiological manifestations. Physiological measurement technologies can be categorized across two dimensions: central (brain) and peripheral physiology, and measures for lab settings with immobile participants, versus measures that capture emotion even when participants are moving.

While it is technically possible to measure central (brain) physiology while participants are moving, using mobile electroencephalography, muscle activity and the richness of visual stimuli completely overwhelms any signal due to emotion. Thus, central physiological measures of emotion are exclusively the domain of research in a laboratory. Peripheral physiological signals include heart rate, breathing rate, facial electromyography, and skin conductance. Heart rate and breathing rate are dramatically affected by the need of muscles for oxygenated blood, signals due to movement and posture overwhelms any sign of emotion, much as for brain activity. Thus, despite publications reporting heart rate measurements in mobile settings (i Agustí et al., 2019; Kohn et al., 2019; Mitas, Cuenen, et al., 2020), heart rate and breathing rate measurement are also best reserved for lab settings.

This leaves skin conductance as a sole promising pathway to record emotion signals from participants who are moving around. Skin conductance is usually recorded from hands or fingers, where sweat secretion is uniquely responsive to emotional arousal (Braithwaite et al., 2015). By passing a small electrical current between two electrodes attached to palms or fingers, wrist-worn devices such as Shimmer GSR are able to accurately record fluctuations in skin conductance. The resulting signal is precisely time-resolved, and can thus also be spatially resolved, and is completely unbiased by conscious processes.

Skin conductance recording in the field has a robust track record. In the field of leisure, tourism, and hospitality experiences, we refer readers to the systematic review by Li et al. (2022). While previous skin conductance research has uncovered technical affordances as well as theoretical contributions, two important limitations have also come to light. First, while skin conductance on the palms is relatively robust to the physiological effects of physical activity, movement can mechanically affect the skin conductance signal (e.g., by loosening or pressing the electrodes 'into' the sweat). The resulting artifacts must be removed by trained researchers supported by detection algorithms like ArtifactZ (Bastiaansen et al., 2022) or EDAExplorer (Taylor et al., 2015). A second limitation is that skin conductance signal is unidimensional, representing emotional arousal exclusively. Skin conductance contains no information whatsoever about the valence or type of emotion being experienced.

2.2 Spatial resolution of emotion data

2.2.1 Overview

Combining emotion data with spatial data from any of the above sources accentuates, rather than compensates, the limitations of emotion measuring technologies. Emotion maps with any measure of validity are only possible with theoretically sensible combinations of emotion and location measuring technologies. In this paper, we review and illustrate three such combinations: experience reconstruction maps, emotion physiology maps, and emotion effectiveness maps.

2.2.2 Experience reconstruction maps

An experience reconstruction is a set of self-report emotion ratings given by participants after an experience, for each separate episode of that experience. In a spatial context, this means that participants report on their emotions each specific location they visited. A map can use polygons covering areas of interest (AOI) and shade them in different colors based on recalled ratings averaged over participants.

To our knowledge, few if any experience reconstruction maps exist. There are, however, instances of maps based on self-report using data from experience sampling. These are usually organized by municipal governments, such as the Happiness Map of London. A particularly rigorous example is the transportation happiness map of the Minneapolis St. Paul region in the United States. Unfortunately, only a non-reviewed methodological document about this effort exists (Fan et al., 2020). Other examples by Panek and colleagues are noteworthy for addressing transport routes (Pánek & Benediktsson, 2017) as well as neighborhood areas (Panek, 2019). As Pánek and Benediktsson (2017) point out, their maps address correlates of emotional experience, such as aesthetics (e.g., 'ugly') or overall evaluation ('good' and 'bad') rather than emotions themselves. Yet another approach to mapping emotions uses sentiment analysis linked to geolocated social media posts (Gupta, 2018). As with much social media research, however, this approach must include a within-user averaging step, as volume of social media postings is heavily skewed and thus risks creating maps shaped by within-individual autocorrelation.

2.2.3 Emotion physiology maps

Emotion physiology maps comprise a simple visualization of location-resolved emotion physiology measurement, usually skin conductance. Skin conductance measurements from single or (usually) multiple participants are either averaged over a regular (Shoval et al., 2018) or irregular spatial bin, or form the input to a kernel density function (Mitas, Mitasova, et al., 2020), portraying smooth gradients in skin conductance in a given location.

Emotion physiology maps have existed for over a decade. The first examples of which we are aware concerned museum exhibits where Bluetooth signals were used to determine participant location, while skin conductance was measured with a special electrode-filled glove (Kirchberg & Tröndle, 2015). Soon thereafter, several urban studies groups began to record location using GPS alongside skin conductance or heart rate, producing the first emotion physiology maps in outdoor settings (i Agustí et al., 2019; Shoval et al., 2018). Soon thereafter, maps of indoor and outdoor museum tours (Mitas, Mitasova, et al., 2020) as well as roller coasters (Bastiaansen et al., 2022) appeared.

While these studies have been useful for identifying which locations during an experience are associated with the strongest emotional responses, limitations of GPS or Bluetooth location tracking and skin conductance reinforce one another. Skin conductance data is highly skewed and unidimensional, while location tracking data tends to be noisy. Thus, many participants (> 50) are needed to cover a study site with sufficient data so that the map represents true averages of emotional arousal across space. Furthermore, the resulting map affords no information about the emotional valence, content, or effect of the experience. These must be inferred from other data, usually obtained by self-response questionnaires or interviews.

2.2.4 Emotion effectiveness maps

In an attempt to visually integrate skin conductance, location, and self-response data, Mitas, Mitasova, et al. (2020) developed the *emotion effectiveness map*. This map essentially visualizes between-participant correlations between *local* within-participant skin conductance and *retrospective* self-reports. In this map, location-resolved skin conductance data is binned, either in evenly-spaced hexbins or AOI polygons. Within each bin, each participant's average skin conductance is computed. This results in a single number representing each participant's emotional arousal within each bin. A Pearson product-moment correlation of emotional arousal within each bin to each participant's self-response on a questionnaire item, for example emotional valence, is then computed. The outcome of these calculations is a correlation coefficient for each spatial bin, representing the between-participant relationship of retrospective self-reported emotion valence to emotional arousal within that bin. On the map, color indicates the direction and strength of the correlation coefficients within each bin.

The resulting map visualizes spatial differences in between-participant associations between momentary emotional arousal and self-reported valence. In other words, it shows *where* individuals with a more positive overall experience felt stronger emotions, and where they felt milder emotions. Besides conveying richer information, a second strength of emotion effectiveness maps is that in principle, they can be implemented with various self-reported experience evaluations besides valence. Mitas, Mitasova, et al. (2020) used intent to recommend for example, while Mitas et al. (2024) used self-reported connection with nature. Given that multiple methods exist of spatially resolving emotion data, each with inherent strengths and limitations, the objective of this paper is to compare and contrast the affordances and caveats of each of these methods of emotion mapping. In this paper we take the three methods presented here—experience reconstruction maps, emotion physiology maps, and emotion effectiveness maps—and for the first time, apply all three methods to the same location. In doing so, we answer the following questions:

- What are the relative affordances and limitations of experience reconstruction maps, emotion physiology maps, and emotion effectiveness maps?
- How do portrayals of an experience offered by reconstruction maps, emotion physiology maps, and emotion effectiveness maps differ?

It is worth noting that these data may also be compared *statistically*, as already demonstrated in comparisons of skin conductance to experience reconstruction (Strijbosch et al., 2021) and spatial change in skin conductance compared to spatial change in emotion effectiveness (Mitas, Mitasova, et al., 2020). The present paper focuses instead of *graphical representation* of data on maps. The implications of differences between statistical and graphical representations will also be touched on, though graphical representations remain the focus of the current inquiry.

3 Methods

The present study is based an intercept sample at a park-like fort site in the Netherlands, where we combined intake and exit questionnaires with mobile GPS location and skin conductance recording to collect data.

3.1 Data collection and sampling

We collected data at Fort Sabina, in the southwest of the Netherlands, on 14 and 15 September, 2024. We asked each visitor entering the site on foot from the main parking lot during opening hours if they would be willing to participate. We obtained informed consent according to procedures under approval TSB-RP698 of the University of Tilburg ethics committee. We asked participant who gave their consent to fill out an intake questionnaire on a tablet, and fitted them with sensors to measure their location and emotion arousal. Subsequently they were welcome to visit the fort as they had normally intended to. Finally, when they completed their visit and prepared to leave the site, we collected the sensors from them and asked them to fill out an exit questionnaire. Of 75 participants who provided data, either questionnaire, wearable, or GPS data were missing for 20 participants, making for a final sample of 55 participants. The primary technical error leading to missing data involved researchers accidentally turning off or on recording on a device at an unintended moment (e.g., turning recording off instead of on at the beginning of a visit). As such, participants with missing data are unlikely to have had a different experience from those who provided complete data.

3.2 Passive mobile sensor measures

To record location, we lent participants a smartphone with the popular workout application Strava that recorded GPS location once per 2 seconds. We separately up-sampled latitude and longitude data from 0.5 Hz to 16 Hz, the frequency of processed skin conductance data, using linear interpolation.

To measure skin conductance as a proxy for emotional arousal, we used Shimmer GSR+ wristbands to measure skin conductance, a proxy for emotional arousal, at 64 Hz. The wristband records skin conductance from 2 wires which attach to pre-gelled electrodes worn on the fingers. The skin conductance signal was cleaned from motion artifacts using the ArtifactZ function of the Breda Experience Lab Toolbox (Bastiaansen et al., 2022), then downsampled to 16 Hz. Tonic changes in the signal due to temperature and wearing of the device were filtered out using deconvolution (Benedek & Kaernbach, 2010). Skin conductance signals were also Z-standardized to cancel out differences in skin responsiveness between participants.

3.3 Self-report measures

3.3.1 Emotion before and after visit

We used self-report questionnaires to measure participants' emotional state at the beginning and end of their visit. In the pre-visit questionnaire, we asked participants to rate to what extent they felt each of a list of emotions "right now." In the post-visit questionnaire, we asked them to recall to what extent they had experienced each emotion "during their visit." Both questionnaires included an identical 5-point response scale ranging from "not at all" to "extremely," and an identical list of 12 emotions based on the SPANE (Diener et al., 2010) including positivity in general, negativity in general, and several specific positive and negative emotions such as joy, contentment, anger, and sadness. As intended by the design of the SPANE, we computed an average of positive items to create a positive emotion index. We omitted negative emotions from the current analysis.

3.3.2 Experience reconstruction

We selected 6 locations as being clearly recognizable and likely to be visited by many, though not all, visitors. We photographed each location from an angle a visitor would be likely to see and recognize. Photos and names of each location were included in the exit questionnaire. For each location, we asked participants to recall and rate how they felt while there on two 5-point semantic differential items reflecting valence (»very negative« to »very postivie«) and arousal (»calm« to »excited«). This implementation of experience reconstruction has been validated in previous research (Strijbosch et al., 2021).

4 Findings

4.1 Descriptive findings

The 55 visitors to Fort Sabina spent an average of 70 minutes at the site. Their self-reported positive emotions were mild before (mean = 2.77, sd = 0.71) and elevated after (mean = 3.27, sd = 0.65) their visit.

4.2 Mapping the data

4.2.1 Experience reconstruction map

To create the experience reconstruction maps (Figure 1), we first created polygons to correspond with the approximate extent of each of the locations addressed by photo-questions in the questionnaire. This polygon layer was visualized over a base map layer. For each location, responses to the valence item (»negative« to »positive«) were averaged together. Polygons were colored according to the percentile rank of their average valence, so the most positive-average locations were colored yellow, and the least positive-average locations colored blue. The resulting map showed that the area in front of the cafe is the most positively-rated of the fort, while the high wall facing the esturary on the west side of the fort, featuring five large gun installations, was the least positively rated. Incidentally, this western wall is also rated as the least arousing. The exhibitions at the eastern side of the barracks were rated as the most arousing.

Figure 1: Experience reconstruction maps of Fort Sabina (valence left, arousal right)

Note: Yellow indicates highest ratings of arousal and valence; blue indicates lowest ratings of arousal and valence.

Source: Authors

4.2.2 Emotion physiology map

Based on the high resolution of GPS and skin conductance data, a hexbin visualization with relatively small hexbins of 6 meters—following a heuristic of two times the typical margin of error for GPS—was chosen. Thus, the visualization aimed to balance the noise-to-signal ratio of spatially resolved skin conductance data, keeping noise in both skin conductance and GPS in mind. Our emotion physiology map (Figure 2) shows several distinct areas of relatively high arousal. The largest covers the entire cafe area, extending to the back of the barracks and exhibition space, and outside over the northern wall of the fort, where visitors can climb for the views of the landscape and the delapidated fort warehouse across the road. On the right side of Figure 2, we also averaged skin conductance over the same AOI as the emotion effectiveness map.

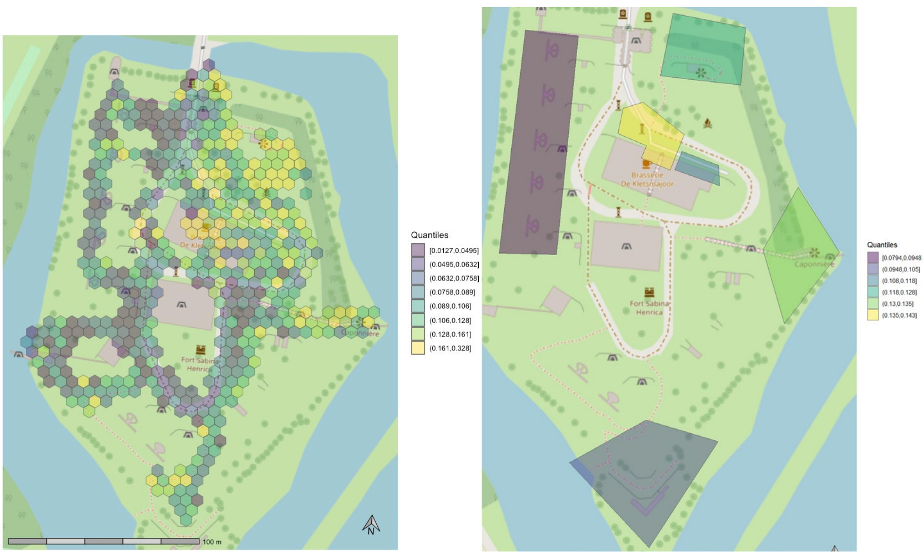

Figure 2: Experience physiology maps of Fort Sabina (6 meter hexbin left, AOI right)
Note: Yellow indicates highest quantiles of arousal; blue indicates lowest quantiles of arousal.
Source: Authors

4.2.3 Emotion effectiveness map

The emotion effectiveness map is based on the same data as the emotion physiology map, but subsequent steps to the data analysis are added. Instead of all skin conductance data being averaged within each bin, regardless of participant, skin conductance data are instead averaged within each bin, within each participant. A filter is used to exclude bins with fewer than 5 participants. Then, a correlation coefficient is computed between the average skin conductance within each hexbin and self-reported positive emotion change from before to after the visit. These correlation coefficients therefore represent the between-participant relationships between skin conductance within each hexbin and positive emotions recalled from the experience as a whole. This procedure leads to a map with implausible differences, from very positive to very negative correlations, in adjacent hexbins. Emotion does not plausibly swing from very positive to very negative in an average participant from meter to meter. Thus, the size of the hexbin is incrementally increased (in this case to 12 meters) until most abrupt adjacent differences in correlations disappear. As a final step to compare the emotion effectiveness map with the emotion reconstruction map, the procedure was applied to the six AOI polygons used to visualize the experience reconstruction map (Figure 3).

Figure 3: Emotion Effectiveness Maps of Fort Sabina (10 meter hexbin left, AOI right)

Note: Blue and dark green correlations are negative; Yellow and light green are positive.

Source: Authors

The resulting emotion effectiveness maps show somewhat differing areas of emotion effectiveness, depending on if correlations are computed over hexbins or AOI polygons. The hexbin map suggests the entrance bridge, the passage to the back of the barracks, and part of the grassy north-eastern wall are locations where the most positive emotion was associated with the greatest arousal. In other words, in these places, participants with higher arousal reported feeling more positive afterward. The eastern caponniere, the northwest corner of the fort wall, and the western section of the barracks show the most negative correlations between arousal and later self-reported positive emotion. In terms of AOI's, all show a positive correlation between arousal later self-reported positive emotion, except the southern double caponniere. The highest positive correlation, as the highest self-reported valence and the highest physiological arousal, occurred at the cafe.

5 Discussion

We visualized emotion data using recalled and reconstructed self-report, as well as wearable physiological meaurement, using three different approaches to spatial resolution of emotion data. The goal was to compare and evaluate existing technologies for mapping emotion in terms of their affordances and limitations. While developments such as wearables to measure physiology afford new possibilities, they also introduce new caveats which must be considered in their application. Our maps show that each of the mapping techniques studied is useful, albeit in different situations. This is an important contribution to academic efforts at emotion mapping, as most previous studies visualized one (Shoval et al., 2018) or at most two (Mitas, Mitasova, et al., 2020) of these maps as the »best« visualization with existing technology. Furthermore, we were able to explain *how* these different map portrayals of emotion over space differ.

5.1 The value of physiology maps

Emotions are multidimensional by definition (Rosenberg, 1998) and physiology is just one of these many dimensions, which related to but not identical to other dimensions (Mauss & Robinson, 2009). A skin conductance recording is therefore no more or less »true« than any other emotion recording. It indexes physiological arousal from emotion, no more and no less. The emotion physiology maps in the present study demonstrate that this metric can be combined with GPS data for a precise, but unidimensional map of individuals' emotional experience across locations. It is clearly visible where participants became emotional on average, and to what extent, but not why, with which emotion, and with which consequence. Therefore, our maps show that an emotion physiology map might be best when researchers would like to know exactly where and when individuals become emotional as they visit a site. In practical contexts, a skin conductance map is therefore useful when a manager has a fairly clear idea of *which* emotions their participants feel during a visit, but not *where* these emotions become the most intense.

Thus, important emotion dimensions such as valence and action tendency (Fredrickson, 1998) are not present in this map. It follows that emotion physiology maps are not useful when researchers would like to know *in what way* participants became emotional. This is especially important as in the current dataset, the physiology maps had more in common with the self-report-based experience reconstruction maps of *valence* rather than arousal. This apparent discrepancy could be due to recall bias or to misinterpretation of self-report item wording by participants, but this is merely conjecture. Such conjecture highlights that a physiology map must be viewed as a rather unidimensional portrayal of emotion, precise in resolution but minimal in content. It cannot be interpreted without companion self-report data or companion knowledge from previous research.

5.2 The *added* value of emotion effectiveness maps

To directly address the limitation that physiology maps show no emotional content besides arousal, emotion effectiveness maps visualize correlations between momentary physiology and retrospective self-report. As such, they add some emotional content to the visualization, by showing where higher arousal was associated with, in our example, a more emotionally positive experience overall. Previous emotion effectiveness maps instead looked at correlations with experience evaluations (Mitas, Mitasova, et al., 2020). Thus, we extend previous research by linking two different dimensions of emotion—momentary arousal and recalled valence—in a single map, a more coherent outcome than momentary arousal and evaluation, which is an outcome rather than a component of emotion.

Adding a second dimension of emotional experience to physiology maps has clear added value, because stakeholders can now see where something positive and emotional was occurring, and where something was not working well. For this added value, emotion effectiveness maps present tradeoffs. First, the spatial resolution and coverage both decrease, necessarily, as the data represent correlations in between-participant variation. Also, the visualization does not control for within-participant autocorrelation. Thus, the map may show different effects than multilevel statistical models, with the latter being a truer representation of within participant development. Statistical analyses of the present data are beyond the scope of this article, but such analyses in conjunction with emotion effectiveness maps have been conducted in previous studies (Mitas, Mitasova, et al., 2020).

Managers can use emotion effectiveness maps when they have at least anecdotal knowledge of the site and which emotions visitors generally experience, but would like to have a heuristic of locations which work »well« or »less well.« However, here also they need to be aware of whether each location is generally negative or positive for the average visitor, and which stimuli at that site might be dominant in triggering emotions.

5.3 Caveats

When synchronizing emotion and location data, there is often an unstated assumption that something about the location triggers emotions in participants. That is, the location contains stimuli which make people emotional, such as a beautiful building or a busy crowd (Bastiaansen et al., 2019). Since maps show participants averaged together, it is reasonable to assume that individual variations unrelated to location such as a participant having an argument with their partner, while another participant becomes hungry, and so forth, are averaged out. However, it cannot be assumed that peaks in emotion in the average participant shown on the map are triggered by any specific physical feature of that location. For example, we saw relatively high emotion at entrance/exit gates of the fort. These may have been triggered by the massive gatehouse, but also the concealing and revealing of the beautiful grassy lawn around the barracks. It is obvious but worth reiterating: emotion maps link emotion to location, not to a specific stimulus.

Second, as noted in the caveats applying to emotion effectiveness maps, mapping data is not the same as analyzing it statistically. This means that differences between locations or participant groups, or even correlations between emotion signals, remain untested against their standard errors to determine statistical significance. While this information could be useful to both researchers and practitioners, there is another more serious limitation to merely mapping without statistical modeling, namely that within-participant autocorrelation is not controlled for. This is especially a problem for emotion physiology and experience reconstruction maps, where there is no between-participants variable brought to bear on within-paticipant effects. As Mitas, Mitasova, et al. (2020) demonstrate, the conclusions implied by an emotion effectiveness map and an appropriate multilevel model can be similar, but are not identical.

The third major caveat is that emotion is multidimensional, and to say that one place is more »happy« than another ignores the need to specify which *dimension* of emotion the »happy« is referring to. Is it »happy« because individuals express many positive emotional words in their verbal expressions there, or because they recall having been happy there when asked at the end of the day? We know from Zajchowski et al. (2016) and Mauss and Robinson (2009) that these comprise separate dimensions of the complex phenomenon of emotion. With the current findings, showing that maps based on self report and physiology lead to different visualizations and different conclusions, we extend these theoretical distinctions to emotion mapping. Our contribution is to assert that there is no one »emotion map« or »happy map.« Rather, multiple valid »emotion maps« are possible, each with a different ideal use case.

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References

Bastiaansen, M., Lub, X., Mitas, O., Jung, T. H., Passos Acenção, M., Han, D., Moilanen, T., Smit, B., & Strijbosch, W. (2019). Emotions as core building blocks of an experience. *International Journal of Contemporary Hospitality Management*, *31*, 651-668.

Bastiaansen, M., Oosterholt, M., Mitas, O., Han, D., & Lub, X. (2022). An emotional roller coaster: Electrophysiological evidence of emotional engagement during a roller-coaster ride with virtual reality add-on. *Journal of hospitality & tourism research*, *46*(1), 29-54.

Benedek, M., & Kaernbach, C. (2010). Decomposition of skin conductance data by means of nonnegative deconvolution. *Psychophysiology*, *47*(4), 647-658.

Braithwaite, J. J., Watson, D. G., Jones, R., & Rowe, M. (2015). *A Guide for Analysing Electrodermal Activity (EDA) & Skin Conductance Responses (SCRs) for Psychological Experiments*.

Diener, E., Wirtz, D., Tov, W., Kim-Prieto, C., Choi, D.-w., Oishi, S., & Biswas-Diener, R. (2010). New well-being measures: Short scales to assess flourishing and positive and negative feelings. *Social Indicators Research*, *97*(2), 143-156.

Fan, Y., Ormsby, T., Wiringa, P., Liao, C.-F., & Wolfson, J. (2020). Visualizing Transportation Happiness in the Minneapolis-St. Paul Region.

Fredrickson, B. L. (1998). What good are positive emotions? *Review of general psychology*, *2*(3), 300-319.

Gupta, N. (2018). *Exploring happiness indicators in cities and industrial sectors using Twitter and Urban GIS data* University of Warwick].

i Agustí, D. P., Rutllant, J., & Fortea, J. L. (2019). Differences in the perception of urban space via mental maps and Heart Rate Variation (HRV). *Applied Geography*, *112*, 102084.

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, *306*(5702), 1776-1780.

Kirchberg, V., & Tröndle, M. (2015). The museum experience: Mapping the experience of fine art. *Curator: The Museum Journal*, *58*(2), 169-193.

Kohn, L., Dastageeri, H., Bäumer, T., Moulin, S., Müller, P., & Coors, V. (2019). *Hot or not – identifying emotional "hot spots" in the city* 3rd International Conference on Smart Data and Smart Cities, Delft, Netherlands.

Li, S., Sung, B., Lin, Y., & Mitas, O. (2022). Electrodermal activity measure: A methodological review. *Annals of tourism research*, *96*, 103460.

Mauss, I. B., & Robinson, M. D. (2009). Measures of emotion: A review. *Cognition & emotion*, *23*(2), 209-237.

Mitas, O., Cuenen, R., Bastiaansen, M., Chick, G., & van den Dungen, E. (2020). The War from both Sides: how Dutch and German Visitors Experience an Exhibit of Second World War Stories. *International Journal of the Sociology of Leisure*, *3*(3), 277-303. https://doi.org/https://doi.org/10.1007/s41978-020-00062-3

Mitas, O., Mitasova, H., Millar, G., Boode, W., Neveu, V., Hover, M., van den Eijnden, F., & Bastiaansen, M. (2020). More is not better: The emotional dynamics of an excellent experience. *Journal of hospitality & tourism research*, 1096348020957075.

Mitas, O., Wielenga, B., Evers, K., Farkić , J., Ward, D. P., Klijs, J., & Bastiaansen, M. (2024). *Relaxing or exciting? Mobile emotion recording in natural settings.* 37th Bled eConference., Bled, Slovenia.

Panek, J. (2019). Emotional and subjective volunteered geographical information. In *Crowdsourcing: Concepts, Methodologies, Tools, and Applications* (pp. 1347-1362). IGI Global.

Pánek, J., & Benediktsson, K. (2017). Emotional mapping and its participatory potential: Opinions about cycling conditions in Reykjavík, Iceland. *Cities*, *61*, 65-73.

Rosenberg, E. L. (1998). Levels of analysis and the organization of affect. *Review of general psychology*, *2*(3), 247-270. https://doi.org/https://doi.org/10.1037/1089-2680.2.3.247

Shoval, N., Schvimer, Y., & Tamir, M. (2018). Real-time measurement of tourists' objective and subjective emotions in time and space. *Journal of Travel Research*, *57*(1), 3-16.

Strijbosch, W., Mitas, O., van Blaricum, T., Vugts, O., Govers, C., Hover, M., Gelissen, J., & Bastiaansen, M. (2021). When the parts of the sum are greater than the whole: Assessing the peak-and-end-theory for a heterogeneous, multi-episodic tourism experience. *Journal of Destination Marketing & Management*, *20*, 100607.

Taylor, S., Jaques, N., Chen, W., Fedor, S., Sano, A., & Picard, R. (2015). Automatic identification of artifacts in electrodermal activity data. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC),

Tuan, Y.-F. (1977). Space and place: The perspective of experience. *U of Minnesota P.*

Zajchowski, C. A., Schwab, K. A., & Dustin, D. L. (2016). The Experiencing Self and the Remembering Self: Implications for Leisure Science. *Leisure Sciences*, 1-8.